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Pandemic knowledge and regulation effectiveness: Evidence from COVID-19

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A B S T R A C T

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

1. Introduction

According to the latest data from the World Health Organization (February, 2022), more than 396 million of COVID-19 infected cases have been reported, with more than 5.7 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 World Health Organization announced the international outbreak of the COVID-19 infection on January 30, 2020, and declared the COVID-19 outbreak a global pandemic on March 11, 2020 (Cucinotta and Canelli, 2020). Since then, the COVID-19 pandemic has reached nearly all countries around the world. However, the pandemic had largely heterogeneous effects, 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 on them. Interestingly, these measures display significant variation in their intensity, with some countries adopting stringency measures very early in the pandemic cycle, whereas others taking a less restrictive approach (Ferraresi *et al.,* 2020).

Of course, the purpose of these measures that restrict mobility and impose social distancing is to strongly reduce 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 intensive care units, which would lead to a dramatic increase in the mortality of the

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[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.

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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.

Interestingly, the lockdown measures have also been the subject of some controversy amongst political, legal scholars, and the public.[2] Several demonstrations against lockdown have taken place in many countries in Europe[3], in the US[4], and elsewhere. It is unclear whether those protests are driven by impatience, a genuine knowledge 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 compliant with government restrictions 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). Recent literature has widely covered this topic across different domains. Mastrorocco and Minale (2018) find an effect of news media on crime perceptions: they use a difference-in-differences approach that compares individual perceptions of those with a wide range of available TV channels to those with limited choice. Scholars have analysed how perception and knowledge affect individual behavior in the case of political elections (Martinand and Yurukoglu, 2017) and crime (Shi, 2009; Spenkuch, 2018; Velásquez *et al.*, 2020).

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

Scholars have begun to investigate the determinants of the effectiveness of stringency measures, identifying variables such as expectations for the duration of self-isolation, 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 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 knowledge 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.[5]

We exploit the staggered implementation of stringency measures adopted by countries over 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 larger the more people get information 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 present the data, in Section 3 we lay down the empirical framework, while in Sections 4 and 5 we discuss the results and perform some robustness tests, respectively. Finally, Section 6 summarises and concludes.

2. Data

2.1. 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.[6] The mobility indicators measure the relative value of each weekday mobility, compared to the baseline value for that weekday, 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. So, the indicator takes on a value of 100 if mobility in given day during the pandemic, say on a Thursday, is equal to the Thursday pre-pandemic median. 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 variable the daily average of the above categories from which we exclude the *residential* category as it has different units of measurement (i.e., change in duration vs change in total visitors).[7] 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.

[2] In the UK, for example, the restrictions that underpin the COVID-19 lockdown measures have been challenged as being unlawful and disproportionate, breaching freedoms protected by the European Convention of Human Rights (Keene, 2020).

[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).

[5] The sample includes only 35 countries which after February 15, 2020 (first day of available data on mobility), experienced at least one day without any Covid-related restrictions. The list of countries is reported in Table A1. This allows us to test for the parallel trend assumption via the Autor test. We explore the robustness of our baseline results by replicating them on the full set of available countries (109 countries), see Table A3.

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

[7] As robustness checks, we use as dependent variable the mobility index excluding one of each component at time (Table 4). We also use as dependent variable the mobility index with its individual components (Table A6).

2.2. Stringency index

In order to deal with the COVID-19 outbreak, governments around the world adopted many and very different containment measures. We take into account the heterogeneity of governments' responses by making use of the *Government Response Stringency index* (*Stringency Index*) developed by Hale *et al.* (2020). The *Stringency Index* is calculated using the mean of nine metrics: school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls. Each of these variables is rescaled by its maximum value to create an overall score between 0 and 100. A higher score indicates a stricter response (i. e., 100 is equal to the strictest response). The index simply records the strictness of government policies, and it does not measure the effectiveness of a country's response. Following Goldstein et al. (2021), starting from the first day of the Stringency Index being greater or equal to 74.5 (which corresponds to the 75th percentile), we build the *lockdown fatigue* variable by counting the number of days for which the Stringency Index was at least equal to 74.5.

