WORKING PAPERS

N° 1189

February 2021

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Coronavirus and Social Distancing: Do Non-Pharmaceutical-Interventions Work (at least) in the Short Run?*

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Abstract

Using detailed daily information covering 100 countries and an event-study approach, we estimate the short run effects of implementing Non-Pharmaceutical Interventions (NPIs) on the spread of the COVID-19 virus at the early stages of the pandemic. We study the impact of two NPIs –stay-at-home requirements and workplace closures– on three outcomes: daily residential and workplace mobility; the daily growth rate of cases; and the daily growth rate of fatalities. We find that immediately after NPIs were implemented, mobility declined by 0.2 standard deviation (SD), and two weeks afterwards it was down by 0.7 SDs. 25 days after the NPIs were implemented, the daily growth rate of cases and deaths was lower by 10% and 8.4% respectively. Our results reveal that between 53 and 72 percent of the reduction of the daily growth rate of cases and deaths associated with a reduction of mobility is caused by NPIs.

JEL Classification: I12, I18, I38.

Keywords: COVID-19, Non-Pharmaceutical Interventions, Pandemic.

*We thank Thomas Van Casteren and Philippe Choné for their useful recommendations. Usual caveats apply.
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1 Introduction

On the 31 December 2019, the World Health Organization was informed by Chinese health authorities about unknown viral pneumonia cases in Wuhan, in the province of Hubei. Since then, the novel coronavirus SARS-CoV-2 (or COVID-19 hereafter) has spread quickly all over the world. By January 22th 2021, more than 98 million cases were reported worldwide, causing more than 2 million deaths.[1] Since the beginning of the COVID-19 epidemic, almost all countries have implemented measures to mitigate COVID-19 consequences. Because at the outset of the epidemic there was no vaccination available, and on the other hand, no medicine have been encountered to be totally efficient against the COVID-19 yet, governments had to rely on the so-called Non-Pharmaceutical Interventions (NPIs). Basically, these mitigation strategies consist in reducing social interactions by limiting mobility in order to slow down the spread of the virus and avoid the collapse of healthcare systems. In this research we study the short-run effects of the two most common NPIs implemented, stay-at-home requirements and workplace closures, on both mobility and the epi-curve.

There is no doubt that social distancing policies have contributed to deepen the economic outcomes by slowing down the domestic production process. Due to the economic recessions observed in most countries, which are partly caused by lockdown policies (Alfaro et al., 2020), and acknowledging that several waves of lockdown can be expected to control the virus resurgence and its variants, it is crucial to have a better understanding of these social distancing policies impacts on the epi-curve. Indeed, while most countries have undertaken NPIs with the explicit objective to alter the epi-curve despite the almost certain dramatic economic repercussions, it is worth to remark that very little is known about their real sanitary impacts.

We use country-specific daily information on cases and deaths from COVID-19, measures of daily residential and workplace mobility, and the exact date in which countries first implemented NPIs to estimate the effect of these policies on the spread of the virus at the early stages of the pandemic. In particular, we compare mobility trends, the growth rate of COVID-19 cases, and the growth rate of COVID-19 deaths before and after the implementation of either stay-at-home requirements or workplace closures, focusing on short windows around the time each policy was enacted for the first time. Our focus on short-run effects of NPIs upon the arrival of the virus

[1] Numbers taken from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU).

allows us to avoid confounding the impact of these measures with other interventions made over time, such as improvements in the capacity of the healthcare system, testing capacity, or even learning about how to better treat the disease.

The variation we use for identification comes from cross-country differences in the date in which the NPIs were implemented within geographically defined regions, which are mostly determined by the arrival date of the virus to each country. We first show that there is a very strong negative correlation between the date of the first reported case or death and the time it took a country to implement NPIs. Countries were the virus arrived later benefited from observing the experiences of those hit early, and implemented NPIs much sooner. We further show that differences in the speed of the policy response at the outset of the pandemic are unrelated with observable characteristics that might be predictive of a faster policy reaction, and varied only as a function of the arrival date of the virus. Since the global spread of the virus was very fast and happened mostly over a period of a few weeks in the month of March, we argue that differences in the exact date in which the virus arrived to a country within a region is plausibly exogenous. To support this assumption, we provide evidence that the identification assumption holds from the absence of policy effects prior to the policy implementation, which implies parallel pre-treatment trends.

There are three main takeaways from our results. First, there is a sharp increase in residential mobility, a measure of the time spent at home, and a decline of workplace mobility, immediately after the implementation of NPIs. We first show that mobility was already changing prior to the implementation of the NPIs, but that this trend was accelerated once the policies were enacted. For example, the day after the stay-at-home requirements were imposed, residential mobility increased on average by 0.20 standard deviations; three days after it was up by 0.44 standard deviations; and by day 15 the effect peaked at 0.7 standard deviations. We observe effects of a similar magnitude but of opposite direction when looking at workplace mobility, and similar effects as well when considering workplace closures. This suggests the NPIs did have a strong effect in limiting social interactions at the early stages of the pandemic.

Second, there is a significant reduction in the rate of growth of daily cases and deaths from COVID-19 after NPIs are implemented. Ten days after stay-at-home requirements are imposed the growth rate of cases is estimated to be 6.1% lower; 15 days after the growth rate is 8.6% lower; and by day 25 the growth rate is 10.0% lower. There is also a significant reduction in the rate of growth of daily deaths by COVID-19, although the effects appear with a lag, something that is expected given the incubation period of the virus. By day 20 after NPIs are imposed, the daily death rate is lower by 6.1%, and by day 25 the rate is down by 8.4%. Given that that we are dealing with daily growth rates, these estimates suggest that NPIs have the capacity to slow-down the spread of the virus very rapidly, effectively flattening the epi-curve in the short run.

