# School Closure, Mobility and COVID-19: International Evidence

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**Abstract**

As a response to the COVID-19 pandemic, most governments have mandated schools to close as a way to reduce social contact and slow the spread of the disease. Using daily country data from January 22nd to May 6th, 2020, we use an event study framework to examine how school closures affected mobility and the spread of COVID-19 within countries. To answer this question, we look at the time spent at home and the growth in COVID-19 cases and deaths days before and after schools closed. We find that the policy increased the time that people spent at home, compared to the baseline, by 2 to 3 percentage points. Although small in magnitude, this effect is reflected on a 10 percentage point reduction in the growth rate of active COVID-19 cases. However, we did not find any effect of the policy on the rate of increase of deaths.

# 1 Introduction

The novel coronavirus has imposed an unexpected challenge to all countries. The way that the disease is transmited from person to person has brought to societies a new way of living: the "socially distanced" way of life.

For this reason, countries across the world have taken a variety of measures, at both local and national levels, for minimizing social contact among the population. Examples of these are: school closure, workplace closure, cancel public events, restriction on gathering sizes, shelter-in-place and home confinement orders, restriction on internal movement, restriction on international movement, among others (Hale et al., 2020).

In this study, we use an event study framework to examine how school closures affected mobility and the spread of the disease. To answer this question, we look at the time spent at home and the growth in COVID-19 cases and related deaths days before and after schools closed, and dig into the causal effect of school closure on those variables.

Among all policies, we chose school closures because it is one of the most standard measures of mobility restriction, and also one of the most "disruptive" ones. In comparison, shelter-in-place and workplace closure policies are also of interest, but given that they do not take the same form across countries, their consequences will not be comparable at the international level.

This paper is structured as follows. Section 2 describes the data and presents some descriptive statistics of the outcomes of interest and the school closure policy internationally. Section 3 describes our econometric model and the assumptions that must be true for it to estimate the causal effect of school closures on our outcomes of interest. Section 4 shows the results of those models. Section 5 discusses the limitations of our study, and Section 6 concludes.

# 2 Data

The data we use comes from three different publicly available sources. The first data source is the Global Mobility Index, constructed by Google [1]. The second is the Oxford Policy Response Tracker, which summarizes the policies that different countries have taken for limiting the spread of the disease and when [2]. The third is the John Hopkins University data, which shows the officially reported number of cases and deaths per country per day [3].

We explain how each data is constructed below.

[1]Available in: `https://www.google.com/covid19/mobility/`

[2]Available in:
`https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker`

[3]Available in: `https://github.com/CSSEGISandData/COVID-19`

## 2.1 Google Mobility Index

The Google Mobility Index data shows how visits and length of stay at different places have changed since the beginning of the year. It uses the same kind of aggregated and anonymized data used to show popular times for places in Google Maps, which consists on gathering information from users who have opted in to Google Location History for their Google Account (Google LLC, 2020a)[4].

The information is at the daily level, with the most recent data representing approximately 2-3 days ago, which is how long it takes the company to produce these datasets. In addition, the geographic level of the information is at the country and local level, with most of the countries having information at the country and regional or State level only (not municipality, county, or city).

As mentioned before, the data presents the percentage change in visits and length of stay at specific places, where each of them has its own variable. The places that are analyzed are the following.

- Grocery & pharmacy: grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.
- Parks: local and national parks, public beaches, marinas, dog parks, plazas, and public gardens.
- Transit stations: public transport hubs such as subway, bus, and train stations.
- Retail & recreation: restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.
- Residential: places of residence.
- Workplaces: places of work.

The percentage change in the number of visits and length of stay for each day is constructed by comparing the number of visits and length of stay to a baseline value for that day of the week. Specifically, the baseline is the median value of visits and hours of stay, for the corresponding day of the week, during the 5-week period January 3rd - February 6th, 2020.

For this study in particular, we analize the daily data at the country level for the dates February 15 - May 6th, 2020. We chose the country level as unit of analysis because the policy tracker data is only available at the national level, and the mobility indicators are not complete for all countries at the local level[5]. The reasons why we chose February 15 to May 6th as time period of analysis are detailed in Section 2.4.

[4]We address the representativeness of this data in Section 5.

[5]The local level missing data for some countries occur because Google leaves out a region if they do not have sufficient statistically significant levels of data for it (Google LLC, 2020a)

Finally, the main variable of analysis is the residential index: the average percentage change in the time that people spend at home in a specific country, in a specific day, compared to the baseline [6].

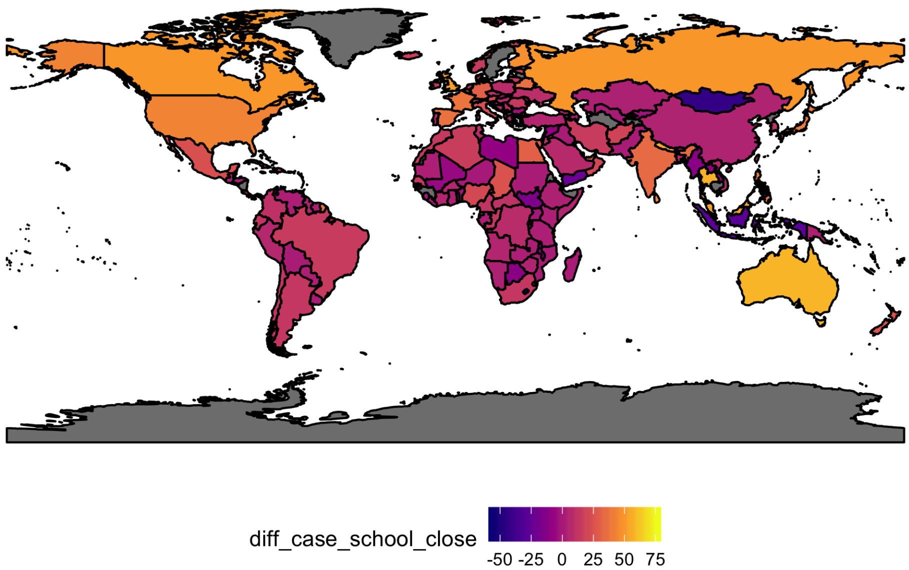
## 2.2 Oxford Policy Data

To capture the international policy responses to COVID we leveraged the database put together by Oxford University – COVID-19 response tracker (OxCGRT) ( Oxford University, 2020). This tracker compiles information about the policies that have been active by day and by country since the beginning of the pandemic and groups them in 13 categories. The first seven categories are measures to increase social distancing and reduce the spread of the disease. These include school closures, workspace closure, cancelation of public events, closure of public transportation, public information campaigns, restrictions on internal movement, and controls to international travels. The next 4 categories provide information about government measures to reduce the economic impact of the crisis. These include fiscal measures, monetary measures, emergency investments in health care, and investments in vaccines. The last two categories indicate the degree of testing being done and whether there were contact tracing efforts in place.

We primarily used the information about school closures, which was presented as three levels: No school closures; recommended closures – indicating that the government mandated the closure of schools in all or some of the levels; and required closures – where the government mandated the cancelation of in person classes. In total, the Oxford COVID - 19 response tracker only includes 11 countries that recomended the closure of schools. Of these, 7 were countries that first recommended school closures for an average period of 3.57 days before requiring them; 2 were countries that recommended school closures for 7 days on average after requiring their closure as part of the re opening path, and the remaining one is Sweden that never required school closures. The bast majority of the countries in this dataset – 154 in total – required the closure of schools, on dates that range from January 26 for the case of China to April 13 in the case of Chad. For our analysis, we considered the requirement of school closures as our policy of analysis given its mandatory nature. In Figure 2.2 we present a map of the world colored by the the number of days that passed form the first case to school closures. It shows how most of the countries closed schools 10 days within the first case.

[6] The time at home is computed by Google according to the number of hours spent at the place of residence, identified through the location history of each phone. For Google to "know" the place of residence of a specific phone, the user must indicate so in her Google Maps Google LLC, 2020b.

Figure 1: Countries by days from first case to school closure




### 2.3 John Hopkins University: Cases and Deaths

To capture the spread of the disease and its associated deaths we leveraged the data put together by John Hopkins Coronavirus Resource Center (Center for Systems Science and Engineering (CSSE) at Johns Hopkins University, 2020). We used the total number of cases and deaths by country by day.