2.3. COVID-19 knowledge

We use data from the Google Trends tool to measure the time-varying pursuit of information about the pandemic by citizens.[8] As in previous works that use Google Trends to predict disease outbreaks (Carneiro and Mylonakis, 2009), trading behavior in financial markets (Preis *et al.,* 2013), and concern of public opinion about pension systems (Fornero, Oggero, and Puglisi, 2019), we assume that Google search indicators provide reliable information about citizens' (search for) knowledge. 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 measure of intensity, which is computed 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 country. 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. To build the variable *Covid searches*, we collect searches related to the term "Covid" for the period from February to December 2020. *Covid searches* ranges in each country from 0 - when there is no search in Google of the term "Covid" - to 100, with 100 denoting the maximum level of Covid searches. In order to conduct a falsification test, we also collect searches related to the terms that were most searched worldwide on Google from February to December 2020, i.e. "translate", "porn", and "maps".

Notice that people's knowledge about COVID-19 might be strictly related to the amount of media coverage devoted to the issue. 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 Google Trends for COVID-19 symptoms such as cough, anosmia (loss of smell) and ageusia (loss of taste) are more strongly related to media coverage than to the underlying pandemic trends.[9] Interestingly, the authors find that peaks for the Google searches on the various symptoms occurred simultaneously, irrespective of the country's pandemic stage.

2.4. Other control variables

We collect data on the total number of COVID-19 related cases from the John Hopkins Center for System Science and Engineering to build the variable *Confirmed cases per capita* as the seven-days moving average of the pandemic related confirmed cases per capita. Finally, we collect daily *temperatures* at country level from the Global Historical Climate Network Daily (National Oceanic and Atmospheric Administration, 2020). Summary statistics for all variables used in the analysis are reported in Table A2 of the Appendix.

3. 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 aspects 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 of the policy with the corresponding changes in mobility that take place in the control group.

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

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

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

[8] We thank an anonymous referee for pushing us towards this interpretation of the Google Trends data.

[9] https://doi.org/10.1371/journal.pone.0152802; https://www.jmir.org/2020/8/e19611