The third main takeaway concerns the effect of mobility on the rate of growth of cases and deaths in the short-run. The mechanism through which NPIs flatten the epi-curve is by reducing mobility and thus lowering the probability of social interactions and thus of contagion. But our data, as well as other studies (Cronin and Evans, 2020), indicate that mobility started to slow down in countries that imposed lockdowns before the implementation of such policies. To measure correctly the impact mobility on public health outcomes, we need to disentangle the fraction of the mobility reduction that is spontaneous, *i.e.* that would have occurred without the different NPIs adopted, and the fraction that can be imputed to NPIs' implementation. For this, we use our reduced-form estimates of the impact of NPIs on mobility to scale the overall effect of mobility on the daily growth rate of cases and deaths, in what is analogous to a two-step instrumental variables approach.

Our results show that a decline of one standard deviation in the mobility index leads to decline in the daily rate of change of cases 20 days afterwards of between -15.2 and -20.8 percent, depending on the NPI and the mobility index considered. Furthermore, a decline of a similar magnitude in mobility leads to a fall in the daily rate of change of deaths 35 days afterward of between -6.2 and -8.6 percent. These results imply that between 53 and 72 percent of the reduction of the daily growth rate of cases and deaths associated with changes in mobility are accounted by the effect of NPIs.

2 Literature review

A rapidly emerging literature has begun to analyse the short-run health effects of NPIs and social distancing policies over the world, with a regional or a cross-country perspective.

Born et al. (2020) conduct a counterfactual lockdown scenario for Sweden applying a synthetic control group method applied to 30 countries of the European Union. They consider a lag of one month after lockdown and find that counterfactual Sweden did not differ from the actual infection dynamics observed in Sweden. They suggest that impact of lockdowns is limited due to the voluntary precautions taken by people. However, Cho (2020) with a similar approach but considering a longer lag find that lockdowns have been effective, suggesting that infection cases in Sweden would have been reduced by almost 75 percent with stricter containment policies. This finding is interesting but this longer lag complicates the causal identification since the COVID-19 policies have not been randomly assigned, and, in some cases, governments' policies were in direct response to specific epidemiological conditions. Due to that, we rather focus on a shorter lag and we use a mobility indicator as instrument variable. It is worth to remark that, despite we consider a shorter length, our results go to a similar direction than Cho (2020).

Dave et al. (2020) study the impact of Shelter in place orders (SIPOs hereafter) between March 19 and April 20, 2020, in 40 States plus the District of Columbia on health outcomes. They use using daily State-level social distancing data from SafeGraph (population movement data set recorded from smartphones) and apply a difference-in-difference estimation. Their results show that adoption of SIPO was associated with a 5 to 10 percent increase in the rate at which State residents remained in their homes full-time. These authors address the potential endogeneity by using data on testing from the COVID Tracking Project. After three weeks following the adoption of a SIPO, they find that this mobility reduction is associated to a cumulative COVID-19 related cases drop by 44 percent even though this average impact masks important heterogeneity across States. In particular, they point out that benefits obtained from SIPOS' implementation is higher for early adopters and high population density States. Regarding mortality, they find a reduction but disclaim none of these estimates are statistically distinguishable from zero at conventional levels. Differently, our cross-countries approach reveal that lockdowns policies are associated to lower mortality.

Dave et al. (2020) use more comparable data than us since their geographical analysis are based at a regional or country levels. They take advantage of their country approach to measure the impact of NPIs on mobility reduction, and in turn, on health outcomes. As Born et al. (2020) and Cho (2020), we focus on cross-country data. Thus, we benefit from a higher heterogeneity, but at the same time, we have to be more cautious on variables measures to ensure their comparability.

Our approach stands out of the previously cited articles since we rely on a worldwide panel analysis to assess the average impact of NPIs on the growth rate of the COVID-19 related cases and deaths. We restrict our analysis to *stay-at-home* and workplace closure policies. We rely on a flexible approach without relying on hypothesis on some parameters of the epidemic dynamic that is influenced by behavioural issues that are difficult to control. Using restrictive countries and times fixed effects allow us to dismantle an important part of country's and epidemic dynamic's heterogeneity. Finally, focusing on the short-run impact of the NPIs allows us to use the discontinuity of the mobility induced by those policies as an instrument variable.

3 Data

We use three main sources of data for the analysis. First, we take the country-specific daily number of COVID-19 related cases and deaths from the publicly available reports of the European Center for Disease Prevention and Control (ECDC). The ECDC collected this information on a daily basis from reports from health authorities worldwide, screening more than 500 relevant sources. The data is validated using the ECDC's standard epidemic intelligence process designed to detect and assess current and emerging threats to human health from communicable diseases. The sample contains information for 182 countries between January 1 and July 19 of 2020. We limit the time span of the analysis because our focus is on the effect of NPIs at the outset of the epidemic in each country. By mid-May, the virus was already present in all the countries in our sample.