### 2.4 Final Dataset

Overall, the final dataset of our analysis included data for 111 countries, which were the nations we had complete data on the residential index, school closure policy implementation, and cases and deaths[7]. Our data included information for each day from January 22nd – when

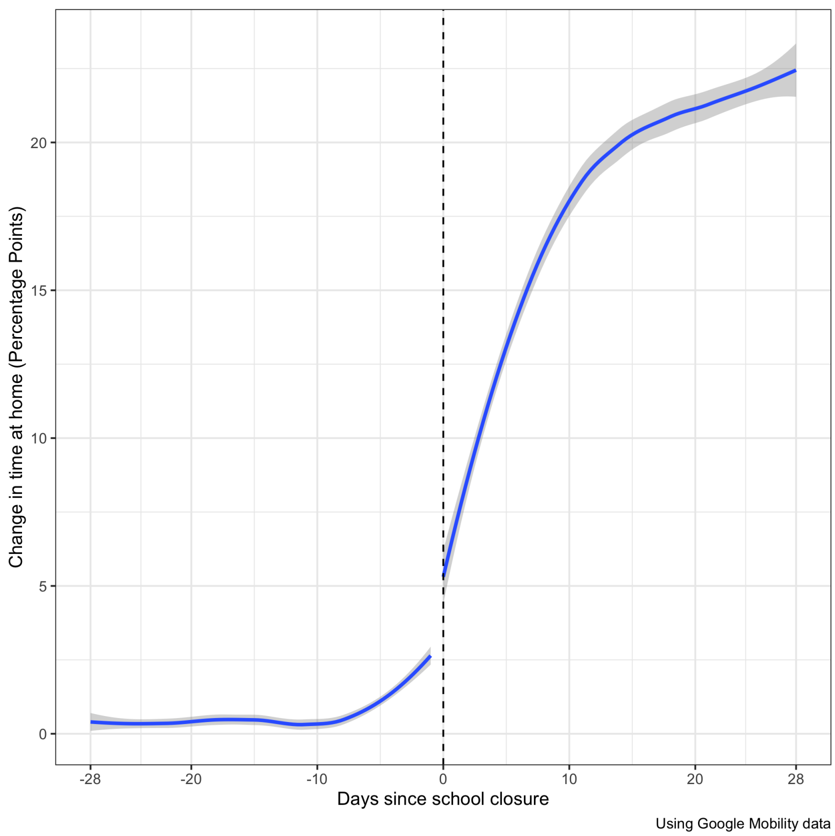
[7]Note that the residential index has data from February 15th onwards only, but we use data of previous dates for analyzing COVID-19 cases and deaths. See Appendix for the complete list of countries that we include in our analysis.

the John Hopkins Coronavirus Resource center started tracking cases and deaths – to May 6th – 28 days after Singapore closed its schools, which is the last country that implemented the policy. The reason why we filter for 28 days after is detailed in the metohdology section.

The graphs below show the average change in time at home compared to the baseline, and the average growth rate of active cases and deaths across countries 28 days before and 28 days after schools closed in each of them[8]

The graph below shows the movement for the residential index. This graph is constructed by running two local polynomials; one that plots the average value of the residential index across countries before the schools closed (from 28 days before to 1 day before), and a different one that plots the same variable but for 28 days after (i.e. we calculate two separate polynomials, one for each side of the graph).

Figure 2: Percent change in time at home across countries overtime




As we can see, there is a discrete jump in mobility around the date that schools closed across countries. Nevertheless, this jump does not necessarily need to be because of school closures, there might be other things that drive this trend. Section 3 describes the method we use to disentangle the causal effect that school closings have over this mobility measure.

[8]See Appendix for a graph with a bigger time window.

In Figure 3 we show the spread of the disease relative to the day since school closure. We plot two different measures: the growth rate of active cases and the growth rate of new deaths. We define these measures below.

- Growth rate of active cases
  Similar to Fowler et al. (2020), we approximate the number of active cases through the logic of an epidemiological SIR model. In the basic version of these models, individuals can be in three different states of nature: Susceptible – individuals can be infected –, Infected – individuals have the disease –, and Recovered – Individuals have recovered or died from the disease. Every person that gets the disease will either recover and never become infected again or die, after $d$ days. Then, if we know the total number of confirmed cases on time $t$, we can estimate the number of active cases by subtracting the active cases of time $t-d$. The equation is described below.

  $$active\_cases_{it} = cases_{it} - cases_{i,t-d}$$

  Then, we can estimate the spread of the disease as the percentage growth in active cases $growth\_active\_cases_{it}$ as:

  $$growth\_active\_cases_{it} = \frac{active\_cases_{it} - active\_cases_{i,t-1}}{active\_cases_{i,t-1} + 1}$$

  We add one to the denominator to ensure that the expression is always defined. Based on a recent systematic study about the average number of days that COVID-19 patients stay in hospitals (Rees et al., 2020), we will use 14 days as the $d$ for our analysis.

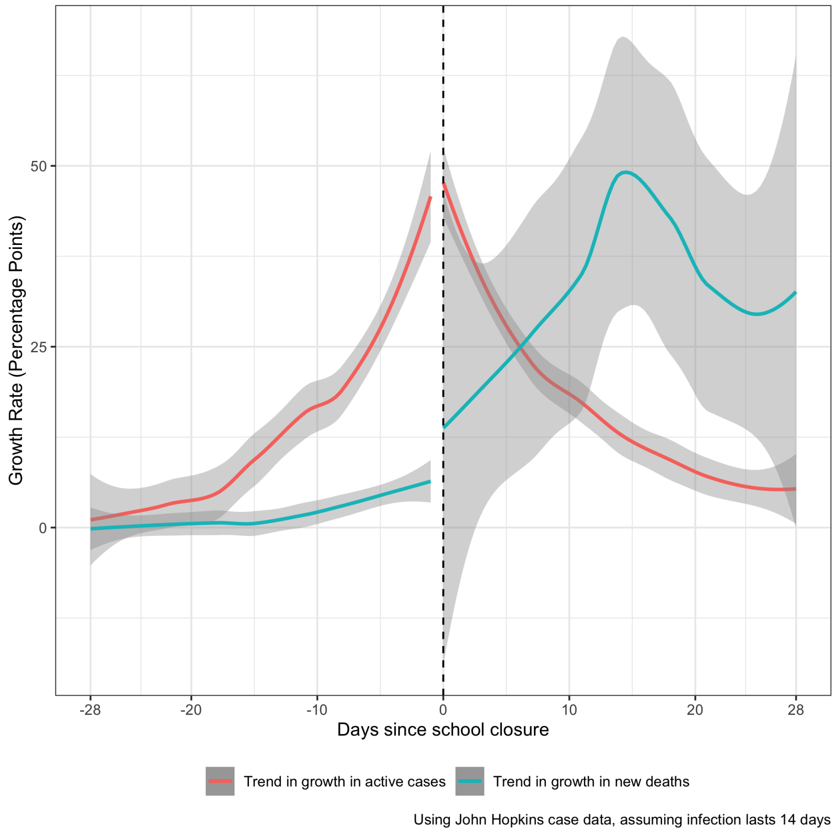
- Growth rate in new deaths
  We can also approximate the spread of the disease using the percentage increase in new deaths from day $t-1$ to day $t$. This approach compares the deaths that occured in one day with the deaths the day before, and estimates the percentage growth rate $growth\_new\_deaths_{it}$ as:

  $$growth\_new\_deaths_{it} = \frac{new\_deaths_{it} - new\_deaths_{i,t-1}}{new\_deaths_{i,t-1} + 1}$$

  Where $new\_deaths_{it} = deaths_{it} - deaths_{i,t-1}$

In Figure 3 we plot the average growth of active cases and new deaths. We can see how the former reaches its highest level when schools were closed, while the later 14 days after. This difference of 14 days between the peak of contagion and the peak of deaths is congruent with the model, where an average individual contracts the disease and recovers or dies after 14 days, which is the average duration found by Rees et al. (ibid.). Then, we would expect that any policy that reduces the rate of contagion in day $t$ would reduce the rate of contagion that a policy achieves by day $t+14$.

Figure 3: Percent change in active cases and new deaths across countries overtime




# 3 The Model: Event Study Design

Given that different countries closed schools at different points in time, our preferred research design is an event study design, initially proposed by Fama et al., 1969 to estimate the effect of the announcement of a stock split on returns of the market. The event study methodology is useful to estimate the impact of an external shock on an outcome of interest on $n$ different periods after the shock and $d$ periods before the shock.

Let time $s_i$ be the time when unit $i$ experienced a shock, and let $y_{it}$ be the outcome of interest for unit $i$ in time $t$, where $t$ is defined as the number of periods before or after period $s_i$. Through this methodology, we define $y_{it}$ as a function of $t$, and estimate one coefficient for each $t$, defined as the impact of the shock $t$ periods after or before its occurence. For our analysis, we will define $s_i$ as the day when schools closed in country $i$, and will define the rest of the days for country $i$ relative to $s_i$. Figures 2 and 3 show how this set up looks like; we take this set up and estimate how much, on average, school closings explain the change in the slope of these curves after the implementation day (day zero/$s_i$).