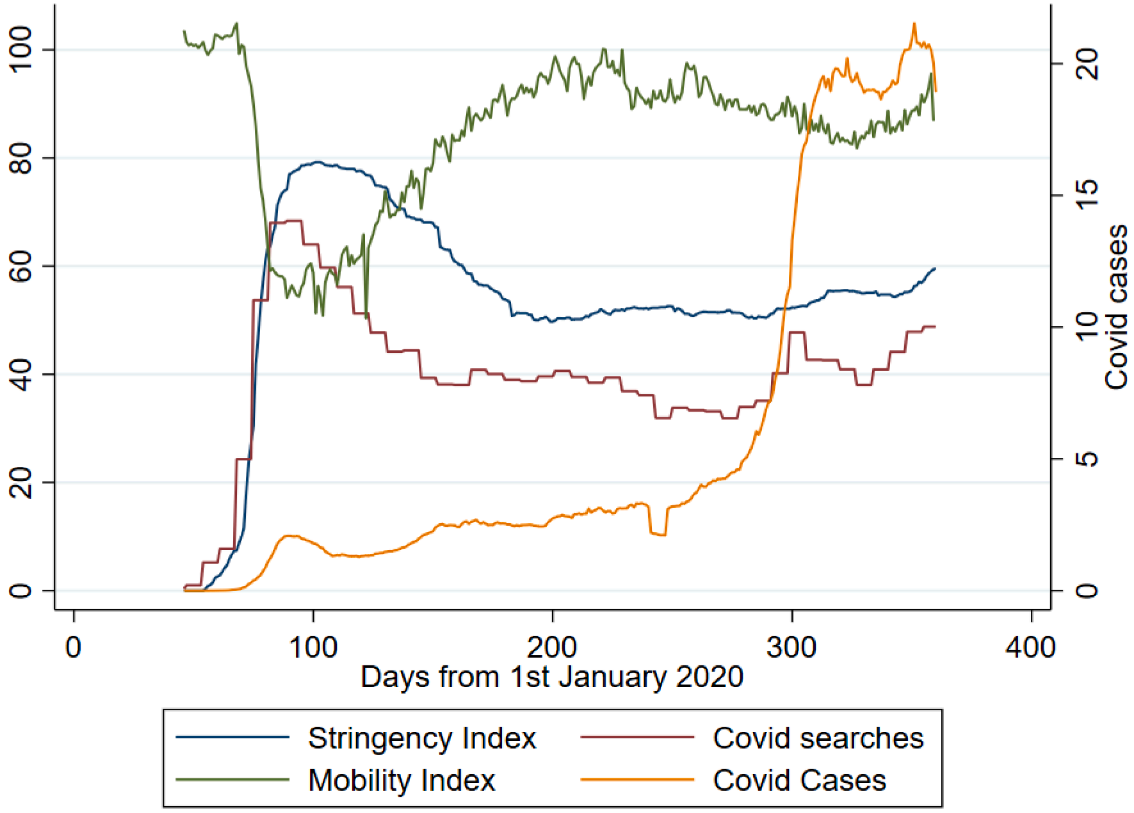

Fig. 1. Evolution of mobility, stringency of lockdown measures, Covid searches, and Covid cases.
Notes: Data are collected from February 15 (day 46) to December 30 (day 365). Observations for 35 countries are averaged by day. The Stringency Index and Covid searches vary from 0 to 100 inside each country. The Mobility Index is equal to baseline value of 100 for each country, if on a given weekday it exactly equals its median value recorded during the first 5 weeks of 2020, i.e., before the start of the pandemic. 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 2.

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, seven-days moving average of the pandemic confirmed cases per capita and the intensity of searches on Google of the term “Covid” for each country a week before[10]; f_c are country fixed effects that control for unobserved cross-country heterogeneity[11]; f_d are daily fixed effects that capture time-specific shocks common to every country, such as Covid-related information that becomes available worldwide in a given day; u_{cd} is the error term, clustered at country level. In some specifications, we also control for country specific trends. Within this specification, γ is the DiD estimate of the (average) effect of the stringency on mobility.

To investigate whether there has been a heterogeneos response to containment measures as a function of the knowledge about COVID-19 on a given day in each country, we interact weekly *Covid searches* with the stringency measures.

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

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

where our coefficient of interest ϑ accounts for the impact of the interaction term between *Covid searches*$_{cw}$, which is the indicator of Covid searches for country c in the week w, and *stringency*$_{cd}$.

[10] 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.

[11] In turn, this heterogeneity might be due to different levels of technology that affect both mobility and Google searches, national differences in the contagion level, health-care systems (such as availability of tests and intensive care units), as well as population density and the age profile of the population.

Table 1
Difference-in-differences estimates, main specification.

Dependent variable: Mobility Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stringency Index	-0.489***	-0.412***	-0.398***	-0.266***	-0.322***	-0.322***	-0.315***
	(0.059)	(0.055)	(0.058)	(0.064)	(0.071)	(0.071)	(0.065)
Confirmed cases per capita	-0.345***	-0.246***	-0.176**	-0.170**	-0.185*	-0.232	-0.218
	(0.100)	(0.088)	(0.085)	(0.083)	(0.092)	(0.312)	(0.290)
Temperatures	-	0.118***	0.122***	0.119***	0.118***	0.118***	0.117***
		(0.017)	(0.018)	(0.017)	(0.020)	(0.020)	(0.019)
Covid searches	-	-	-0.079**	0.136	0.112	0.117	0.082
			(0.038)	(0.090)	(0.082)	(0.083)	(0.077)
Stringency Index*Covid searches	-	-	-	-0.003***	-0.003**	-0.003**	-0.002*
				(0.001)	(0.001)	(0.001)	(0.001)
Stringency Index*Confirmed cases pc	-	-	-	-	-	0.001	0.001
						(0.004)	(0.004)
Lockdown fatigue	-	-	-	-	-	-	-0.225*
							(0.118)
Lockdown fatigue^2	-	-	-	-	-	-	0.001***
							(0.0003)
Observations	11,025	11,025	11,025	11,025	11,025	11,025	11,025
R-squared	0.755	0.790	0.793	0.797	0.8180	0.8181	0.826
Country FE	YES	YES	YES	YES	YES	YES	YES
Daily FE	YES	YES	YES	YES	YES	YES	YES
Country trend	NO	NO	NO	NO	YES	YES	YES

Notes: 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). *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4. Results

4.1. Main results

Fig. 1 plots the relationship between a measure of people's movement (conveniently called *Mobility Index*), the extent of the lockdown (*Stringency Index*),[12] the spread of COVID-19 (*Covid cases*) and a measure of public knowledge of the pandemic (*Covid searches*). For the first 80 days of 2020 there is a clear inverse relationship between lockdown measures and Covid-19 online searches with population movement. After this initial period *Covid searches* decrease faster than lockdown measures, while, at the same time, mobility starts increasing. This divergence between lockdown measures and Covid searches and its relationship with mobility raises the issue of the role of citizens' knowledge about the seriousness of COVID-19 pandemic.