Second, we use data collected by the Oxford COVID-19 Government Response Tracker (OxCGRT) on 19 indicators of government responses, including containment and closure policies, economic policies, and health system policies. The data is collected from publicly available sources such as news articles and government press releases and briefings. These are identified via internet searches by a team of over one hundred Oxford University students and staff. OxCGRT records the original source material so that coding can be checked and substantiated (Hale et al., 2020). The data includes daily records on new policies implemented, as well as those that remained active, in each country, as well as a measure capturing their degree of stringency.

To keep the analysis manageable, we focus on the two most common, encompassing, and potentially more economically disruptive NPIs implemented across the sample of countries:

stay-at-home requirements and workplace closures.[2] Stay-at-home requirements are supposed to prevent people from leaving their homes, with minimal exceptions like daily exercise, grocery shopping, and "essential" trips. Workplace closures are requirements to close (or work from home) all-but-essential workplaces (*e.g.* grocery stores, doctors). We restrict the analysis to countries that had implemented either stay-at-home requirements (100 in total) or workplace closures (96 in total) at some point during the sample period. Two caveats are worth to stress. In some cases, the measures are implemented at a sub-national level, but not at the country level. In those situations we record the policy as being active for the entire country. If the NPIs are effective, this could potentially introduce an attenuation bias to our estimates. Second, the degree to which the policies are enforced might differ across countries. If the policies are implemented but in practice there is no enforcement, they might be less effective. Yet, this would potentially introduce an attenuation bias to the estimates, and indicate that the effects might be better interpreted as an intention-to-treat effect.

The third source of data is Google's COVID-19 Community Mobility Reports. Using anonymised data provided by apps such as Google Maps, the company has produced a regularly updated dataset that shows how populations' movements have changed throughout the pandemic. In particular, the dataset contains measures of visitor numbers to specific categories of location like workplaces, grocery stores, parks, and train stations. It also includes a measure of the duration of time spent at the place of residence, called residential mobility. Each measure is constructed as a daily index defined relative to a baseline value that is specific to each geographical location and day of the week. Baseline days are meant to represent a normal value for that day of the week and are defined as as the median value over the five-week period from January 3rd to February 6th 2020.

We focus on two mobility measures in our analyses: residential mobility and workplace mobility. These two measures have a direct relation with the two NPIs considered, stay-at-requirements and workplace closures, so that they are likely to be the most responsive to these two policies. Moreover, work and home are the two places that people are most likely to visit or spend time on a regular basis, so that they can adequately capture changes in mobility patterns. Note that by the way it is defined, an increase in residential mobility should be interpreted as

[2]Other NPIs recorded in the data set include school closures, cancelling of public events, closures of public transportation, restrictions on movements across regions or cities, and international travel controls. Although we limit the analysis to two NPIs, countries that implemented one of the measures usually implemented a subset of them at the same time. The cross-policy implementation correlation is above 0.6, and in many cases is above 0.8.

an increased in the time people spend at their residence, which in turn indicates an actual fall in mobility. Hence, NPIs are expected to increase residential mobility but decrease workplace mobility.

4 Non-Pharmaceutical Interventions, Mobility, and the Early Spread of the Virus

The outbreak of COVID-19 was first identified in Wuhan, China, in December 2019, and spread rapidly across neighbouring countries, but it was in March that the pandemic became truly global. The virus spreads rapidly, but countries where the virus arrived later benefited from observing the experiences of those hit early. A sign that countries were learning about the impact of the pandemic is that policymakers began to implement NPIs much sooner after the arrival of the virus, and in some cases even before there were fatalities. On average, the time between the first reported case in a country and the implementation of stay-at-home requirements was 22 days, but having one extra day without the virus reduced the response time by 0.65 days. For example, countries with reported cases in January and February took on average 40.2 days to impose an NPI, while countries with the first reported case after the beginning of March spent only 16.1 days.

We classify countries in three groups according to the date of the first COVID-19 related death: i. early affected (before February 29); ii. affected during the period of rapid expansion (first three weeks of March); and countries in which the virus arrived later (after March 24th). Given the exponential growth of the virus, if NPIs are effective, the speed of the policy response plausibly had significant effects on the speed of contagion in each country, at least in the short run. Figure **??** presents suggestive evidence that this was the case. The figure shows the relation between the date of the first COVID-19 related death in each country and the log cumulative number of deaths 30 days after. There is a clear negative relation between the timing of the arrival of the virus and how deadly it was by the end of the first month: having one extra day without the virus is associated with a decline in the *log* cumulative number of deaths in day 30 of 4.2 percent. The arrival time of the virus is then closely linked to the speed of the policy response and the supposed fatality rate of the virus at the beginning of the pandemic.

NPIs can affect the spread of the virus by reducing interactions among individuals and thus lowering the probability of contagion, however, the efficiency of NPIs to do so remains an empirical question. To explore this channel, we use country-specific daily information from Google mobility data on mobility patterns to approximate social interactions and social distancing. Figure 1 shows the evolution of residential and workplace mobility before and after the first implementation of either stay-at-home requirements or workplace closures, averaged across countries. To facilitate interpretation, the mobility indexes are normalised so that they take a value of zero at the date each policy was implemented in each country and have a cross-country variance of one. We focus on a short period around the date of the policy implementation: between 10 days prior to and 25 days afterward the policy was implemented. Our emphasis is then on the immediate impacts of NPIs on mobility. There are two immediate takeaways from Figure 1. First, the patterns of mobility started to change before NPIs' were implemented. In other words, individuals had already reduced their mobility even before formal restrictions had been applied. Second, there is an acceleration of the reduction of mobility exactly at the time the policy was implemented. In that sense, NPIs at early stages reinforced a pattern that was already in place.