### 3.1 Effect of School Closure on Time at Home

We attempt to estimate the average treatment effect of school closures on the time that people spent at home. For that, we run the following model:

$$residential\_index_{it} = \sum_{r=-14}^{R=14} \tau_r SC_i \times \mathbf{1}[days\_post\_regulation = r]_{it} + \sum_{l=-6}^{L=-1} \beta_l residential\_lag_{it} + \alpha_i + \delta_t + \epsilon_{it}$$

Where $residential\_index_{it}$ is the percentage change in time at home compared to the baseline, $SC_i \times \mathbf{1}[days\_post\_regulation = r]_{it}$ are dummy variables that take the value of one if country $i$ in time $t$ is $r$ periods after schools closed, zero otherwise. Note that negative values of $r$ represent days prior to the day schools closed, and that $r = 0$ is the first day that schools were closed. The comparison day is the day prior to the school closure day ($r = -1$), as a way to compare the scenario with the policy with the scenario without the policy[9]. $residential\_lag_{it}$ are lag variables that control for the trend in time spent at home for the 6 days before day $t$. With these lag variables we look to control for any preexisting trends in mobility before the policy was implemented (even though Figure 2 suggests that, on average, there is not a significant downward trend, but rather the change in time at home compared to the baseline is moving around zero in the pre-period).

Finally, $\alpha_i$ are country fixed effects that control for country-specific time-invariant observable and unobservable characteristics, and $\delta_t$ are date fixed effects that control for time-period-specific characteristics or 'shocks' that are common to all the countries in our sample.

The parameters of interest are $\tau_r$ for $r \geq 0$, which pick up the average treatment effect $r$ periods after schools closed. For these parameters to be interpreted as a causal effect, it must be true that, in the absence of the school closure policy, the trends in our outcome of interest (change in time spent at home compared to the baseline) across countries would have been the same. If pre-trends across countries are not parallel, we would be concerned that the parallel trends assumption does not hold. One advantage of the event study research design is that the pre-school closure period parameters will help us partially test this identifying assumption. If the pre-treatment parameters are centered on zero and not trending, it would be a good indicator for saying that the parallel trends assumption holds.

Finally, we cluster standard errors by country, to take account of the fact that observations between countries across time are not independent from each other.

The main results for this model are shown in section 4.1

[9]In other words, we want to dig into the question of how school closure changed mobility compared to the scenario without school closure. This is the reason why $r = -1$ is the comparison day and not $r = 0$, which is the first day of implementation of the policy

### 3.2 Effect of School Closure on COVID spread

To analyze the effect of school closures on the spread of COVID-19 we also conduct an event study for the percentage increase in active cases and deaths. The models include dummies by days relative to the day of school closure and fixed effects by country and date. The main difference with the mobility model is the number of days we estimate individual effects for - 28 days after the policy rather than 14.

$$COVID\_spread_{it} = \sum_{r=-14}^{R=28} \tau_r SC_i \times \mathbf{1}[days\_post\_regulation = r]_{it} + \sum_{l=-6}^{L=-1} \beta_l COVID\_incidence_{it} + \alpha_i + \delta_t + \epsilon_{it}$$

Where $COVID\_spread_{it}$ measures the speed at which COVID-19 is spreading in country $i$ in day $t$. We ran the model for the growth rate in active cases and the growth rate in deaths, defined in the previous section. To reduce the noise in the data, we first transformed the active cases and deaths data to a 3-day rolling mean, and then we estimated the growth rates.

To conclude that closing schools helped control the spread of COVID, we would need to see negative coefficients for the days after the policy. The specific day varies by the dependent variable. For the model of active cases, we would expect these effects to appear after day 5 of closing schools[10]; for the model of deaths, we would expect this behavior after the average number of days that a person remains infected, which we have assumed as 14.

It is important to have in mind some of the limitations of the data before exploring the results. One important setback of using data on cases is that its reliability greatly varies by country; this is for several reasons. Countries performing fewer tests will have less confirmed cases artificially. Countries with a lower number of testing facilities can have definitive test results several days after the test was initiated, generating a delay in the official count. The transparency of information in each country can also impact the reliability of the data, since it can be modified for political, electoral or other reasons. Because of this, we try to exploit the data on deaths.

We believe that using data from death count is more reliable than from case count for two reasons. First, regardless of the total tests available, the population most likely to be tested are those that are most likely to be infected. Then, we think that if a country has a low number of tests available, it will prioritize testing those that are showing the worst symptoms and, thus, that have a higher probability of death. Therefore, testing capacity will have less impact on the number of confirmed deaths from COVID. Second, the mechanisms to register mortality are better established than the mechanisms to report positive tests because countries capture data on the diseased regardless of experimenting a pandemic. Then, we think they are

[10]This is because the average number of days for presenting symptoms is, approximately, 5-6 days World Health Organization, 2020

less succeptible to errors or modifications caused for political purposes than the case counts.

As mentioned before, we changed the number of days after intervention from 14 to 28 days. We did this to better capture the effect –if any –of closing schools on the spread of COVID because it takes longer for changes in the rate of contagion of disease to be reflected in the cases or death count data than changes in mobility, which is almost automatically detected by the Google location data. After all, there is a relevant period between being infected, showing symptoms, and being tested. Furthermore, we also include lags of the dependent variable. This plays a crucial role in these models because the spread of a disease has a high temporal dependence - the spread in day $t$ will greatly impact the spread in subsequent days, and we need to control for these trends when estimating the effect of an intervention.

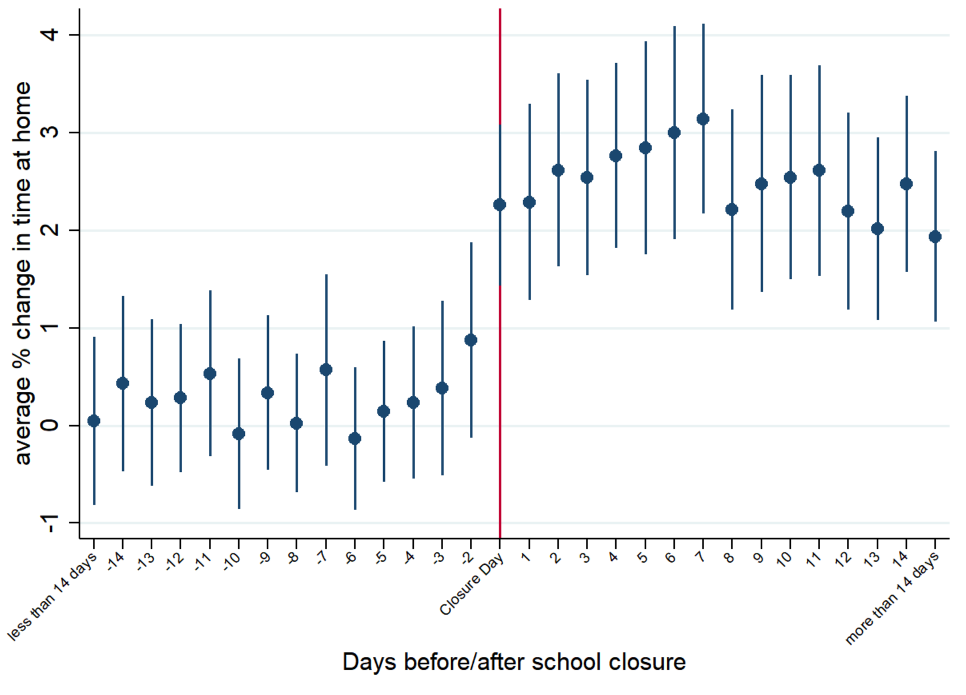
Similar to the model explained above for mobility, the parameters of interest are also $\tau_r$ for $r \geq 0$, and the base category is the day before schools closed ($r = -1$).

# 4 Results

## 4.1 Effect of School Closure on Time at Home

The pre and post-school closure estimates for the effects of the policy on time at home are shown in Figure 4. The parameters from school closure day onwards should be interpreted as the average percentage increase in time at home compared to the day before schools closed across countries.

Figure 4: Event Study Coefficients Percentage Change in Time at Home Compared to the Previous Day of School Closure




As we can see, there is a positive statistically significant effect of school closures in the time spent at home, which ranges between 2 and 3 percent and remains for the whole period of analysis. Even though these parameters are statistically significant at conventional levels, their magnitude is small. Taking the minimum time at home as 1 hour a day and the maximum time at home as 24 hours, in absolute terms the effect of this policy ranges, on average, between 1 minute and 28.8 minutes (however one cannot be at home more than 24 hours, so this upper bound is not realistic but it serves as point of reference).

Seeing this results from a broader perspective, we see that the average change in time at home compared to the baseline was, in the week prior to school closure, of a 0.7 percentage points increase, whereas this number increased to 18.3 percentage points in the week after the schools closed. Our results imply that, from 17.62 percentage points increase in the time that people spent at home (compared to the baseline) in the weeks before and after schools closed, 2 percentage points are due to the fact that schools closed.

