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PANDEMIC PERCEPTION AND REGULATION EFFECTIVENESS: EVIDENCE FROM THE COVID-19

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JEL Classification: D7, E7, I18
Keywords: mobility, lockdown measures, COVID-19, stringency Index, perception, public health, public policy

Pandemic perception and regulation effectiveness: Evidence from the COVID-19

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Abstract

The spread of COVID-19 led countries around the world to adopt lockdown measures of varying stringency to restrict movement of people. However, the effectiveness of these measures on mobility has been markedly different. Employing a difference-in-differences design and a set of robustness checks, we analyse the effectiveness of movement restrictions across different countries. We disentangle the role of regulation (stringency measures) from the role of people's perception about the spread of COVID-19. We proxy the COVID-19 perception by using Google Trends data on the term "Covid". We find that lockdown measures have a higher impact on mobility the more people perceive the severity of COVID-19 pandemic. This finding is driven by countries with low level of trust in institutions.

Keywords: Mobility, Lockdown measures, COVID-19, Stringency Index, Perception, Public health, Public policy.

JEL Codes: D7; E7; I18.

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1 Introduction

According to the latest data from the World Health Organization (June, 2021), more than 150 million of COVID-19 infected cases have been reported, including more than 3.8 million deaths.[1] The pandemic has had a devastating impact on population health and well-being, and on the economy of countries across the globe (Levy Yeyati and Filippini, 2021).

The COVID-19 pandemic, which began in December 2019 in the city of Wuhan in China, has reached nearly all countries in the world. However, the effects of the pandemic show a large degree of heterogeneity, since countries have differed in their exposure to the virus, in the public and private response to it, and in the overall level of preparedness.

National governments have been implementing measures which restrict the movement of individuals (referred to, colloquially, as 'lockdown', a term we will also adopt throughout the paper) and impose social distancing. Interestingly, these measures display significant variation in their intensity, with some countries announcing stringency measures very early in the pandemic cycle, whereas others taking a less restrictive approach (Ferraresi *et al.,* 2020).

The purpose of these measures that restrict mobility and impose social distancing is of course the one of strongly reducing the spread of the virus, in order to contain the number of severe cases and deaths. From this point of view, policy makers and experts typically aim at avoiding an excessive pressure on hospitals and ICUs, which would lead to a dramatic increase in the mortality of the disease. However, the accomplishment of this purpose not only depends on the design and timeliness of those coercive measures, but also on how citizens react to those measures, strengthening or weakening them with their individual course of action.

[1] Daily coronavirus disease (COVID-19) reports are available on the World Health Organization's webpage (https://covid19.who.int/. The actual number of infected cases is likely to be significantly higher as asymptomatic carriers of the infection are not detected.

Interestingly, the lockdown measures have also been the subject of some controversy amongst political, legal/law commentators and the public.[2] In fact, several demonstrations against the lockdown have taken place in many countries in Europe[3], in the US[4] and elsewhere. In fact, it is unclear whether those protests are driven by impatience, a genuine perception that the lockdown measures are disproportionate to the pandemic threat, or simply an instance of aversion against an authoritarian turn in the actions of democratic and non-democratic governments alike.

Individual level reactions might be more collaborative the more citizens are worried about the risks of contagion and of severe health outcomes. In turn, those perceived risks are affected by the information that citizens have about the pandemic, which they obtain by personal contacts and by being exposed to the mass media, both traditional and internet-based ones (namely, websites and social networks). The recent literature has widely covered this topic across different domains. Mastrorocco and Minale (2018) found an effect of news media on crime perceptions. They use a difference-in-difference approach that compares individual perceptions of those with a wide range of available TV channels to those with limited choice. The topic of perception affecting individual behavior has been also addressed in the case of political elections (Martinand and Yurukoglu, 2017) and within the crime literature (Shi, 2009; Velásquez *et al.*, 2020; Spenkuch, 2018).

[2] In the UK, for example, the restrictions that underpin the COVID-19 lockdown measures have been recently challenged as being unlawful and disproportionate, breaching freedoms protected by the European Convention of Human Rights (Keene 2020). In New Zealand the government's decision to impose a month-long lockdown to stem the spread of coronavirus has also been challenged in court.

[3] See 'German police cracks down on anti-lockdown protesters', FT, May 17, 2020 (J. Miller).

[4] See 'US anti-lockdown protests: 'If you are paranoid about getting sick, just don't go out', FT, April 22, 2020 (D. Crow).

In this paper we investigate, at the country level, the effects of stringency measures on citizen's daily mobility, taking into account a daily and country-specific measure of citizens' concern about the pandemic, i.e. the relative amount of Google searches about COVID-19 itself.

Scholar have begun to investigate the determinants of the effectiveness of stringency measures, identifying variables such as expectations for the duration of self-isolation and belief and trust in science (Briscese *et al.*, 2020), political affiliation (Allcott *et al.*, 2020; Painter and Qiu, 2020), social responsibility and social trust (Oosterhoff and Palmer, 2020), and the trust in policymakers' ability to handle the crisis (Bargain and Aminjonov, 2020; Brodeur *et al.*, 2020; Farzanegan and Hofmann, 2021). But, to the best of our knowledge, there is no empirical analysis of the relationship between stringency measures and mobility which explicitly incorporates the perception of COVID-19 spread and seriousness.

We implement a difference-in-differences (DiD) research design by focusing on the consequences of the stringency measures on the mobility level of the population. In particular, we use daily observations from February 15, 2020 to December 25, 2020 (315 days), across 35 countries for which these data are available. The COVID-19 perception is measured in terms of Google searches on the pandemic.

Figure 1 plots the relationship between a measure of movement (conveniently called 'mobility index'), the extent of the lockdown ('Stringency Index'),[5] the spread of the COVID-19 (COVID-19 cases per capita) and a measure of the public perception of the pandemic (Covid searches in Google). For the first 80 days of 2021, there is a clear inverse relationship between the lockdown measures and COVID-19 online searches with population movement. After this period Covid searches in Google decreases faster than lockdown measures, while, at the same

[5] See Hale *et al*. 2020, "*Government Response Stringency Index"*.

time, mobility starts increasing. This divergence between lockdown measure and COVID-19 search raises the issue of the role of the perception in the effectiveness of lockdown measures.