The descriptive evidence presented in this section shows that i. countries where the virus arrived later implemented NPIs sooner after the arrival of the virus; ii. the implementation of NPIs is associated with a significant reduction in mobility, and hence in social interactions; and iii. countries where the virus arrived later had lower death rates during the initial stages of the pandemic. These three pieces of evidence suggest that NPIs could have been effective in slowing the spread of the virus, at least in the short run. In the next section we test this hypothesis and provide quantitative estimates of the effect of implementing NPIs on both mobility and mortality in the short-run.

5 The Short-Run Impact of NPIs on the Spread of the Pandemic

Our empirical strategy is that of an event study design, where the event is the implementation of an NPI. For each country, we compare mobility trends, the growth rate of COVID-19 cases, and the growth rate of COVID-19 deaths before and after the implementation of either stay-at-home requirements or workplace closures. We focus only on short windows around the time each policy was implemented for the first time, from 10 days before to 25 days afterwards. This short length of time allows us to avoid confounding the impact of NPIs with other policy interventions made over time, such as improvements in the capacity of the healthcare system, testing capacity, or even learning about how to better treat the disease.

More formally, let c index countries and t index time, measured in days. Time runs from -10 to 25, where we fix $t = 0$ in each country at the date when the policy was implemented for the first time. We analyse the effect of the stay-at-home requirements and workplace closures separately, and in each case we restrict the sample to the countries that implemented the NPI at some point between January and July 2020.

We first estimate the effect of NPIs on mobility. The equation takes the form:

$$\text{Mobility}^j_{c,t} = \sum_{i=-10}^{-1} \phi^m_i \mathbf{1}[i = t] + \sum_{i=1}^{25} \phi^m_i \mathbf{1}[i = t] + \eta^m_{r,d} + \mu^m_c + \epsilon^m_{c,t}, \tag{1}$$

where $\text{Mobility}^j_{c,t}$ is the normalised mobility index j, either residential or workplace mobility;[3] $\mathbf{1}[\cdot]$ is an indicator function that takes the value of one if the condition inside the square brackets holds; $\eta^m_{r,d}$ is a region[4] $\times$ calendar day fixed effect; and μ^m_c is a country fixed effect. The parameters of interest are the ϕ^m_i's. These parameters capture differences in mobility at each day relative to the baseline defined at $t = 0$, conditional on the structure of fixed effects. Thus, the estimates of ϕ^m_i for $i \in [-10, -1]$ provide a test of the parallel trends assumption; while the estimates of ϕ^m_i for $i \in [1, 25]$ identify dynamic effects of the NPIs on mobility.

The variation we use for identification comes from cross-country differences in the date in which the policies were implemented within a region, which we take to be exogenously determined by the arrival date of the virus, once time-invariant country characteristics are accounted for. As shown in Figure **??**, the spread of the virus across countries was very fast and happened mostly over a few weeks in the month of March. Within regions, the exact date in which the virus arrived at a country was plausibly random. Moreover, once the virus entered, how fast governments imposed NPIs varied as a function of the arrival date (see Figure **??**), but it was not correlated with observable characteristics that might be predictive of a faster policy reaction. For example, Table 1 shows that variables like population size, population density, GDP per capita, the share of older and more vulnerable populations, and aggregate indicators of health status are not correlated with how fast NPIs were implemented. We provide further evidence that the identification assumption holds from the absence of policy effects prior to the

[3] Mobility indexes are normalised so that they take a value of zero at the date each policy was implemented in each country and have a cross-country variance of one.

[4] Regions include Africa, Asia, Europe, Latin America and the Caribbean, North America (United States and Canada); and Oceania.

policy implementation.

Panels (a)-(d) of Figure 2 show the estimated effects of the two NPIs on the mobility indexes. The top panels focus on residential mobility, while the bottom panels focus on workplace mobility. In all cases, the evidence suggests that the parallel trends assumption holds: we cannot reject that the patterns of mobility prior to the implementation of the NPIs followed a common trend across countries within a region. This is true even though mobility started to change before the implementation of the policy (see Figure 1). It must be said that even though mobility started to change before the implementation of NPIs, our estimates account for changing mobility prior to their implementation, and thus our parameter estimates identify the additional change in mobility generated by the policy.

Specifically, we estimate how residential mobility changed almost immediately after the NPIs were implemented. The day after the stay-at-home requirements where imposed, residential mobility increased by 0.20 standard deviations; three days after it was up by 0.44 standard deviations; and by day 15 the effect peaked at 0.7 standard deviations. These values indicate substantial changes in mobility patterns. We find that workplace closures had a similar effect on residential mobility, both qualitatively and quantitatively. Moreover, the patterns of workplace mobility mirrors those of residential mobility: the timing of the effect coincides, and, given the uncertainty of the estimates, the magnitudes are not statistically different. All in all, our results provide clear evidence that these two NPIs had substantial effects on mobility, which lowers the probability of contagions by reducing social interactions.