One could think that for countries that closed schools few days after the first COVID-19 case was diagnosed, the effects on mobility could be bigger, because people are still not feeling very threaten to catch the virus.

To test this hypothesis, we separate countries into "early" and "late" action countries, depending on how many days took them to close schools after the first case was reported [11],

[11] An "early action" country is defined as a country that closed schools within six or less days after the first

and conduct the same event study as before, but adding interaction variables of the school closure dummies with a dummy that takes the value of 1 if the country is classified as an "early" action country, and zero if as "late" action.

If people in countries that acted earlier increased more their time at home because of the policy, these new parameters should be positive and statistically significant; however, this is not the case. Therefore, the timing of the policy does not affect mobility differently for "early" versus "late action" countries. The appendix shows this new regression in mathematical form as well as its results.

One important thing to note is that although some kids older than 14 or 15 years old have cellphones these days, the changes in mobility that we find are most likely reflecting how adults' mobility patterns change because their kids are not going to school. One can think of this as parents asking their employers to work from home to take care of their children, or parents that regularly do not go out to work leaving the house less frequently because of it. Also, given that the purpose of the policy was to minimize the role of children as "contagious agents", a most relevant outcome to look at is the effect of school closures on active cases and deaths. We show the result for that analysis in the next section [12].

## 4.2 Effect of School Closure on COVID-19 spread

The results of the models to explain COVID spread are shown in this section. Similar to the results for mobility, the coefficients should be interpreted as the average difference on the dependent variable with respect to its level one day before the intervention. From our estimations, we were able to identify an effect of the policy in the rate of increase of active cases but, surprisingly, we were unable to conclude the same for the deaths data.

The first results we show, on Figure 5, are for the percentage increase in active cases. Our results would indicate that, relative to the day before the policy, the growth rate in active cases was reduced by around 10 percentage points after 5 days of closing schools, which is what we expected.

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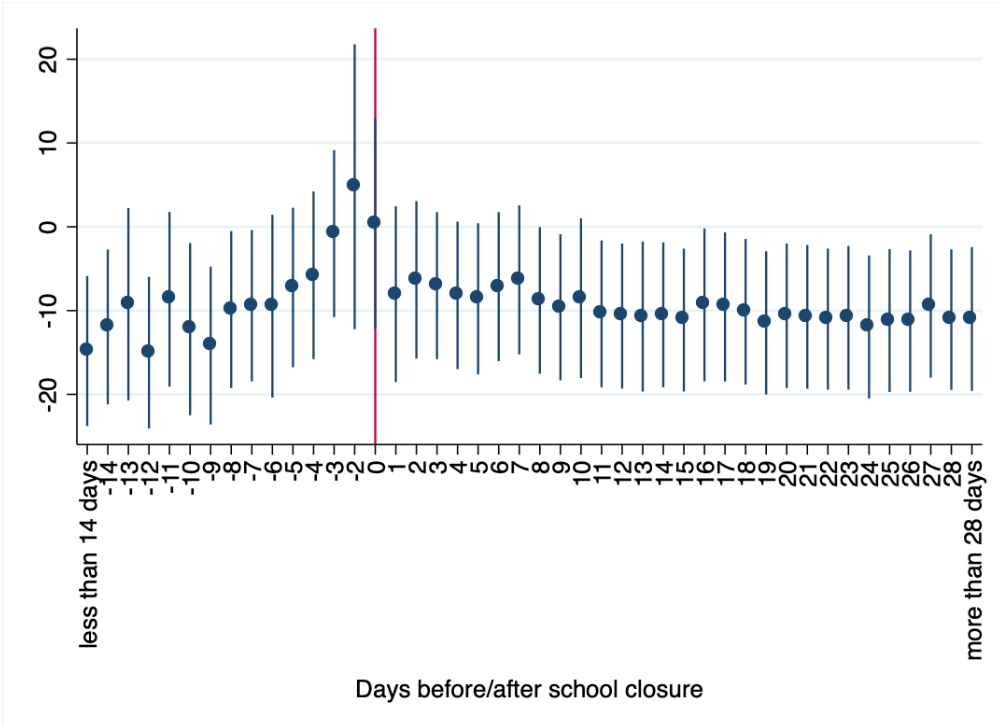
case. This number corresponds to the median number of days that countries waited before closing schools. Overall, there are 83 "early action" and 79 "late action" countries in our dataset.

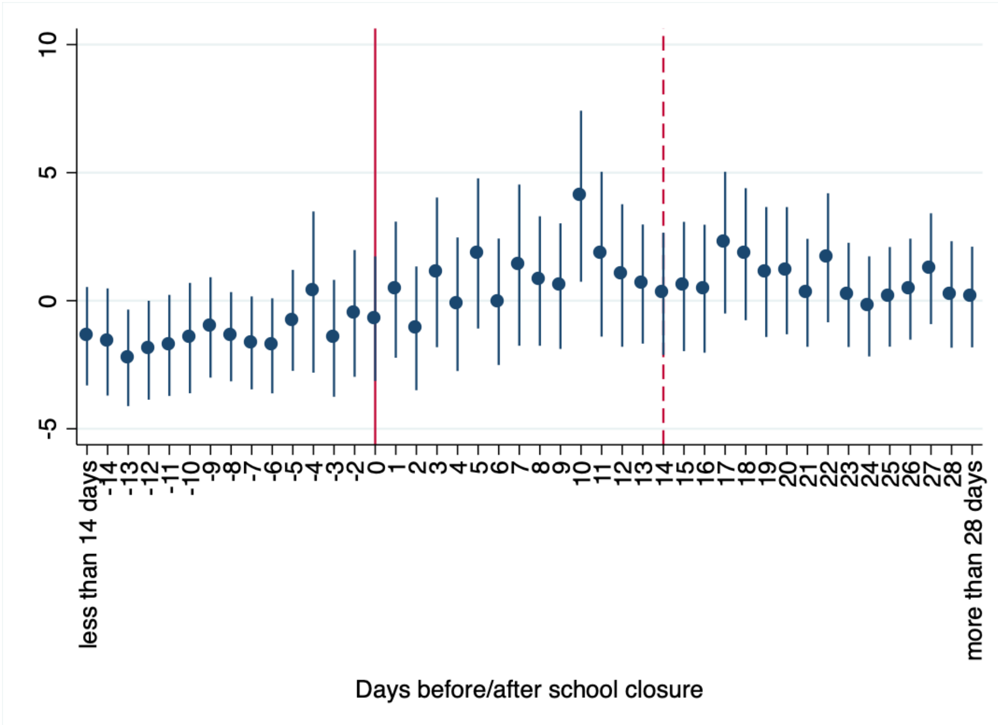
[12] See Appendix for the results of the same model on other measures of mobility

Figure 5: Event Study Coefficients Percentage Increase in Active Infections




In Figure 6, we show the results for the percentage increase in new deaths. We include a dashed vertical line for day 14, when we expected to observe the effect of the policy. However, as it can be seen from the figure, we did not find any effect of closing schools on the growth rate of deaths. The coefficients after the policy, and in particular after day 14, are centered around zero, implying the same average growth rate of deaths for these days compared to the day prior to the policy.

Figure 6: Event Study Coefficients Percentage Increase in New Deaths




How would reducing the growth rate of active cases would not translate into a reduction in the growth rate of deaths? We have come with some hypothesis that could explain this behaviour, but that we do not test for this article. One possibility is that closing schools reduced the spread of active cases in the student population, who face the lowest risk of death from COVID because of their age group, but did not do the same for the elderly or adults with chronic conditions. Then, it would be expectable to see a decline in the growth rate of active cases but not the same for deaths. For this hypothesis to maintain, inter-generational contact should be low enough such that the reduction in active cases in the student population did not affect that of the elderly and adults at highest risk. Even though there is not enough data for confirming this assertion, data from the United Nations shows that, between 2010 and 2018, multigenerational households across low income countries was between 40 to 50 percent, while this number decreases to 20 percent in high income countries (United Nations, Department of Economic and Social Affairs, 2019)[13].

A second idea is that deaths are not only a function of the number of cases, but also of the capacity of the medical system to treat them. Then, it could be that the reduction in the rate of new cases occured after several days of a high growth of cases that had overloaded the medical system already, reducing its capacity to cure the new infected people, and closing schools would not be able to reverse that situation.

[13]It is important to analyze this numbers with caution, because most of the data is for years between 2010 and 2015, and we do not know which changes might have happened across time, specially in low-income countries

# 5 Limitations

One of the main weaknesses of our analysis is that the Google Mobility Index calculates the changes in time at home by comparing it to January 2020, instead of comparing it to the median number of hours on the same date in previous years. This is problematic because if the mobility patterns change significantly across months in a "normal" year, our estimations could not be capturing the effect of our policies of interest on mobility. However, the date fixed effects try to adjust for this seasonality issue.