Table 1 displays findings from our regression analysis. The first three columns report results based on different specifications of Eq. (1) for 35 "baseline" countries: these are countries that – within our time frame- 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.[13]

The baseline specification, which includes *Stringency Index, Confirmed cases per capita*[14], and country and time fixed effects, is reported in Column 1. Column 2 adds to the previous specification the temperature variable, which captures weather-related drivers of mobility. In Column 3 we include as control variable *Covid searches*. The last three columns show the results that are based on different versions of Eq. (2). In Column 4 we add the interaction between *Covid searches* and the *Stringency Index*, while in Column 5 we also include country-specific linear trends. 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' knowledge about those events, we add the interaction between *Confirmed cases per capita* and the *Stringency Index* itself. Finally, in Column 7, we include a variable capturing the so called "lockdown fatigue". We include this variable in the regression both linearly and as a squared term.

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 11.42 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

[12] See Hale *et al.* 2020, "*Government Response Stringency Index*".
[13] Table A3 extends the results of Table 1 with all countries available. Note that the main results do not change significantly.
[14] In Table A4, we replicate the regressions in Table 1 by replacing the 7-days moving average of per capita confirmed cases with the 14 days lag of per capita confirmed deaths. The correlation coefficient between the 7-day moving average of confirmed cases per capita and the 14-day lagged confirmed deaths per capita is equal to 0.46. We do not observe any relevant difference in the coefficients of interest *vis a vis* the main specification.