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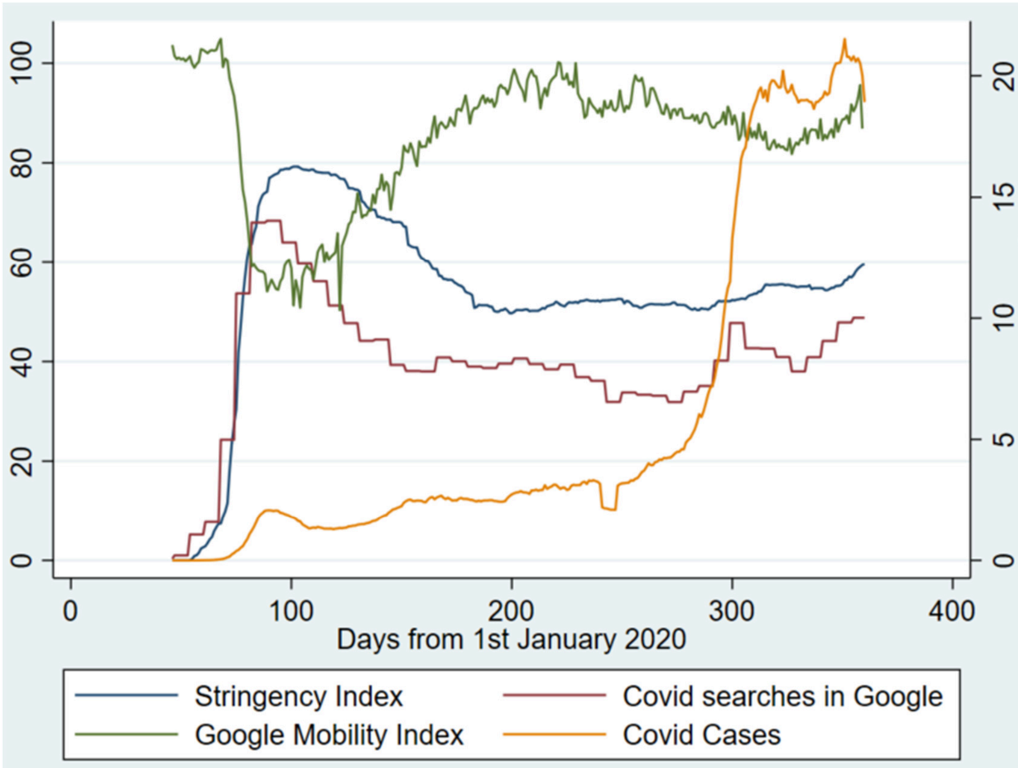
Figure 1 - Mobility, stringency of lockdown measures, Covid searches, and Covid cases per capita.



Note: This figure displays the Stringency Index, the Google Mobility Index, Covid searches on Google and weekly moving average of per capita Covid Cases over 2020, from February 15 (day 46) to December 30 (day 365). Observations for 35 countries are averaged by day. The Stringency Index and Covid searches vary from 0 to 100. The Mobility Index is equal to 100 at the baseline value calculated as the median value recorded during the first 5 weeks of 2020. Per capita Covid Cases correspond to new active cases and are calculated as the difference in per capita cumulated cases between day *t* and day *t-1*. For more details, see Section 3.

We exploit the staggered implementation of stringency measures adopted by countries along time, while controlling for country and daily fixed effects. We find that stricter lockdowns are significantly associated with lower mobility, and that this effect is greater the more people are concerned about the spread of COVID-19. These results survive a set of robustness tests, including the traditional event-study test *à la* Autor (2003).

The remainder of the article is organized as follows: in Section 2 we lay down the empirical framework; in Section 3 we present the data, while in Sections 4 and 5 we discuss the results and perform some robustness tests, respectively. Finally, Section 6 summarises and concludes.

2 Empirical strategy

Our baseline empirical model builds on the large and expanding literature that makes use of the DiD method to investigate the net impact of a policy or a program on given outcomes. The standard case for applying DiD is when an exogenous shock such as a lockdown measure (treatment) affects only a group of units (treated), in the presence of another group (control) which is similar in all respects but not affected by the intervention.

As noted in the introduction, while all countries eventually adopted lockdown measures in the year 2020 due to the COVID-19 outbreak, they differ in the timing of this adoption. This allows us to compare the change in the mobility index in the treatment group before and after the adoption to the change in outcomes in the control group.

The estimated difference-in-difference (DiD) model is the following:

$$mobility_{cd} = \alpha + \gamma stringency_{cd} + \beta X_{cd} + f_c + f_d + u_{cd} \quad (1)$$

where $mobility_{cd}$ is the Google mobility index for country *c* in day *d*; $stringency_{cd}$ is the Stringency Index in country *c* and day *d*, ranging from 0—when lockdown measures have not been adopted yet—to 100, with 100 denoting the maximum level of lockdown; X_{cd} are daily variables at country level, such as temperatures, weekly moving average of the pandemic confirmed cases per capita and the intensity of Covid searches a week before[6]; f_c are country fixed effects that control for unobserved cross-country heterogeneity[7]; f_d are daily fixed effects

[6] We use this lagged measure of Covid searches since the mobility variable (our dependent variable) is at a daily frequency, while Google searches are only available at weekly frequency. In case we used the contemporaneous intensity of Google searches we would pick up searches that happen in days that *follow* the mobility indicator.
[7] In turn, this heterogeneity might be due to different levels of technology that affect both mobility and Google hits, national differences in the contagion level, health-care systems (such as availability of testing and Intensive Care Unit capacity), as well as population density and the age profile of the population.

that capture time-specific shocks common to every country, such as Covid-related information that becomes available worldwide in a given day; and u_{cd} is the error term, clustered at country level. In some specifications, we also control for country-by-day fixed effects. In this model, γ is the DiD estimate of the (average) effect of the lockdown on mobility.