A second threat is the fact that the Google mobility data is gathered using information on users who have opted in to Google Location History for their Google Account only; therefore, the data represents a sample of the population, which may or may not represent the exact behavior of the whole population. If, in fact, mobility patterns of these users do not reflect the behavior of the whole population, our estimates for the effect of school closure on time spent at home among the world's population would be biased (specially towards the behavior of wealthier populations). In our view, this would be more evident in African, South Asian, some countries in Latin America and the Caribbean, and some small islands in Oceania, where mobile internet connectivity can be even less than 50 percent among the population (International Telecommunication Union, 2018; GSMA Intelligence, 2019; Pew Research Center, 2016). However, restricting the sample to North America and Europe only does not change our results from Section 4.2 substantially (although the effect is 1 percentage point lower)[14]. However, the representativeness of the data is still a concern, therefore, a remaining excercise for the future is to redo this same analysis but with different data sources; for example, with cellphone location data obtained from cellphone towers.

A final threat to our analysis that we can mention is that most of the countries implement other policies besides school closure in very close dates to the school's closure day. The specification of our model can control for it only if the implementation days are different from the school closure day. If not, the coefficients will be confounding the effect of closing schools with other policies' effects. Given that all other policies are trying to do the same thing (i.e. reduce mobility among the population), our results can be interpreted as an upper bound for the effect of school closure on time that people spent at home and on COVID-19's spread. To check if this is the case, we ran the following regressions that controls for those policies:

$$
\begin{aligned}
residential\_index_{it} = & \sum_{r=-14}^{14} \tau_r SC_i \times \mathbf{1}[days\_post\_regulation = r]_{it} + \\
& \sum_{l=-6}^{L=-1} \beta_l residential\_index_lag_{it} + \alpha_i + \delta_t + \\
& \qquad \eta_1 WC_{it} + \eta_2 CPE_{it} + \eta_3 ROG_{it} + \eta_4 SIP_{it} + \epsilon_{it}
\end{aligned}
$$

[14]The specific results of this analysis are on the Appendix.

Where $WC_{it}$, $CPE_{it}$, $ROG_{it}$, $SIP_{it}$ are dummy variables that take the value of 1 if country $i$ had its workplaces closed, cancelled public events, restricted gatherings, and/or issued shelter in place (or home confinement) orders in date $t$, zero otherwise.

What we find is that adding these controls does, indeed, reduce the average magnitude of the effect of school closure in time at home by 1 percentage point approximately, but the results are still statistically significant. Table A.X of the Appendix summarizes the results of this robustness check.

For the models that explain the spread of COVID-19, we ran the following regression for the growth rate in active cases and the growth in deaths:

$$
\begin{aligned}
COVID\_spread_{it} = \sum_{r=-14}^{28} \tau_r SC_i \times \mathbf{1}[days\_post\_regulation = r]_{it} + \\
\sum_{l=-6}^{L=-1} \beta_l COVID\_spread_{it} + \alpha_i + \delta_t + \\
\eta_1 WC_{it} + \eta_2 CPE_{it} + \eta_3 ROG_{it} + \eta_4 SIP_{it} + \epsilon_{it}
\end{aligned}
$$

Where $COVID\_spread$ is either the growth rate of cases or deaths, and the rest of the variables are variables are the same as in the equation above. For this case, including information of other policies did not modify our estimates. Table A.X of the Appendix summarizes these results.

## 6 Conclusion

With our analysis we wanted to understand how closing schools impacted people's mobility within countries (measured as the change in time spent at home) and the spread of COVID-19 (which was the main objective of the policy).

Leveraging data from Google's mobility index, Oxford Policy Response Tracker and John Hopkins COVID repository, we built a country-day level database with 111 countries and observations from January 22nd to May 6th, 2020. Through an event study design, we were able to estimate the day-to-day impact of this policy on the mentioned outcomes.

For mobility, we concluded that closing schools tended to make people spent between 2 to 3 percentage points more time at home compared with the day prior to the policy. We found this effect to be almost constant across the time period we analyze. Although small in magnitude, it is important to take into consideration that the Google mobility index will only reflect the changes in mobility for the people with smartphones, excluding a large portion of the kids not old enough to own a smart device. Therefore, our results mainly reflect the change in time spent at home by adults given school closure, and not necessarily the increase in time spent at home by the students.

In terms of the effect of school closures on the spread of COVID-19, the visual analysis let us see that, on average, countries closed schools when experimenting the highest level of growth rate in active cases and 15 days prior to the highest level of percentage increase in deaths. With this information in mind, we first performed an event study analysis for the growth rate in active cases. Our results confirmed our visual conclusions, showing that the growth rate in active cases after the policy was, on averag,e 10 percentage points lower than the growth rate of the day prior to the policy. These results indicate that closing schools substantially slowed down the spread of the disease.

We then studied the effect of the policy on the growth rate of deaths, but we did not identify any effect of the policy. The apparently contradicting results of reducing the growth rate of active cases but not that of deaths could be explained by the fact that closing schools mostly impacts the social contact between students, who face the lowest risk of dying from COVID. However, due to lack of data, we did not test this hypothesis in our analysis.

In summary, we found that closing schools reduced mobility and the growth rate of active cases, slowing down the spread of the disease. Further analysis include conducting the same study with other mobility data sources, as well as analyzing the increase in COVID-19 deaths in a lower temporal granularity.

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# Appendix

## Countries of Analysis

Table A.1: Countries of Analysis

| | | | |
|---|---|---|---|
| Afghanistan | Angola | Argentina | Australia |
| Austria | Bahrain | Bangladesh | Belarus |
| Belgium | Benin | Bolivia | Bosnia and Herzegovina |
| Botswana | Brazil | Bulgaria | Burkina Faso |
| Cameroon | Canada | Chile | Colombia |
| Costa Rica | Cote d'Ivoire | Croatia | Czech Republic |
| Denmark | Dominican Republic | Ecuador | Egypt |
| El Salvador | Estonia | Finland | France |
| Gabon | Georgia | Germany | Ghana |
| Greece | Guatemala | Honduras | Hungary |
| India | Indonesia | Iraq | Ireland |
| Israel | Italy | Jamaica | Japan |
| Jordan | Kazakhstan | Kenya | Kuwait |
| Kyrgyz Republic | Laos | Lebanon | Libya |
| Lithuania | Malaysia | Mali | Mauritius |
| Mexico | Moldova | Mongolia | Mozambique |
| Myanmar | Namibia | Nepal | Netherlands |
| New Zealand | Nicaragua | Niger | Nigeria |
| Norway | Oman | Pakistan | Panama |
| Paraguay | Peru | Philippines | Poland |
| Portugal | Qatar | Romania | Rwanda |
| Saudi Arabia | Senegal | Serbia | Singapore |
| Slovak Republic | Slovenia | South Africa | South Korea |
| Spain | Sri Lanka | Sweden | Switzerland |
| Taiwan | Tanzania | Thailand | Trinidad and Tobago |
| Turkey | Uganda | United Arab Emirates | United Kingdom |
| United States | Uruguay | Venezuela | Vietnam |
| Yemen | Zambia | Zimbabwe | |

## Regression Table for Effect of School Closure on Mobility

Table A.2: Event Study Percentage Change in Time at Home Compared to the Previous Day of School Closure

| Variable | (1) | (2) |
|---|---|---|
| 15 days or more before | -1.893 | 0.0423 |
| | (1.383) | (0.436) |
| 14 days before | -1.235 | 0.428 |
| | (0.978) | (0.454) |
| 13 days before | -1.128 | 0.235 |
| | (0.942) | (0.433) |
| 12 days before | -1.010 | 0.280 |
| | (0.854) | (0.384) |
| 11 days before | -0.558 | 0.534 |
| | (0.808) | (0.428) |
| 10 days before | -0.815 | -0.0885 |
| | (0.726) | (0.390) |
| 9 days before | -0.612 | 0.335 |
| | (0.689) | (0.400) |
| 8 days before | -0.734 | 0.0248 |
| | (0.649) | (0.359) |
| 7 days before | -0.268 | 0.570 |
| | (0.609) | (0.495) |
| 6 days before | -0.652 | -0.133 |
| | (0.555) | (0.368) |
| 5 days before | -0.524 | 0.145 |
| | (0.493) | (0.365) |
| 4 days before | -0.387 | 0.234 |
| | (0.463) | (0.392) |
| 3 days before | -0.164 | 0.384 |
| | (0.405) | (0.452) |
| 2 days before | 0.418 | 0.875* |
| | (0.390) | (0.505) |
| Closure Day | 2.017*** | 2.261*** |
| | (0.362) | (0.417) |
| 1 day after | 3.250*** | 2.290*** |
| | (0.558) | (0.507) |
| 2 days after | 4.268*** | 2.620*** |
| | (0.676) | (0.499) |