We then estimate the reduced-form effect of NPIs on both the rate of growth of daily COVID-19 cases and deaths. We use a similar event study specification for each dependent variable:

$$\Delta \text{Log Cases}_{c,t} = \sum_{i=-10}^{-1} \phi_i^x \mathbf{1}[i=t] + \sum_{i=1}^{25} \phi_i^x \mathbf{1}[i=t] + \eta_{r,d}^x + \mu_c^x + \epsilon_{c,t}^x, \tag{2}$$

$$\Delta \text{Log Deaths}_{c,t+15} = \sum_{i=-10}^{-1} \phi_i^d \mathbf{1}[i=t] + \sum_{i=1}^{25} \phi_i^d \mathbf{1}[i=t] + \eta_{r,d}^d + \mu_c^d + \epsilon_{c,t}^d, \tag{3}$$

where ΔLog Cases$_{c,t}$ is the daily change in the total (log) cumulative number of cases, and Δ_tLog Deaths$_{c,t+15}$ is the daily change in the total (log) cumulative number of deaths at $t+15$

days. The 15 days lag is intended to account for the fact that the incubation period of COVID-19 can take up to 14 days, so one would expect most critical cases appeared after this period. When defining this lag we are being overly conservative, since most fatalities occurred after two weeks. Moreover, most cases had not been reported at the moment of contagion, but we expect that they also started to appear in the data with some lag, once symptoms appear or people get tested. The specification of the event study allows us to study these dynamics.

Panels (a)-(d) of Figure 3 show the estimated effects of the two NPIs on the daily growth rate of cases (panels (a) and (b)) and deaths (panels (c) and (d)). In all specifications, the evidence suggests that the parallel trends assumption holds: we cannot reject that the rate of growth of cases or deaths prior to the implementation of the NPIs followed a common trend across countries within a region. We estimate that stay-at-home restriction lowered the average rate of growth of daily cases, but the effect is only statistically significant at the five percent level after a lag of between 10 to 15 days (see Panel (a) of Figure 3). Ten days after the implementation of the policy the daily growth rate of cases is estimated to be 6.1% lower; 15 days after the implementation the daily growth rate is 8.6% lower; and by day 25 the growth rate is 10.0% lower. We observe a sharper decline in the growth rate of cases after the implementation of workplace closures (see Panel (b) of Figure 3). Ten days after the implementation of the policy the growth rate of cases is estimated to be 11.1% lower; 15 days after the implementation the growth rate is 15.2% lower; and by day 40 the growth rate is 19.4% lower.

We also observe a sharp decline in the daily rate of COVID-19 related deaths, but, as expected, the effect also appears with a lag. Up to 19 days after the implementation of stay-at-home requirements, we do not observe any statistically significant changes in the fatality rate, although the point estimates are all negative (see Panel (c) of Figure 3). By day 20, the daily death rate is lower by 6.1%, and by day 25 the rate is down by 8.4%. A similar pattern is observed after the implementation of workplace closures, although we only observe statistically significant declines in the daily death rate at the five percent level after 30 days (-5.2%) (see Panel (d) of Figure 3). The evidence then strongly suggests that NPIs flattened the epi-curve in the short-run, successfully reducing the speed in which the virus spread at the early stages of the pandemic.

We can combine the three reduced-form estimates from Equations 1-3 to study the effect of mobility, more broadly, on the rate of growth of cases and deaths in the short-run. The mechanism through which NPIs flatten the epi-curve is by reducing social interactions and thus lowering the probability of contagion. In that sense, we can think of Equation 1 as a first-stage regression in an instrumental variables estimate of the effect of mobility on the rate of growth of cases and deaths. To see this more clearly, consider the equation:

$$\Delta\text{Log Cases}_{c,t+j} = \alpha_j^z \text{Mobility}_{c,t} + \eta_{r,d}^z + \mu_c^z + \epsilon_{c,t}^z, \tag{4}$$

where α_j^z captures the effect of changes in mobility at time t on the daily growth rate of cases at time $t+j$. We allow the effect to appear with a lag since the evidence from Figures 2 and 3 suggests the response of mobility and cases to NPIs is not immediate. All other variables are defined in an analogous way to the previous models. Replacing $\text{Mobility}_{c,t}$ in Equation 4 with the right-hand side of Equation 1, and simplifying the expression, we get

$$\begin{aligned} \Delta\text{Log Cases}_{c,t+j} &= \alpha_j^z \left(\sum_{i\neq 0} \phi_i^m \mathbf{1}[i=t] \right) + \eta_{r,d} + \mu_c + \epsilon_{c,t}, \\ &= \sum_{i\neq 0} \underbrace{\alpha_j^z \phi_i^m}_{\phi_{i+j}^x} \mathbf{1}[i=t] + \eta_{r,d} + \mu_c + \epsilon_{c,t}. \end{aligned} \tag{5}$$

Here, $\alpha_j^z \times \phi_i^m$ captures the reduced-form effect of NPIs on the daily growth of cases at $t = i+j$. This is equivalent to the estimate of ϕ_{i+j}^x in Equation 2.[5] In other words, we can recover α_j^z using $\alpha_j^z = \phi_{i+j}^x / \phi_i^m$. Following a similar procedure and analogous notation, the effect of mobility on the rate of growth of deaths is given by:

$$\Delta\text{Log Deaths}_{c,t+15} = \sum_{i\neq 0} \underbrace{\alpha_j^w \phi_i^m}_{\phi_{i+j}^d} \mathbf{1}[i=t] + \eta_{r,d} + \mu_c + \epsilon_{c,t}, \tag{6}$$

where $\alpha_j^w = \phi_{i+j}^d / \phi_i^m$ captures the effect of changes in mobility at time t on the daily growth rate of deaths at time $t+15+j$.