We use the intensity of daily searches on Google of the term "Covid" for each country. This variable ranges from 0 - when there is no search in Google of the term "Covid" - to 100, with 100 denoting the maximum level of Covid searches. To investigate whether there has been a heterogeneous response according to the perception of COVID-19 on a given day in each country, we interact Covid searches with the stringency measures.

The estimated model is a generalised version of Equation (1), taking the following form:

$$mobility_{cd} = \alpha + \gamma stringency_{cd} + \lambda covid\ searches_{cd} + \vartheta stringency_{cd} \times covid\ searches_{cd} + \beta X_{cd} + f_c + f_d + u_{cd} \tag{2}$$

where our variable of interest is the coefficient ϑ of the interaction term.

3 Data

3.1 Movement of individuals

To measure the daily movement of people during the spread of COVID-19, we use the COVID-19 *Community Mobility Reports* provided by Google.[8] The mobility indicators record the differences of each day's mobility, compared to the baseline value for that day of the week, which in turn is calculated as the median value recorded during the 5-week period from January 3 to February 6, 2020, i.e. before the start of the pandemic. The *Community Mobility Reports* provide six different place categories: *grocery & pharmacy, parks, transit stations, retail & recreation, residential* and *workplaces*. In the main regression, we use as dependent the variable the daily average of the above variables from which we exclude the '*residential'* trend as it has different units of measurement (i.e. change in duration vs change in total visitors).[9] Following Helsingen *et al.* (2020), we use observed data on mobility because they are more reliable than individual surveys due to the potential confounding role of individual biases in the way respondents self-report their behavior.

3.2 Stringency Index

During the same period of the COVID-19 outbreak, governments around the world adopted many and very different containment measures. To take into account the heterogeneity of the governments' response we make use of the *Government Response Stringency Index* (*Stringency Index*) developed by Hale *et al*. (2020). The *Stringency Index* is a composite indicator (consisting of a series of standardized indicators, S1-S7, described below) on specific government interventions. In particular, since January 1, 2020, Hale *et al*. (2020)

[8] For details see: https://www.google.com/covid19/mobility/

[9] As robustness check we use as dependent variable the mobility index excluding one of each component at time.

collected daily information on: i) closings of schools and universities (S1), ii) closings of workplaces (S2), iii) cancellation of public events (S3), iv) closing of public transport (S4), v) presence of public information campaigns (S5), vi) restrictions on internal movement (S6), and vii) restrictions on international travel (S7). It is worth noting that the sub-indicator S5 takes on the value of 1 if a COVID-19 public information campaign is put in place, and 0 otherwise, while for the other six policy response variables a value of 1 is assigned if the closing is recommended, a value of 2 if the measure is mandatory, and 0 otherwise. For each sub-indicator a score of 1 is added if the policy is applied throughout the entire country and not only on a particular region/area. This implies a score between 0 and 2 for the sub-indicator S5, and from 0 to 3 for the other six sub-indicators. Then, each of these values is rescaled by its maximum value to create an overall score between 0 and 100. These seven scores are then averaged to get the composite one: the *Stringency Index*.

3.4 COVID-19 perceptions

We use data from the Google Trends tool to measure the perception of the pandemic. As in previous work using Google Trends to successfully predict disease outbreaks (Carneiro and Mylonakis, 2009), trading behaviour in financial markets (Preis *et al.,* 2013), and concern of public opinion about pensions (Fornero, Oggero and Puglisi, 2019), we assume that Google search indicators provide reliable information about citizens' perceptions. The tool provides an index for online search intensity of a specific term (and its components) over the time period under consideration within a specific area. The index is a weekly intensity measured as the number of weekly searches for the term divided by the maximum number of its weekly searches over the whole time period, in a given geographical area. The result is scaled from 0 to 100, where 100 is the peak popularity and 0 means that there was not enough search volume for that specific term during that week. For our purposes, we collect the searches related to the term "Covid" for the period from February 2020 to December 2020. In order to conduct some falsification tests, we also collect the searches related to the main terms searched worldwide in Google from February 2020 to December 2020, i.e. “translate”, “porn”, and “maps”.

Notice that people’s perception about COVID-19 might be strictly related to the amount of media coverage devoted to the issue. In fact, the link between media coverage and Google Trends searches has been emphasized by the literature, with specific reference to the pandemic: for example, Sousa-Pinto *et al.* (2020) show that the Google Trends for COVID-19 symptoms such as cough, anosmia and ageusia are more strongly related to media coverage than to the underlying pandemic trends.[10] Interestingly, the authors find that the peaks for the Google searches on the various symptoms occurred simultaneously, irrespective of the country’s pandemic stage. This suggests that Covid online searches are not solely and endogenously driven by the pandemic.

The summary statistics for all of the variables used in the analysis are reported in Table A2 of the Appendix.

4 Results

4.1 Main results

The first three columns of Table 1 report the results based on the different specifications of Equation (1) for 35 “baseline” countries: these are the countries that – within our time frame- actually experienced an initial phase with no COVID-related restrictions, so that it is possible to test for the parallel trend assumption via the Autor test.[11] The baseline specification, which

[10] https://doi.org/10.1371/journal.pone.0152802; https://www.jmir.org/2020/8/e19611
[11] Table A3 extends the results of Table 1 with all countries available. Note that the main results do not change significantly.

includes country and time fixed effects and the confirmed per capita cases as control variables, is reported in Column (1). Column (2) adds to the previous specification the temperature variable, which would capture weather-related drivers of mobility[12]. In Column (3) we include as control variable the Covid searches. The last three columns show the results that are based on different versions of Equation (2). In Column (4) we include country and daily fixed effects, the temperature variable, and the interaction between Covid searches and the Stringency Index, while in Column (5) we include country-by-day fixed effects. Finally, in Column (6), in order to check whether the potentially heterogeneous reaction to the Stringency Index depends on real world events rather than on citizens' perceptions about those events, we add the interaction between confirmed per capita cases and the Stringency Index itself.

Table 1 – Difference in difference estimates, main specification.