| | | |
|---|---|---|
| 3 days after | 5.084*** | 2.541*** |
| | (0.686) | (0.505) |
| 4 days after | 6.187*** | 2.765*** |
| | (0.745) | (0.479) |
| 5 days after | 6.877*** | 2.846*** |
| | (0.842) | (0.552) |
| 6 days after | 7.846*** | 3.004*** |
| | (0.992) | (0.553) |
| 7 days after | 8.921*** | 3.142*** |
| | (1.028) | (0.491) |
| 8 days after | 8.872*** | 2.215*** |
| | (1.078) | (0.519) |
| 9 days after | 9.399*** | 2.480*** |
| | (1.131) | (0.562) |
| 10 days after | 10.09*** | 2.545*** |
| | (1.155) | (0.528) |
| 11 days after | 10.62*** | 2.612*** |
| | (1.161) | (0.544) |
| 12 days after | 10.70*** | 2.198*** |
| | (1.233) | (0.509) |
| 13 days after | 10.95*** | 2.016*** |
| | (1.276) | (0.473) |
| 14 days after | 11.67*** | 2.477*** |
| | (1.274) | (0.457) |
| 15 or more days after | 12.46*** | 1.937*** |
| | (1.480) | (0.442) |
| Constant | 5.590*** | 0.566 |
| | (0.866) | (0.352) |
| Observations | 9,903 | 9,183 |
| R-squared | 0.817 | 0.925 |
| Time fixed effects | Yes | Yes |
| Country fixed effects | Yes | Yes |
| Six lags of dependent variable | No | Yes |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

## Early vs Late Action Countries Model for Mobility

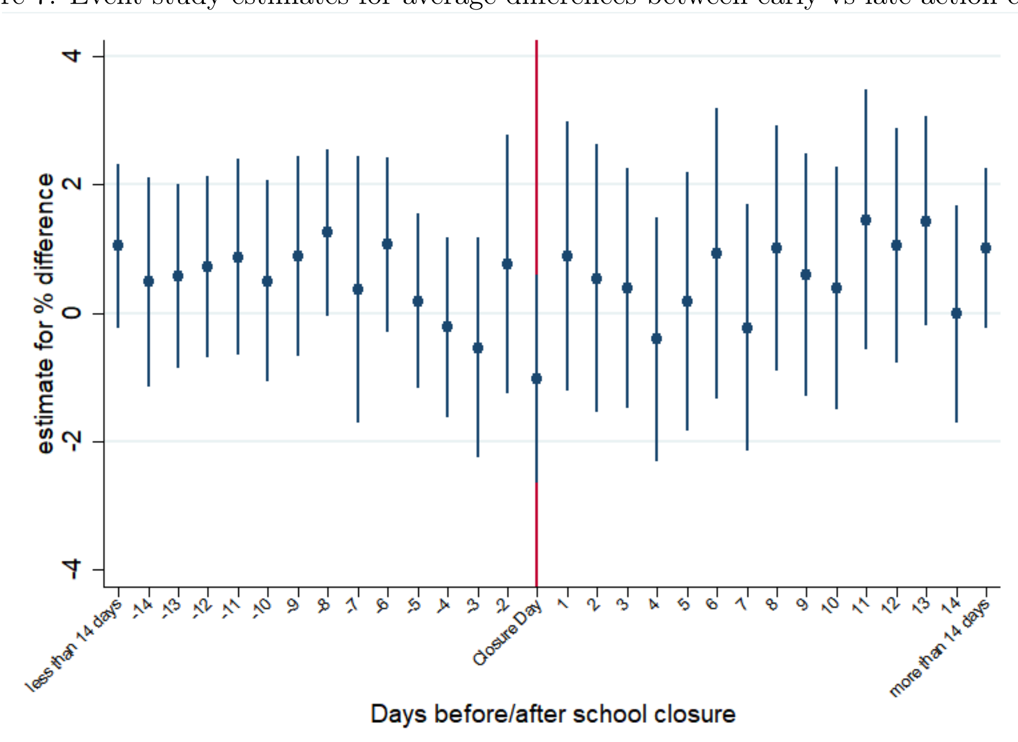
An "early action" country is defined as a country that closed schools within 6 or less days after the first case. This number corresponds to the median number of days that countries wait before closing schools. Overall, there are 83 "early action" and 79 "late action" countries in our dataset.

The regression that we ran is the following.

$$
\begin{aligned}
residential\_index_{it} = &\sum_{r=-14}^{R=14} \tau_r SC_i \times \mathbf{1}[days\_post\_regulation = r]_{it} + \\
&\sum_{r=-14}^{R=14} \gamma_r SC_i \times \mathbf{1}[days\_post\_regulation = r]_{it} \times early_i \\
&\sum_{l=-6}^{L=-1} \beta_l residential\_lag_{it} + \alpha_i + \delta_t + \epsilon_{it}
\end{aligned}
$$

The coefficients that we get for the interaction terms ($\gamma_r$s) are plotted below.

Figure 7: Event study estimates for average differences between early vs late action countries




As we can see, none of the coefficients are significant, which means that, for the 111 countries that we analyze, the effect of school closure on mobility, on average, is the same for those countries that closed schools within the first week after the first case was diagnosed, and after it.

## Regression Table for Effect of School Closure on the spread of COVID-19

Table A.3: Event Study Percentage Change in active cases and deaths Compared to the Previous Day of School Closure

| | Active cases | Deaths |
|---|---|---|
| lag_1 | 0.519*** | 0.739*** |
| | (0.0466) | (0.0262) |
| lag_2 | 0.117*** | 0.0599* |
| | (0.0195) | (0.0262) |
| lag_3 | -0.133*** | -0.310*** |
| | (0.0327) | (0.0244) |
| lag_4 | 0.0641*** | 0.251*** |
| | (0.0206) | (0.0215) |
| lag_5 | 0.0178 | 0.0116 |
| | (0.0109) | (0.0265) |
| lag_6 | -0.00733 | -0.0431** |
| | (0.00961) | (0.0178) |
| 15 or more days before | -14.83*** | -1.387 |
| | (4.516) | (0.969) |
| 14 days before | -11.96** | -1.613 |
| | (4.657) | (1.055) |
| 13 days before | -9.248 | -2.233** |
| | (5.797) | (0.951) |
| 12 days before | -15.02*** | -1.934** |
| | (4.566) | (0.974) |
| 11 days before | -8.657 | -1.746* |
| | (5.259) | (0.995) |
| 10 days before | -12.21** | -1.461 |
| | (5.180) | (1.087) |
| 9 days before | -14.17*** | -1.044 |
| | (4.753) | (0.989) |
| 8 days before | -9.873** | -1.407 |
| | (4.725) | (0.879) |
| 7 days before | -9.430** | -1.649* |
| | (4.555) | (0.916) |
| 6 days before | -9.470* | -1.763* |
| | (5.507) | (0.936) |
| 5 days before | -7.246 | -0.770 |
| | (4.803) | (0.995) |
| 4 days before | -5.797 | 0.337 |
| | (5.046) | (1.588) |
| 3 days before | -0.820 | -1.470 |
| | (5.024) | (1.151) |
| 2 days before | 4.783 | -0.498 |
| | (8.575) | (1.249) |
| Closure day | 0.373 | -0.703 |
| | (6.344) | (1.226) |

| | | |
|---|---|---|
| 1 day after | -8.043 | 0.429 |
| | (5.292) | (1.341) |
| 2 days after | -6.333 | -1.081 |
| | (4.739) | (1.219) |
| 3 days after | -7.024 | 1.106 |
| | (4.426) | (1.474) |
| 4 days after | -8.186* | -0.140 |
| | (4.438) | (1.316) |
| 5 days after | -8.592* | 1.845 |
| | (4.548) | (1.480) |
| 6 days after | -7.145 | -0.0426 |
| | (4.488) | (1.246) |
| 7 days after | -6.335 | 1.388 |
| | (4.485) | (1.588) |
| 8 days after | -8.785** | 0.767 |
| | (4.413) | (1.275) |
| 9 days after | -9.601** | 0.567 |
| | (4.400) | (1.237) |
| 10 days after | -8.518* | 4.079** |
| | (4.810) | (1.684) |
| 11 days after | -10.39** | 1.814 |
| | (4.423) | (1.624) |
| 12 days after | -10.66** | 0.984 |
| | (4.365) | (1.404) |
| 13 days after | -10.71** | 0.649 |
| | (4.517) | (1.173) |
| 14 days after | -10.51** | 0.270 |
| | (4.364) | (1.203) |
| 15 days after | -11.13** | 0.554 |
| | (4.301) | (1.273) |
| 16 days after | -9.322** | 0.468 |
| | (4.605) | (1.260) |
| 17 days after | -9.565** | 2.266 |
| | (4.491) | (1.396) |
| 18 days after | -10.14** | 1.815 |
| | (4.381) | (1.301) |
| 19 days after | -11.47*** | 1.120 |
| | (4.311) | (1.280) |
| 20 days after | -10.62** | 1.171 |
| | (4.348) | (1.253) |
| 21 days after | -10.75** | 0.308 |
| | (4.328) | (1.064) |
| 22 days after | -11.02** | 1.675 |
| | (4.248) | (1.271) |
| 23 days after | -10.86** | 0.226 |
| | (4.325) | (1.027) |
| 24 days after | -11.95*** | -0.224 |
| | (4.307) | (0.986) |

### Effect of School Closure on Other Measures of Mobility

The table below shows the effect of school closure on the other measures of mobility reported by Google.