Yet, the estimates show that a decline of one standard deviation in the mobility index leads to a decline in the daily rate of change of cases 20 days afterwards of between -15.2 and -20.8 percent, depending on the NPI and the mobility index considered (see Table 2). This is quite a significant effect, especially considering how fast the virus spreads. Furthermore, a decline of a similar magnitude in mobility leads to a fall in the daily rate of change of deaths 35 days

[5] $\eta_{r,d} \equiv \alpha_j^z \eta_{r,d}^m + \eta_{r,d}^z$; $\mu_c \equiv \alpha_j^z \mu_c^m + \mu_c^z$ and $\epsilon_{c,t} \equiv \alpha_j^z \epsilon_{c,t}^m + \epsilon_{c,t}^z$.

afterward of between -6.2% and -8.6%. Again, these are quite substantial numbers.

Finally, we can compare the reduced-form effect of NPIs on daily growth rate of cases and deaths with the overall effect of mobility on those same outcomes. This comparison provides an estimate of the relative importance of NPIs in driving the mobility effect. Our results imply that between 53 and 72 percent of the reduction of the daily growth rate of cases and deaths associated with changes in mobility are accounted by the effect of NPIs. Even if the behavioural response by individuals is strong in the absence of lockdown policies, these measures have a substantial role in flatting the epi-curve.

6 Conclusion

Measuring the impact of NPIs during this pandemic of COVID-19 is complex since we still face a lot of uncertainties about this virus, and on the other hand, this impact crucially depends on people behaviours in response to the pandemic and governments' mitigation measures. We provide evidence that NPIs implemented during the initial stages of the pandemic had an immediate effect on mobility, and reduced the daily growth rate of cases and deaths in the short run, effectively flattening the epi-curve. We claim that these results can be useful since we may face several waves of this virus and its variants and governments, national as well as local ones, are likely to adopt a new batch of NPIs to control the virus spread.

Our results must be interpreted cautiously thinking about new peaks of the pandemic. First, even though we still face a lot of uncertainties about this virus, we know more about it than eight months ago. Second, this better knowledge has contributed to improve the efficiency of some treatments, in particular for severe cases. Even though it may not affect the variable that measures the number of cumulative cases, partly thanks to that, we observe that the mortality rate is lower now than six months ago. Third, due to the economic consequences that generate lockdowns, it is unlikely to observe NPIs taken at a national scale. Thus, this type of analysis should be replicated at a local level.

Finally, for identification purpose we limited our analysis to a reduced length of time. However, it would be interesting to evaluate NPIs impact with a longer length, since short term victories do not necessarily guarantee the best outcomes for countries at the end of the pandemic. On the one hand, the interplay between economics and public health has to be taken into account, and beyond the pure public health aspects, life quality also matters. On the other hand, even if one wants to strictly focus on public health, several researches shine a light on lockdowns consequences from a sanitary point of view. For instance, in United Kingdom, a report of the National Health Service indicates that lockdown may cost 200,000 lives for the next years. We believe that it is necessary to include our positive results regarding lockdowns' short term impacts in a longer and broader perspective. It is part of our research agenda.

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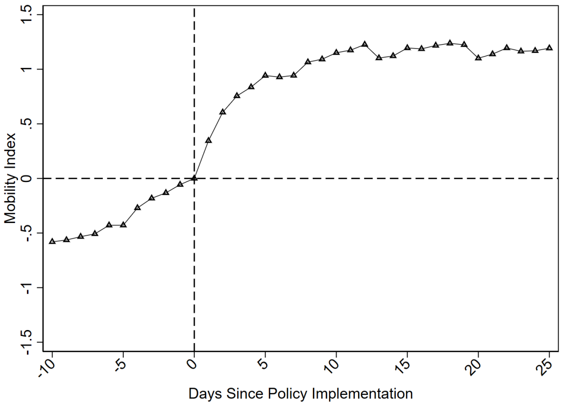
7 Tables and Figures

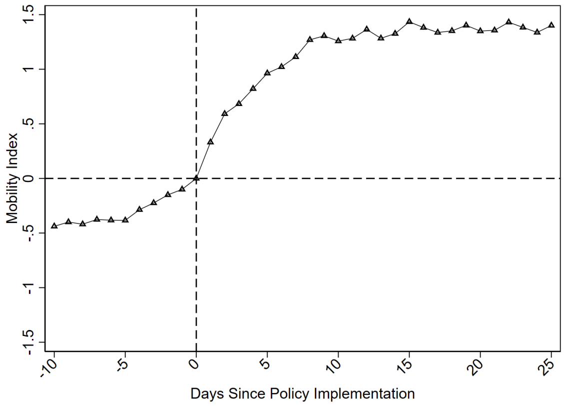
Figure 1: Mobility index before and after implementations of NPIs