Dependent variable: Mobility	(1)	(2)	(3)	(4)	(5)	(6)
Stringency Index	-0.489***	-0.412***	-0.398***	-0.266***	-0.322***	-0.322***
	(0.059)	(0.055)	(0.058)	(0.064)	(0.071)	(0.071)
Confirmed cases per capita	-0.345***	-0.246***	-0.176**	-0.170**	-0.185*	-0.232
	(0.100)	(0.088)	(0.085)	(0.083)	(0.092)	(0.312)
Temperatures		0.118***	0.122***	0.119***	0.118***	0.118***
		(0.017)	(0.018)	(0.017)	(0.020)	(0.020)
Covid searches			-0.079**	0.136	0.112	0.117
			(0.038)	(0.090)	(0.082)	(0.083)
Stringency Index*Covid searches				-0.003***	-0.003**	-0.003**
				(0.001)	(0.001)	(0.001)
Stringency Index*Confirmed cases pc						0.001
						(0.004)
Observations	11,025	11,025	11,025	11,025	11,025	11,025
R-squared	0.76	0.79	0.79	0.80	0.99	0.99
Country FE	YES	YES	YES	YES	YES	YES
Daily FE	YES	YES	YES	YES	YES	YES
Country trend	NO	NO	NO	NO	YES	YES

Notes: This table shows the effect of Covid searches on mobility. We regress country's mobility index on different set of variables. In Column (1) Stringency Index and per capita Confirmed Cases (Eq. 1); in Column (2) we additionally control for temperatures (Eq. 1); in column (3) we add Covid searches as a control (Eq. 1); in Column (4) we also include the interaction between Stringency Index and Covid searches (Eq. 2), while in Column (5) we add country-specific linear trends; finally, in Column (6) we additionally include the interaction term between Stringency Index and per capita Confirmed Cases (Eq.

[12] Temperatures are retrieved from Global Historical Climate Network Daily (National Oceanic and Atmospheric Administration, 2020).

2). For all specifications we include country and daily fixed effects. In columns 5 and 6 we also include country specific trend. The dataset is a country by day panel, for 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** p<0.01, ** p<0.05, * p<0.1

In the first three specifications we find a negative and statistically significant relationship between mobility and stringency. The point estimates range from –0.489 to –0.398. This implies that, during the Covid-19 outbreak, the mobility in countries with stronger stringency measures decreases more than in those with weaker measures. Since the stringency variable measures the treatment intensity, we capture the impact of being treated by comparing the effect on mobility level when the stringency and Covid searches are at extreme values of their joint distribution. For instance, following the point estimates of Column (3), the mobility is reduced by approximately 11.41 percentage points when considering a shift from Uruguay, whose level of both the stringency measure and Covid searches are the closest to the 25th percentile value, to Dominican Republic, whose level of both the stringency measure and Covid searches are the closest to the 75th percentile value.[13]

In Column (4) the coefficient on the interaction term *Stringency Index*Covid searches* is negative and statistically significant at the 1% confidence level, with a point estimate of -0.003, while it is 5% statistically significant in the last two specifications (column 5 and 6). This implies that the magnitude of the effect of the stringency measures on mobility is stronger for higher level of COVID-19 perceptions, i.e., the effectiveness of stringency is amplified by the perception of the severity of the pandemic. On the other hand, the interaction of the stringency measure with the number of confirmed cases (Column 6) is not significant at ordinary confidence levels, while the interaction of stringency with Covid searches remains significant

[13] This effect is computed as follows: -11.42 = [–0.3979666× (76.033-47.342)], and it is statistically significant at the 1% level.

and of the same magnitude. This suggests that the role of Covid searches in determining the impact of stringency on mobility appears to be more relevant than real world events connected to the pandemic evolution itself.

Using the point estimates of Column (6), mobility is reduced by 35.90 percentage points[14] when the Stringency Index and the Covid searches are the closest to their 75th percentile values, i.e. 76.033 and 53.411 respectively; conversely, when the Stringency Index and the Covid searches are the closest to their 25th percentile value (47.342 and 29.069) the reduction in mobility is equal to 19.10 percentage points.[15] Therefore, the difference in mobility reduction is 16.80 percentage points, which is greater than what we obtained with the specification that does not include the interaction term between Covid searches and the stringency index (11.42 percentage points). Therefore, the Google search interaction term contributes to the mobility reduction by increasing it by 47%.

4.2 Heterogeneity Analysis

How to explain the fact that the interest in the pandemic –as proxied by Google searches- affects the compliance with the stringency measures? Our intuition is that people comply with these regulations when they perceive them as salient. When the pandemic becomes more relevant in their perception, people likely feel more pressure to comply with stringency measures themselves. In turn, the perception of the pandemic might matter more in economic and political environments where the quality of institutions and freedom of media coverage is *low*, i.e. when citizens not necessarily trust the appropriateness of government interventions and/or news about those interventions.

[14] This effect is computed as follows: -35.90 = [-0.3215919 ×76.033–-0.0028192 (76.033×53.411)], and it is statistically significant at the 1% level.
[15] This effect is computed as follows: -19.10 = [-0.3215919×47.342–0.0028192 (47.342×29.069)], and it is statistically significant at the 1% level.

The importance of mass media in influencing public perception about the pandemic is likely to be strongly related to governance indicators, such as *voice and accountability* and *rule of law* (Kaufman et al., 2010).[16] It is reasonable to think that with high levels of governance indicators, people's perception about the severity of the pandemic –as influenced by the media- is likely to be less relevant in affecting the average compliance with regulations. Transparency of institutions (voice and accountability) and citizens' confidence in the rules of society (rule of law) should narrow down the effect of their perception, as measured by the volume of Google searches: people are more likely to trust institutions and abide by the law, so that people's perception should not amplify or diminish the effects of stringency measures. Consistent with this argument, Table 2 shows that the effect of pandemic perception in reducing mobility is driven by countries with lower level of government indicators, namely *voice and accountability* and *rule of law*. On one hand, in the case of countries whose governance indicators are below the median, the coefficient on the interaction term is 1% statistically significant, and double the size (-0.006) of that estimated in the main specification. On the other hand, countries above the median show a negative but smaller effect that, however, is not statistically significant.