Table A.4: Event Study Percentage Change in Visits to Places of Interest Compared to the Day Before of Schools Closed

| VARIABLES | *Workplaces* | *Retail and Recreation* | *Grocery and Pharmacy* | *Parks* | *Transit Stations* |
|---|---|---|---|---|---|
| 15 or more days before | -2.168* | -0.0183 | -3.804*** | 2.278 | -0.0911 |
| | (1.219) | (1.043) | (1.194) | (1.737) | (0.911) |
| 14 days before | -1.952 | 0.0572 | -3.207*** | 2.471 | -0.295 |
| | (1.520) | (1.085) | (1.207) | (2.117) | (1.023) |
| 13 days before | -1.111 | -0.882 | -4.302*** | -0.854 | -0.523 |
| | (1.229) | (0.977) | (1.139) | (1.602) | (0.902) |
| 12 days before | -1.260 | 0.361 | -4.002*** | 0.285 | -0.0268 |
| | (1.136) | (1.058) | (1.162) | (1.893) | (0.964) |
| 11 days before | -3.588** | 0.793 | -3.381*** | 3.767 | -0.376 |
| | (1.558) | (1.047) | (1.215) | (2.583) | (0.836) |
| 10 days before | -1.564 | 0.223 | -3.797*** | 2.230 | -0.0758 |
| | (1.274) | (0.953) | (1.147) | (1.613) | (0.869) |
| 9 days before | -2.700** | -0.146 | -4.282*** | 2.422 | -0.412 |
| | (1.164) | (0.941) | (1.088) | (1.644) | (0.928) |
| 8 days before | -1.906 | 0.870 | -3.883*** | 2.664 | 0.293 |
| | (1.196) | (0.920) | (1.186) | (1.795) | (0.815) |
| 7 days before | -3.262* | -0.341 | -4.492*** | 2.235 | -1.235 |
| | (1.835) | (0.937) | (1.130) | (1.970) | (0.958) |
| 6 days before | 0.0579 | 0.0824 | -3.655*** | 0.443 | 0.274 |
| | (1.110) | (0.784) | (1.125) | (1.840) | (0.803) |
| 5 days before | -1.454 | 0.871 | -3.228*** | 1.277 | -0.131 |
| | (1.144) | (0.869) | (1.139) | (1.912) | (0.827) |
| 4 days before | -1.663 | 1.336 | -2.817** | 2.855 | -0.0831 |
| | (1.328) | (0.870) | (1.256) | (2.308) | (0.805) |
| 3 days before | -2.529 | 0.143 | -3.516** | 1.373 | -1.002 |
| | (1.564) | (1.226) | (1.530) | (2.407) | (1.234) |
| 2 days before | -3.267* | -1.230 | -3.948*** | 1.429 | -1.723 |
| | (1.870) | (0.863) | (0.878) | (1.969) | (1.040) |
| Closure Day | -7.233*** | -3.568*** | -3.024** | -1.276 | -3.647*** |
| | (1.399) | (1.065) | (1.363) | (1.692) | (0.974) |
| 1 day after | -7.251*** | -3.659*** | -4.785*** | 1.934 | -3.775*** |
| | (1.414) | (1.091) | (1.519) | (1.787) | (1.095) |

| | | | | | |
|---|---|---|---|---|---|
| 2 days after | -6.511*** | -3.607*** | -6.068*** | -0.388 | -4.495*** |
| | (1.255) | (1.204) | (1.544) | (2.279) | (0.975) |
| 3 days after | -7.454*** | -4.586*** | -6.297*** | -0.649 | -4.737*** |
| | (1.353) | (1.225) | (1.653) | (1.821) | (1.007) |
| 4 days after | -7.854*** | -6.264*** | -9.342*** | -1.160 | -5.686*** |
| | (1.256) | (1.381) | (1.880) | (2.019) | (1.131) |
| 5 days after | -8.065*** | -5.379*** | -9.440*** | -3.690* | -5.759*** |
| | (1.530) | (1.341) | (1.879) | (1.920) | (1.190) |
| 6 days after | -9.208*** | -6.489*** | -12.32*** | -1.348 | -6.322*** |
| | (1.438) | (1.465) | (1.939) | (2.266) | (1.252) |
| 7 days after | -10.43*** | -5.065*** | -10.31*** | -2.212 | -5.570*** |
| | (1.397) | (1.190) | (1.784) | (2.017) | (1.040) |
| 8 days after | -7.400*** | -4.363*** | -9.466*** | -2.304 | -4.220*** |
| | (1.353) | (1.223) | (2.021) | (1.808) | (1.136) |
| 9 days after | -7.374*** | -5.315*** | -10.39*** | -2.097 | -4.723*** |
| | (1.324) | (1.534) | (1.763) | (1.967) | (1.201) |
| 10 days after | -8.209*** | -5.295*** | -10.83*** | -4.770** | -5.661*** |
| | (1.361) | (1.234) | (1.657) | (1.942) | (1.156) |
| 11 days after | -7.943*** | -4.423*** | -9.562*** | -3.384* | -4.832*** |
| | (1.356) | (1.317) | (1.705) | (1.927) | (1.147) |
| 12 days after | -7.028*** | -4.823*** | -10.18*** | -4.321** | -4.704*** |
| | (1.404) | (1.168) | (1.532) | (2.022) | (1.105) |
| 13 days after | -7.377*** | -4.360*** | -9.930*** | -2.208 | -3.999*** |
| | (1.381) | (1.130) | (1.491) | (1.933) | (1.034) |
| 14 days after | -8.682*** | -3.951*** | -9.111*** | -2.218 | -4.446*** |
| | (1.292) | (1.170) | (1.590) | (1.849) | (1.077) |
| 15 or more days after | -7.654*** | -4.559*** | -10.35*** | -3.123* | -4.529*** |
| | (1.256) | (1.107) | (1.431) | (1.719) | (1.031) |
| Constant | -0.361 | -1.969** | 3.212*** | -1.799 | -1.686** |
| | (0.968) | (0.860) | (1.078) | (1.467) | (0.776) |
| Observations | 8,436 | 8,436 | 8,414 | 8,436 | 8,436 |
| R-squared | 0.895 | 0.951 | 0.799 | 0.854 | 0.961 |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes |
| Six lags of dependent variable | Yes | Yes | Yes | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

| | | |
|---|---|---|
| 25 days after | -11.19** | 0.150 |
| | (4.299) | (0.982) |
| 26 days after | -11.25*** | 0.450 |
| | (4.258) | (0.995) |
| 27 days after | -9.450** | 1.248 |
| | (4.315) | (1.091) |
| 28 days after | -11.08*** | 0.242 |
| | (4.229) | (1.049) |
| 29 or more days after | -11.00** | 0.143 |
| | (4.326) | (0.992) |
| Constant | 14.43*** | 1.780** |
| | (4.279) | (0.840) |
| | | |
| Observations | 11,877 | 11,100 |
| R-squared | 0.492 | 0.672 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Robustness Check: Restricting the Sample to High Connectivity Countries**

Table A.5: Event Study with North America and Europe Only

| VARIABLES | (1) |
|---|---|
| 15 or more days before | -0.359 |
| | (0.506) |
| 14 days before | -0.231 |
| | (0.623) |
| 13 days before | -0.0671 |
| | (0.704) |
| 12 days before | -0.465 |
| | (0.572) |
| 11 days before | -0.405 |
| | (0.533) |
| 10 days before | -0.905 |
| | (0.576) |
| 9 days before | -0.371 |
| | (0.526) |
| 8 days before | -0.640 |
| | (0.488) |
| 7 days before | -0.142 |
| | (0.546) |
| 6 days before | -0.271 |
| | (0.593) |
| 5 days before | -0.147 |
| | (0.441) |
| 4 days before | -0.149 |
| | (0.553) |
| 3 days before | -0.0501 |
| | (0.517) |
| 2 days before | 0.999 |
| | (0.916) |
| Closure Day | 1.776*** |
| | (0.531) |
| 1 day after | 1.560** |
| | (0.664) |
| 2 days after | 1.144** |
| | (0.455) |
| 3 days after | 1.532** |
| | (0.599) |
| 4 days after | 1.600** |
| | (0.607) |

| | |
|---|---|
| 5 days after | 1.305* |
| | (0.696) |
| 6 days after | 1.009 |
| | (0.619) |
| 7 days after | 1.440** |
| | (0.607) |
| 8 days after | 0.947 |
| | (0.609) |
| 9 days after | 0.723 |
| | (0.631) |
| 10 days after | 1.704** |
| | (0.672) |
| 11 days after | 1.549** |
| | (0.651) |
| 12 days after | 1.109 |
| | (0.672) |
| 13 days after | 1.061* |
| | (0.562) |
| 14 days after | 1.584*** |
| | (0.544) |
| 15 or more days after | 1.470** |
| | (0.608) |
| Constant | 1.688*** |
| | (0.466) |
| Observations | 3,268 |
| R-squared | 0.939 |
| Time fixed effects | Yes |
| Country fixed effects | Yes |
| Six lags of dependent variable | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## Robustness Check: Controlling for Other Policies in Mobility Event Study