Mobility Residential

(a) Stay-at-home

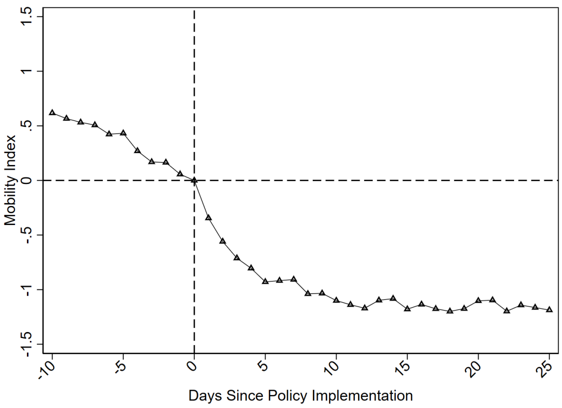


(b) Workplace closing

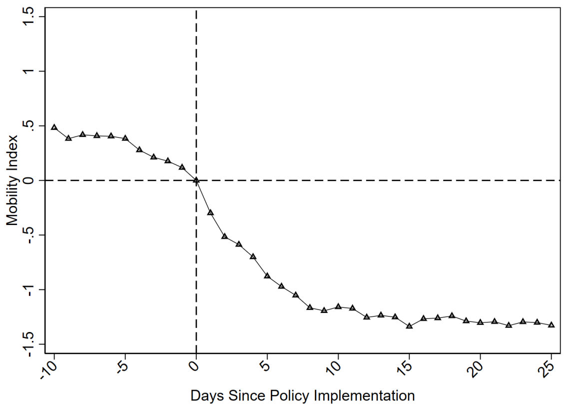


Mobility Workplace

(c) Stay-at-home



(d) Workplace closing

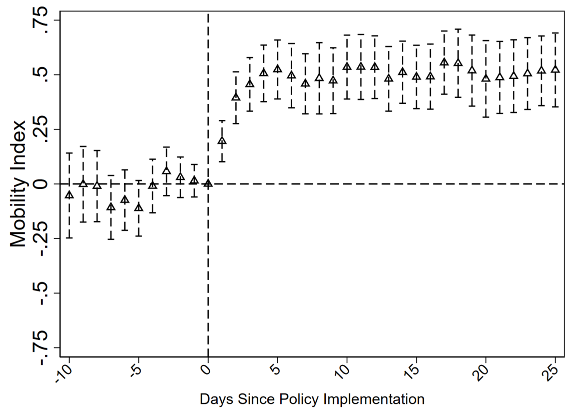


Note: Authors' calculations are based on Google mobility data and the University of Oxford's Blavatnik School of government responses tracker.

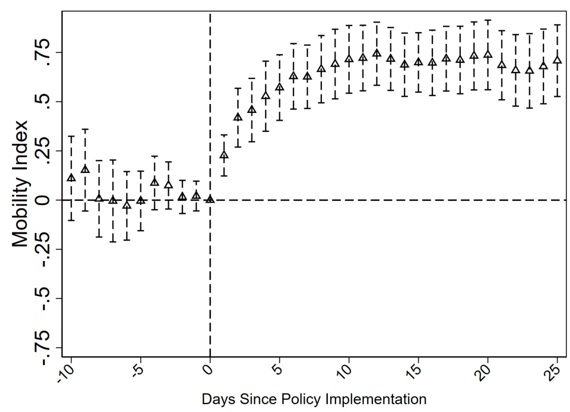
Figure 2: Mobility Index and Policy Response

Mobility Residential

(a) Stay-at-home

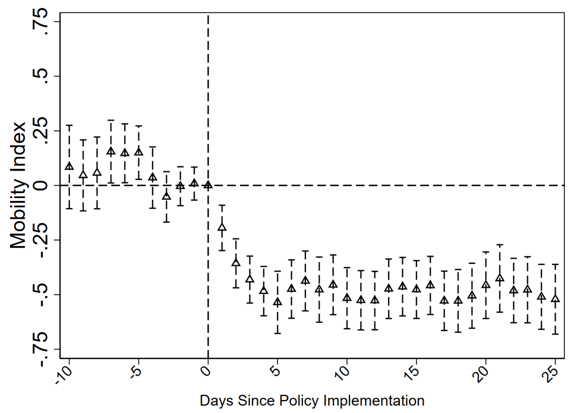


(b) Workplace closing

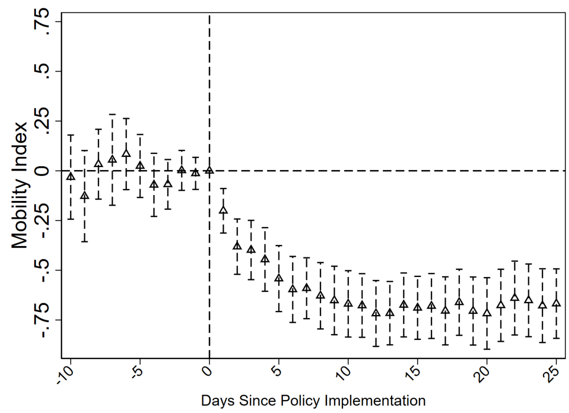


Mobility Workplace

(c) Stay-at-home



(d) Workplace closing

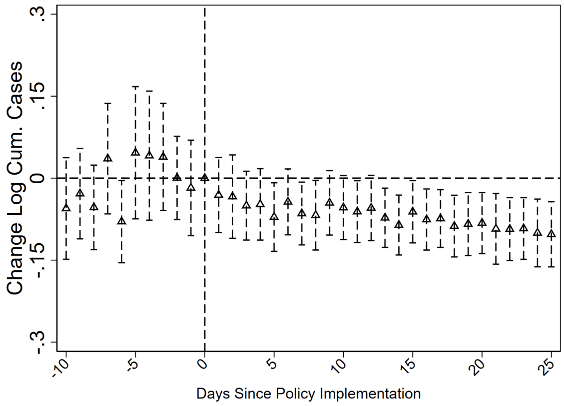


Note: Standard errors clustered by country. 95 percent confidence intervals reported around each point estimate. Mobility indexes taken from Google mobility data. Mobility indexes are normalised so that they take a value of zero at the date each policy was implemented in each country and have a cross-country variance of one. Dates in which NPIs are implemented taken from the University of Oxford's Blavatnik School of government response tracker.