[16] "Voice and Accountability: capturing perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. […] 5. Rule of Law: capturing perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence."

Table 2 – Difference in difference estimates. Effect of Covid searches on mobility, by governance indicators.

	Governance indicators	
	(1)	(2)
Dependent variable: Mobility	< Median	>=Median
Panel A	*Voice and Accountability*	
Stringency Index*Covid searches	-0.004***	-0.001
	(0.001)	(0.002)
Panel B	*Rule of Law*	
Stringency Index*Covid searches	-0.004***	-0.000
	(0.002)	(0.002)
Observations	5,355	5,670
Country FE	YES	YES
Daily FE	YES	YES
Country trend	YES	YES

Notes: This table shows the effect of Covid searches on mobility for countries with low and high governance index. We split the dataset in two subsets, i.e. 18 countries below the median and 17 countries above the median, both observed for 315 days. Panel A refers to Voice and Accountability index, Panel B refers to Rule of Law. The estimated coefficient is the coefficient of interest, ϑ, of Equation (2). We regress mobility on Stringency Index, Covid searches, the interaction between Stringency Index and Covid searches (ϑ), per capita Confirmed Cases and temperatures. We include country and daily fixed effects and country specific trends. Robust standard errors are clustered at country level (and shown in parentheses).

4.3 Autor test

The key identifying assumption for DiD estimates is that the change in movement in the control countries is an unbiased estimate of the counterfactual. While we cannot directly test this assumption, we can test whether the time trends in the control and treatment countries were the same in the pre-intervention periods. If the trends are the same in the pre-intervention periods, then it is likely that they would have been the same in the post-intervention period, had the treated countries not adopted any lockdown measure. An event-study analysis can shed some light on the validity of the research design. Following Autor (2003), we create a dummy variable which takes on the value of 1 on the first day of the lockdown, and zero otherwise. We do not introduce this dummy variable directly in our specification but we interact it with the mean of the Stringency Index adopted by each country in order to account for the overall intensity of the government measures. Hence, starting from this variable, we create its leads (one for each day prior the day of the lockdown) and lags variables[17] (one for each day after the lockdown measure was introduced). If the trends in the mobility measure in adopting versus non-adopting countries are the same, then the leads should not be statistically significant. An attractive feature of this test is that the lags are informative and can show whether the effect changes over time. We estimate the following specification:

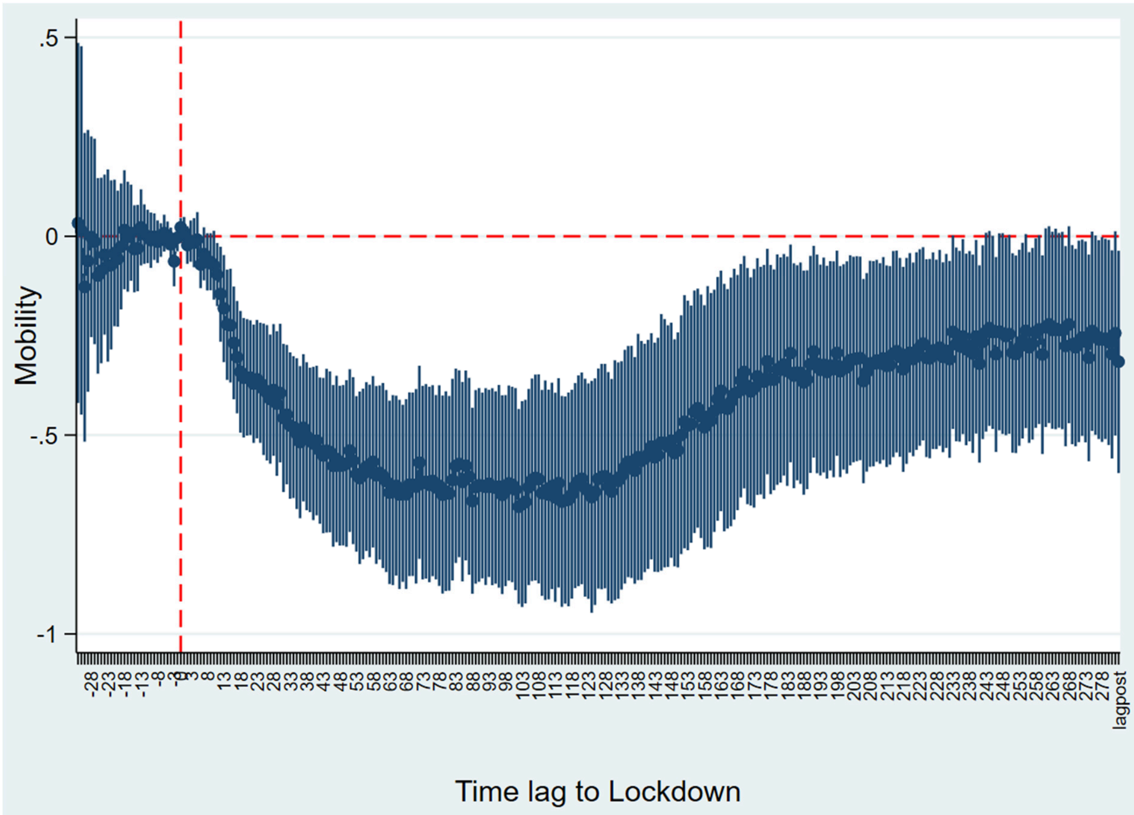
$$mobility_{cd} = \alpha + \sum_{\pi=-32}^{-2} \beta_\pi stringency_{c(d+\pi)} * Mean\ stringency_c + \sum_{\tau=0}^{283} \beta_\tau stringency_{c(d+\tau)} * Mean\ stringency_c + \beta X_{cd} + f_c + f_d + u_{cd}$$

This specification allows for testing parallel trends in the pre-treatment period, namely, whether the coefficients associated with the lead (β_π, with π going from -32 to -2) are not statistically different from zero. This approach also helps understand whether the treatment effect fades, increases, or stays constant over time, depending on the estimated coefficients on the lags (β_τ, with τ going from 1 to 283).