Table A.6: Robustness Check of Event Study Controlling for Other Policies

| VARIABLES | (1) |
|---|---|
| Workplace Closure | 1.454*** |
| | (0.284) |
| Cancel Public Events | 0.845*** |
| | (0.271) |
| Restriction on Gatherings | 0.0970 |
| | (0.250) |
| Stay at Home Order | 1.128*** |
| | (0.273) |
| Close Public Transport | 0.594** |
| | (0.231) |
| 15 or more days before | 0.00146 |
| | (0.482) |
| 14 days before | 0.457 |
| | (0.469) |
| 13 days before | 0.251 |
| | (0.445) |
| 12 days before | 0.278 |
| | (0.398) |
| 11 days before | 0.615 |
| | (0.437) |
| 10 days before | -0.0191 |
| | (0.391) |
| 9 days before | 0.367 |
| | (0.406) |
| 8 days before | 0.0761 |
| | (0.355) |
| 7 days before | 0.626 |
| | (0.511) |
| 6 days before | -0.0764 |
| | (0.367) |
| 5 days before | 0.251 |
| | (0.369) |
| 4 days before | 0.246 |
| | (0.385) |
| 3 days before | 0.505 |
| | (0.454) |
| 2 days before | 0.672 |
| | (0.423) |
| Closure Day | 1.870*** |
| | (0.393) |
| 1 day after | 1.885*** |
| | (0.479) |

| | |
|---|---|
| 2 days after | 2.075*** |
| | (0.448) |
| 3 days after | 1.843*** |
| | (0.444) |
| 4 days after | 2.124*** |
| | (0.424) |
| 5 days after | 2.048*** |
| | (0.485) |
| 6 days after | 2.253*** |
| | (0.494) |
| 7 days after | 2.438*** |
| | (0.462) |
| 8 days after | 1.581*** |
| | (0.509) |
| 9 days after | 1.814*** |
| | (0.533) |
| 10 days after | 1.712*** |
| | (0.501) |
| 11 days after | 1.890*** |
| | (0.514) |
| 12 days after | 1.476*** |
| | (0.464) |
| 13 days after | 1.295*** |
| | (0.448) |
| 14 days after | 1.695*** |
| | (0.450) |
| 15 or more days after | 1.088** |
| | (0.449) |
| Constant | 0.0842 |
| | (0.378) |
| Observations | 8,360 |
| R-squared | 0.932 |
| Time fixed effects | Yes |
| Country fixed effects | Yes |
| Six lags of dependent variable | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Robustness Check: Controlling for Other Policies for COVID Spread Event Study**

Table A.7: Robustness Check of Event Study Controlling for Other Policies

| | Active cases | Deaths |
|---|---|---|
| Workplace Closure | -1.158 | 0.541 |
| | (0.848) | (0.342) |
| Cancel Public Events | 1.555 | 0.694 |
| | (1.211) | (0.501) |
| Close Public Transport | 0.909 | -0.0591 |
| | (0.618) | (0.279) |
| Stay at Home Order | -0.550 | -0.123 |
| | (0.653) | (0.284) |
| $lag_1$ | 0.517*** | 0.738*** |
| | (0.0467) | (0.0263) |
| $lag_2$ | 0.117*** | 0.0603* |
| | (0.0195) | (0.0311) |
| $lag_3$ | -0.133*** | -0.312*** |
| | (0.0327) | (0.0246) |
| $lag_4$ | 0.0632*** | 0.250*** |
| | (0.0206) | (0.0218) |
| $lag_5$ | 0.0171 | 0.0135 |
| | (0.0110) | (0.0265) |
| $lag_6$ | -0.00818 | -0.0440** |
| | (0.00955) | (0.0178) |
| 15 days or more before | -14.61*** | -1.174 |
| | (4.600) | (0.959) |
| 14 days before | -11.75** | -1.434 |
| | (4.743) | (1.046) |
| 13 days before | -8.998 | -2.067** |
| | (5.883) | (0.941) |
| 12 days before | -14.74*** | -1.764* |
| | (4.650) | (0.962) |
| 11 days before | -8.412 | -1.584 |
| | (5.340) | (0.995) |
| 10 days before | -11.94** | -1.288 |
| | (5.262) | (1.078) |
| 9 days before | -13.94*** | -0.892 |
| | (4.844) | (0.997) |
| 8 days before | -9.582** | -1.262 |
| | (4.808) | (0.867) |
| 7 days before | -9.252** | -1.527* |
| | (4.621) | (0.907) |

| | | |
|---|---|---|
| 6 days before | -9.149 | -1.629* |
| | (5.582) | (0.924) |
| 5 days before | -7.067 | -0.642 |
| | (4.870) | (0.989) |
| 4 days before | -5.611 | 0.441 |
| | (5.118) | (1.593) |
| 3 days before | -0.869 | -1.360 |
| | (5.061) | (1.158) |
| 2 days before | 4.856 | -0.475 |
| | (8.659) | (1.259) |
| Closure day | 0.272 | -0.836 |
| | (6.392) | (1.243) |
| 1 day after | -8.424 | 0.223 |
| | (5.305) | (1.376) |
| 2 days after | -6.604 | -1.322 |
| | (4.782) | (1.255) |
| 3 days after | -7.265 | 0.831 |
| | (4.454) | (1.511) |
| 4 days after | -8.216* | -0.365 |
| | (4.459) | (1.357) |
| 5 days after | -8.601* | 1.554 |
| | (4.569) | (1.489) |
| 6 days after | -7.221 | -0.371 |
| | (4.558) | (1.285) |
| 7 days after | -6.602 | 0.758 |
| | (4.510) | (1.585) |
| 8 days after | -9.106** | 0.478 |
| | (4.444) | (1.295) |
| 9 days after | -9.708** | 0.209 |
| | (4.429) | (1.257) |
| 10 days after | -8.575* | 3.604** |
| | (4.849) | (1.709) |
| 11 days after | -10.55** | 1.200 |
| | (4.474) | (1.660) |
| 12 days after | -10.78** | 0.607 |
| | (4.409) | (1.444) |
| 13 days after | -10.91** | 0.223 |
| | (4.558) | (1.222) |
| 14 days after | -10.65** | -0.267 |
| | (4.415) | (1.237) |
| 15 days after | -11.36** | 0.136 |
| | (4.349) | (1.319) |
| 16 days after | -9.476** | 0.0643 |
| | (4.670) | (1.313) |
| 17 days after | -9.741** | 1.840 |
| | (4.533) | (1.452) |
| 18 days after | -10.33** | 1.362 |
| | (4.404) | (1.359) |

| | | |
|---|---|---|
| 19 days after | -11.69*** | 0.647 |
| | (4.335) | (1.329) |
| 20 days after | -10.87** | 0.743 |
| | (4.370) | (1.305) |
| 21 days after | -11.01** | -0.246 |
| | (4.359) | (1.113) |
| 22 days after | -11.27*** | 1.151 |
| | (4.268) | (1.342) |
| 23 days after | -11.11** | -0.306 |
| | (4.343) | (1.096) |
| 24 days after | -12.21*** | -0.702 |
| | (4.315) | (1.060) |
| 25 days after | -11.44*** | -0.332 |
| | (4.310) | (1.051) |
| 26 days after | -11.55*** | -0.0666 |
| | (4.264) | (1.077) |
| 27days after | -9.718** | 0.628 |
| | (4.307) | (1.162) |
| 28 days after | -11.42*** | -0.311 |
| | (4.219) | (1.122) |
| 29 days or more after | -11.32*** | -0.436 |
| | (4.302) | (1.087) |
| Constant | 14.21*** | 1.460* |
| | (4.371) | (0.838) |
| | | |
| Observations | 11,735 | 10,965 |
| R-squared | 0.491 | 0.672 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1