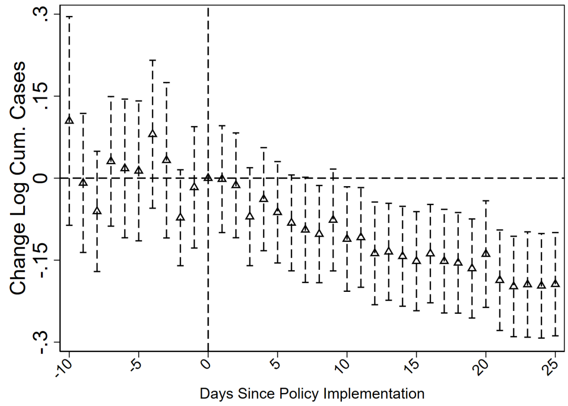
Figure 3: Change in Log Cumulative Deaths or Cases

Cases

(a) Stay-at-home

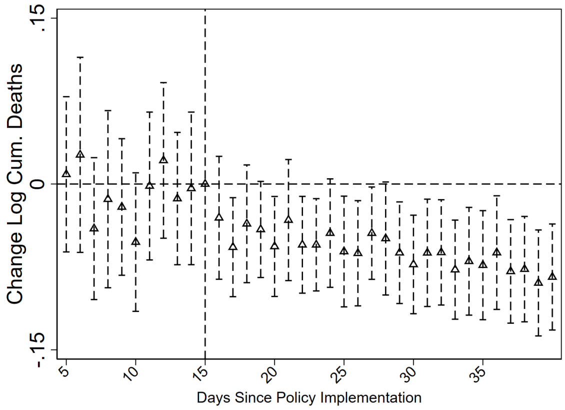


(b) Workplace closing

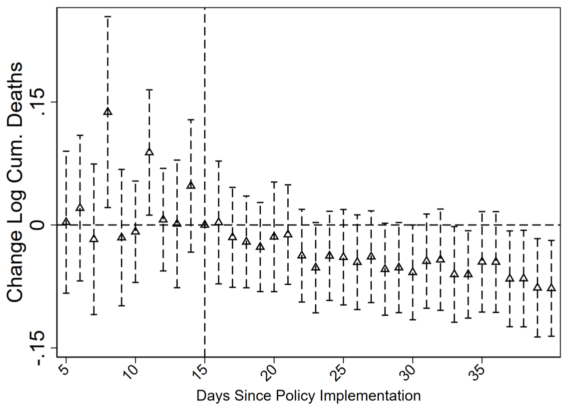


Deaths

(c) Stay-at-home



(d) Workplace closing



Note: Notes: Standard errors clustered by country. 95 percent confidence intervals reported around each point estimate. Cases and fatalities taken from the European Center for Disease Prevention and Control (ECDC). Dates in which NPIs are implemented taken from the University of Oxford's Blavatnik School of government response tracker.

Table 1: Correlation between speed of policy response and country characteristics

	Days Between Policy and First Death			Days Between Policy and First Case		
	I	II	III	I	II	III
Speed of Policy Response						
Date First Death	-0.699***	-0.749***	-0.813***			
	(0.139)	(0.139)	(0.146)			
Date First Case				-0.741***	-0.755***	-0.774***
				(0.070)	(0.076)	(0.087)
Country Characteristics						
Log(Population)			-0.151			0.782
			(0.862)			(0.753)
Log(GDP pp)			-1.831			-4.235
			(2.148)			(3.192)
Population Density			-0.013			-0.014
			(0.009)			(0.009)
Share of Population 70 Years or Older			-0.277			-0.059
			(0.523)			(0.603)
Mortality Rate Cardiovascular Disease			0.009			-0.001
			(0.009)			(0.009)
Prevalence of Diabetes in Polpulation			-0.102			-0.105
			(0.257)			(0.254)
Observations	100	100	100	100	100	100
R2	0.626	0.658	0.707	0.639	0.681	0.706
Region FE	No	Yes	Yes	No	Yes	Yes

Notes: The speed of policy response is measured as the number of days between the first reported COVID-19 death/case in each country and the implementation of stay-at-home requirements.

Table 2: Effect of mobility on the daily rate of growth of cases and deaths

	Stay-at-home		Workplace Closure	
	Residential mobility	Mobility workplace	Residential mobility	Mobility workplace
Reduced-form effect of NPIs on mobility at $t+10$ (ϕ^m_{10})	0.535	-0.516	0.715	-0.669
Reduced-form effect of NPIs on rate of change of cases at t+20 (ϕ^x_{20})	-0.081	-0.082	-0.138	-0.139
Reduced-form effect of NPIs on rate of change of deaths at t+35 (ϕ^d_{35})	-0.044	-0.044	-0.045	-0.045
Effect of mobility on rate of change of cases at t+20 (α^z_{20})	**-0.152**	**0.159**	**-0.193**	**0.208**
Effect of mobility on rate of change of deaths at t+35 (α^w_{35})	**-0.082**	**0.086**	**-0.063**	**0.067**

Notes: The table summarises the reduced-form effects of NPIs on i. mobility, ii. rate of change of cases, and iii. rate of change of deaths for different NPIs and mobility indexes used in the estimation. The last two rows provide estimates of the overall effect of mobility on the rate of change of cases and deaths.