The omitted day is the day before the lockdown, which (given the staggered time of the adoption) differs by country. For example, in Sweden the lockdown started on the 9th March, 2020, therefore there are 13 leads and 270 lags.

[17] As the number of countries with more 282 lags sharply decreases after the 283rd day from the stringency adoption, we replace each individual lag for the remaining 13 days with a single dummy variable interacted with the stringency mean.

Figure 2 – Autor test.



Notes: This figure plots estimates γ from Equation (1), with their respective pointwise 90% confidence intervals. The plotted estimated coefficient is the interaction between the leads and lags and the mean over the all period of the stringency index adopted by each country. The dependent variable is the Mobility Index. The day before the lockdown is omitted, so the estimates are normalized to zero in that day. The model also includes country and daily fixed effects and temperatures and per capita confirmed cases as covariates. Errors are clustered at country level. The sample include 35 countries observed over 315 days.

The estimates, together with their 90% confidence intervals, are plotted in Figure 2. According to the point estimates, in the pre-treatment period there is no difference in the movement until around the 10th day after the adoption of the lockdown.

Turning now to the lag coefficients, we find that the lockdown measures contribute to a reduction in mobility, but it takes some days for the effects to materialise. In fact, the coefficient associated with the lags turns out to be negative and statistically significant at the 5% after 11 days since the first day of the lockdown. The effect of the stringency on mobility is stronger at the beginning and, while remaining negative and statistically significant, it decreases approximately 130 days after the start of the lockdown.

5 Robustness test

In this section, we use a battery of robustness checks to address possible issues related to the research design that could bias our baseline estimates. First, we replace the main dependent variable by excluding one by one each component of the Google mobility index; then we move to a country sensitive test to show that the estimated effects do not depend from a specific country, and lastly, we run a falsification test, replacing the Covid searches with other relevant terms searched on Google during the same time-span.

5.1 Alternative dependent variables

The dependent variable used in the main regression (Table 1) is a composite indicator built with the average of the mobility for visits to retail & recreation, workplaces, grocery & pharmacy, transit stations, and parks.

To check whether results are not driven by a specific individual component of the Google mobility composite indicator, in Table 3 we exclude one component at a time from the dependent variable. The coefficient on the interaction term *Stringency Index*Covid searches* remains negative and statistically significant in all specifications, which is consistent with the fact that the results do not depend on one particular component of the index.

Table 3– Difference in difference estimates, using alternative dependent variables.

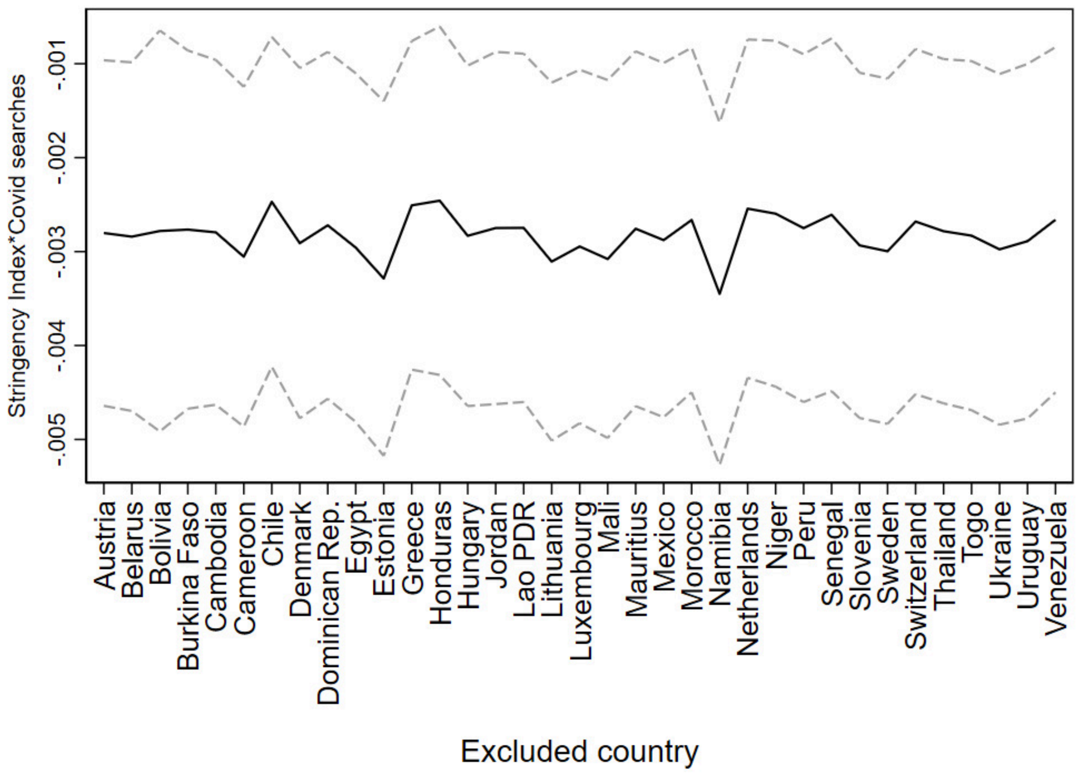
	(1) Mobility without retail and recreation	(2) Mobility without workplaces	(3) Mobility without grocery and pharmacy	(4) Mobility without transit stations	(5) Mobility without parks
Stringency Index	-0.318***	-0.344***	-0.342***	-0.313***	-0.304***
	(0.075)	(0.072)	(0.073)	(0.075)	(0.073)
Covid searches	0.109	0.089	0.118	0.125	0.131
	(0.085)	(0.085)	(0.086)	(0.090)	(0.080)
SI*Covid searches	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SI*Conf. cases pc	0.002	0.001	0.000	0.001	-0.001
	(0.004)	(0.005)	(0.005)	(0.004)	(0.002)
Conf. cases pc	-0.331	-0.276	-0.235	-0.220	-0.078
	(0.351)	(0.362)	(0.377)	(0.340)	(0.150)
Temperatures	0.132***	0.149***	0.136***	0.134***	0.039***
	(0.022)	(0.023)	(0.023)	(0.021)	(0.011)
Observations	11,025	11,000	11,025	11,025	11,025
R-squared	0.78	0.80	0.80	0.79	0.79
Country FE	YES	YES	YES	YES	YES
Daily FE	YES	YES	YES	YES	YES
Country trend	YES	YES	YES	YES	YES

Notes: This table shows the effect of Covid searches on different measures of mobility. In each Column from (1) to (5) we average the mobility index removing one component at a time, namely we exclude retail and recreation (1), workplaces (2), grocery and pharmacy (3), transit stations (4), and parks (5). We regress different dependent variables on Stringency Index (SI), Covid searches, the interaction between Stringency Index and Covid searches, per capita Confirmed Cases and their interaction with Stringency Index and temperatures, as in Equation (2). We include country and daily fixed effects and country specific trends. The dataset is a country by day panel, for 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** p<0.01, ** p<0.05, * p<0.1

5.2 Country Sensitivity

We also test whether our main findings are sensitive to the exclusion of a single country. For this reason, we estimate Equation (2), by dropping one country at a time. The estimated coefficients of the interaction term *Stringency Index*Covid searches* and their 95% confidence interval (Figure 3) are very similar to those obtained in our baseline specification. Hence, it can be concluded that our main result is not driven by a particular country.

Figure 3 – Country sensitivity analysis.



Notes: This figure shows the coefficient of interest, ϑ, of Equation (2) for different set of countries. ϑ is the coefficient of interaction between Stringency Index and Covid searches in the regression of mobility on Stringency Index, Covid searches, the interaction between Stringency Index and Covid searches (ϑ), per capita confirmed cases and their interaction with the Stringency Index and temperatures. We exclude from the original set of 35 countries one country at a time (reported on the x-axis). We include country and daily fixed effects and country specific trends. The dataset is a country by day panel, for 34 countries and 315 days. Robust standard errors are clustered at country level.

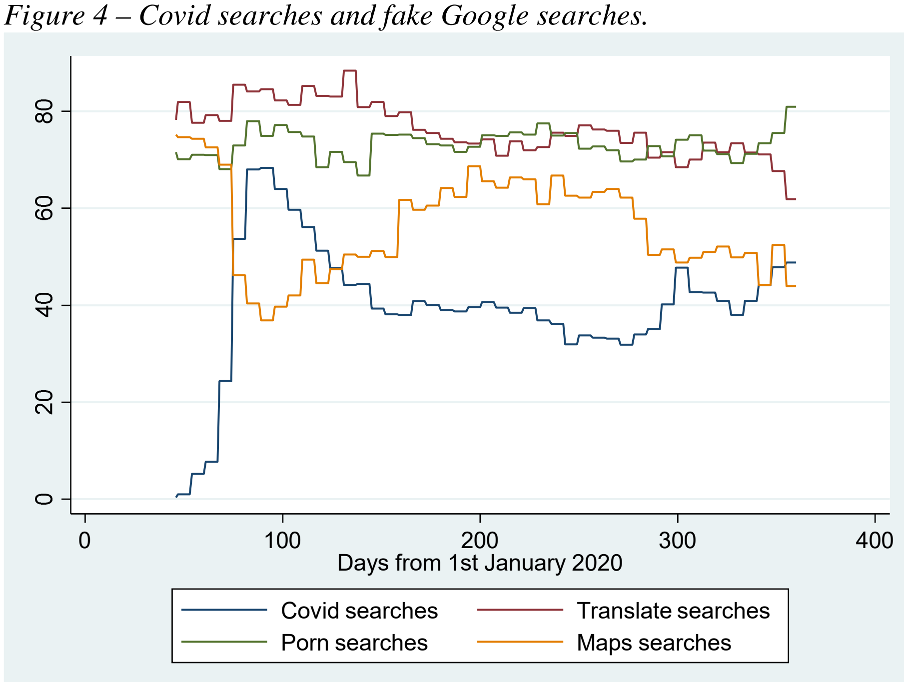
5.3 Falsification exercise on Google searches

Within our DiD analysis we conduct a placebo test to simulate how alternative Google searches that are unrelated to the pandemic might impact mobility. This test arises from the concern that

Covid related searches could be endogenous to mobility, e.g. the week by week volume of Google searches can be correlated with the fact of staying at home, i.e. with lower mobility.

If the relationship between Covid searches and mobility were spurious, namely due to the stay-at-home order, using our placebo variables we would get similar results to the ones obtained in the baseline specification which makes use of "Covid" searches. Specifically, we replicate the main analysis in Equation (2) by replacing *Covid* searches with the main three terms searched in Google in the year 2020 (*translate, porn,* and *maps*). As a preliminary analysis, from **Errore. L'origine riferimento non è stata trovata.**, we observe that these three Google searches are not correlated with the Covid searches in the time-span of our analysis, but still relevant in terms of intensity.

Figure 4 – Covid searches and fake Google searches.



Notes: This figure describes Covid searches, Porn searches, Translate searches, and Maps searches over 2020, from February 15 (day 46) to December 30 (day 365). Observations for 35 countries are averaged by day. All the variables vary from 0 to 100.

In Table 4, we use as explanatory variable “translate” searches (Column 1), “porn” searches (Column 2) and “maps” searches (Column 3). In all specifications we find that the coefficients on the interaction terms are statistically indistinguishable from zero, which implies that Google searches different from Covid-19 do not affect the impact of stringency on mobility.

Table 4 - Difference in difference estimates, falsification test.

Dependent variable: Mobility	(1)	(2)	(3)
Google searches	*Translate*	*Porn*	*Maps*
Stringency Index	-0.228	-0.501***	-0.495***
	(0.161)	(0.137)	(0.096)
Google searches	0.042	0.037	0.075
	(0.085)	(0.083)	(0.050)
Stringency Index*Google searches	-0.003	0.001	0.001
	(0.002)	(0.002)	(0.001)
Stringency Index*Confirmed cases	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.003)
Confirmed cases per capita	-0.155	-0.149	-0.102
	(0.297)	(0.292)	(0.277)
Temperatures	0.114***	0.116***	0.106***
	(0.018)	(0.020)	(0.017)
Observations	10,696	10,696	10,696
R-squared	0.82	0.82	0.82
Country FE	YES	YES	YES
Daily FE	YES	YES	YES
Country Trend	YES	YES	YES

Notes: This table shows the effect of different fake searches on mobility. In Column from (1) to (3) we report searches for “Translate” (1), “Porn” (2), and “Maps” (3). We regress the Mobility Index on Stringency Index, fake searches, the interaction between Stringency Index and fake searches, per capita Confirmed Cases and their interaction with the Stringency Index and temperatures, as in Equation (2). We include country and daily fixed effects and country specific trends. The dataset is a country by day panel, for 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** p<0.01, ** p<0.05, * p<0.1

6 Conclusions

This paper has empirically shown that implementing lockdown measures has a significant and sizeable impact on individual mobility, as required to control the spread of the virus. In particular, mobility decreases by 11.42 percentage points when considering a shift from a country in the 25th percentile of the Stringency Index (on average) to a country in the 75th percentile of the stringency measure.

Interestingly, we show that the decrease in mobility due to the implementation of lockdown measures is sensitive to citizens' perception about the severity of pandemic itself. We proxy this perception by using the Google search of the term "Covid". It is reasonable to think that search intensity is a reliable measure of people's concerns about the pandemic in a given country in a given day. More precisely, mobility is reduced by 35.90 percentage points when the Stringency Index and the Covid searches are the closest to their 75th percentile values; conversely, when the Stringency Index and the Covid searches are the closest to their 25th percentile value, the reduction in mobility is equal to 19.10 percentage points. Therefore, the Google search interaction term would enhance the mobility reduction impact of stringency measures by about 47%.

In fact, we find that this enhancing effect of citizens' perceptions is driven by countries with low quality of governance. One might argue that the lower the trust in political institutions, the more the adherence of people to coercive regulations ends up being guided by individual level perceptions.

Therefore, the perception of the gravity of the pandemic is crucial in making lockdown measures effective, especially in countries with low institutional quality. This result suggests that any lockdown measure must be accompanied by an adequate communication effort, which could work as a short-medium term substitute for the quality of institutions.

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Appendix

Table A1 – List of countries in the sample.

Austria	Mali
Belarus	Mauritius
Bolivia	Mexico
Burkina Faso	Morocco
Cambodia	Namibia
Cameroon	Netherlands
Chile	Niger
Denmark	Peru
Dominican Republic	Senegal
Egypt	Slovenia
Estonia	Sweden
Greece	Switzerland
Honduras	Thailand
Hungary	Togo
Jordan	Ukraine
Lao PDR	Uruguay
Lithuania	Venezuela
Luxembourg	

Table A2 – Summary statistics

	(1) N.	(2) Mean	(3) Std. Dev.	(4) Min.	(5) Max.
Covid searches	11,025	38.94	26.44	0	100
Confirmed cases per capita	11,025	5.779	13.91	-28.51	114.3
Maps searches	10,701	57.63	23.94	0	100
Mobility	11,025	84.79	24.18	6.800	175
Mobility without retail and recreation	11,025	86.83	24.84	7.500	194
Mobility without workplaces	11,000	86.35	27.31	6	207.8
Mobility without grocery and pharmacy	11,025	82.86	26.00	7.250	191.8
Mobility without transit stations	11,025	88.19	25.33	7.250	198
Mobility without parks	11,025	79.74	20.47	6	146.5
Porn searches	10,701	73.17	14.90	14	100
Stringency Index	11,025	53.60	25.90	0	100
Temperatures	11,025	200.5	90.99	-77.50	388
Translate searches	10,701	76.16	15.05	7	100

Notes: This table provides summary statistics. For more details about the variables, see Section 3.

Table A3 – Difference in difference estimates, main specification, all countries.

Dependent variable: Mobility	(1)	(2)	(3)	(4)	(5)	(6)
Stringency Index	-0.505***	-0.446***	-0.432***	-0.312***	-0.386***	-0.384***
	(0.042)	(0.036)	(0.036)	(0.049)	(0.051)	(0.051)
Confirmed cases per capita	-0.264***	-0.228***	-0.171***	-0.177***	-0.203***	-0.055
	(0.058)	(0.057)	(0.059)	(0.057)	(0.066)	(0.261)
Temperatures		0.085***	0.086***	0.086***	0.082***	0.083***
		(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
Covid searches			-0.075***	0.153**	0.100	0.080
			(0.026)	(0.066)	(0.064)	(0.066)
Stringency Index*Covid searches				-0.003***	-0.003***	-0.003***
				(0.001)	(0.001)	(0.001)
Stringency Index*Confirmed cases pc						-0.002
						(0.004)
Observations	34,320	34,320	34,005	34,005	34,005	34,005
R-squared	0.74	0.77	0.77	0.77	0.99	0.99
Country FE	YES	YES	YES	YES	YES	YES
Daily FE	YES	YES	YES	YES	YES	YES
Country specific trend	NO	NO	NO	NO	YES	YES

Notes: This table shows the effect of Covid searches on mobility. We regress country's mobility index on different variables. In Column (1) Stringency Index and per capita Confirmed Cases (Eq. (1)); in column (2) we additionally control for temperatures (Eq. (1)); in Column (3) we add Covid searches as a control (Eq. (1)); in Column (4) we also include the interaction between Stringency Index and Covid searches (Eq. (2)); finally, in Column (6) we additionally include the interaction term between Stringency Index and per capita Confirmed Cases (Eq. (2)). For all specifications we include country and daily fixed effects. In Column 5 and 6 we also include country specific trend. The dataset is a country by day panel, for 109 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** p<0.01, ** p<0.05, * p<0.1