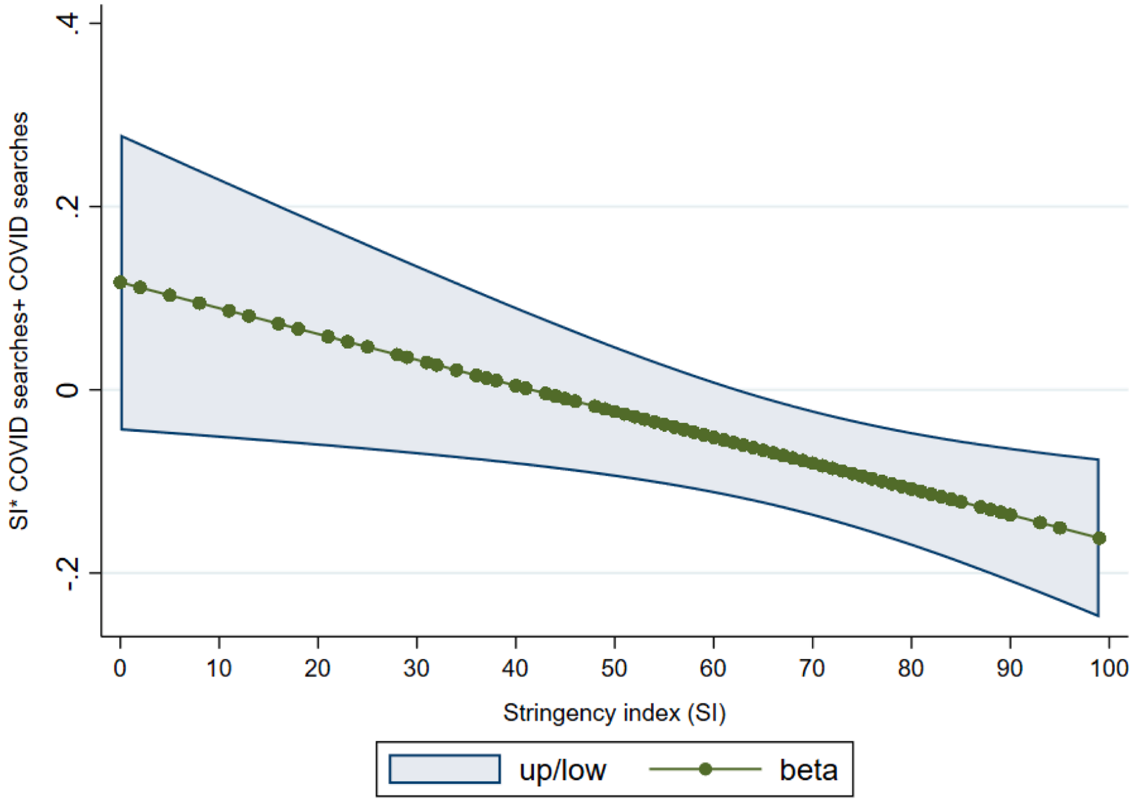

Fig. 2. Plot of the linear combination of the interaction term and the Covid searches for different values of the Stringency Index.
Notes: Estimated coefficients in Eq. 2 on Covid searches for different values of the *Stringency Index*, together with their 95% confidence intervals. Point estimates of the coefficients are calculated for the mean values of each percentile of the *Stringency Index*.

searches are the closest to the 75th percentile value.[15] 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 Columns 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 knowledge, i.e., the effectiveness of stringency is amplified by the knowledge of the severity of the pandemic. On the other hand, the interaction of the stringency measure with the number of confirmed cases per capita (Column 6) is not significant at ordinary confidence levels, while the interaction of stringency with Covid searches remains significant and with the same magnitude. This suggests that the role of Covid searches in determining the impact of stringency on mobility appears to be relevant and the real world events that are connected with the evolution of the pandemic by itself do not matter.

In Fig. 2, we show the values of the coefficient of interest (interaction term *Stringency Index*COVID searches*) by plotting the estimated coefficient on *Covid searches* for different values of the *Stringency Index*. The point estimates of the partial correlation of *Covid searches* with mobility are positive for low values of the *Stringency Index*, and negative for high values thereof. However, the confidence intervals are such that we cannot reject the null hypothesis that the partial correlation of searches with mobility is zero for low values of the *Stringency Index*, while we reject the null hypothesis of a zero correlation for a large interval of high values of the *Stringency Index*.

Using the point estimates of Column 6, mobility is reduced by 35.90 percentage points[16] 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.[17] 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 Covid searches interaction term contributes to the mobility reduction by increasing it by 47% confirming that the impact of the stringency measures on mobility is not linear but it depends on the knowledge of the severity of the pandemic,

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

[16] 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.

[17] 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.

Table 2
Difference-in-differences estimates. Effect of Covid searches on mobility, by institutional indicators.

Dependent Variable: Mobility Index Institutional dummy:	(1) Rule of Law	(2) Voice & Accountability	(3) Media repression	(4) Low Education
Stringency Index (SI)*Covid searches (CS)	-0.004***	-0.004***	0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
SI * CS * Institutional dummy	0.004**	0.003	-0.006**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	11,025	11,025	11,025	11,025
R-squared	0.8384	0.8418	0.8355	0.8385
Country FE	YES	YES	YES	YES
Daily FE	YES	YES	YES	YES
Country specific trend	YES	YES	YES	YES

Notes: The dataset includes 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

proxied by the Google search for "Covid".

In Column 7 the coefficient of the interaction term *Stringency Index*Covid searches* is negative and mildly significant at the 10% confidence level, with a point estimate of -0.002. We find a negative and significant coefficient on *lockdown fatigue* (-0.225, standard error 0.118) and a positive and significant coefficient on its squared term (0.001, standard error 0.0003): this suggests that for higher values of the variable the impact on mobility turns out to be positive. More precisely, if we compute the first order condition with respect to *lockdown fatigue*, we find that the coefficient becomes positive after about 94 days of stringency above 74.5.[18] This implies that *lockdown fatigue* is negatively associated with mobility at lower levels thereof, while it is positively associated with mobility at values above 94 days. In other terms, *lockdown fatigue* is associated with temporally vanishing -and after a while counteractive- effects of stringency measures on mobility. From a policy perspective, this result implies that stringency measures have additional, intrinsic limits, i.e., their effectiveness drops as time goes by. After about three months, the estimated correlation of *lockdown fatigue* with mobility turns out to be positive: in other terms, citizens apparently tend to go back to previous mobility levels.

4.2. Heterogeneity analysis

How to explain the fact that the interest in the pandemic –as proxied by Google searches- appears to affect the compliance with the stringency measures? Our intuition is that people comply with these regulations when they get to know more about the pandemic. When the pandemic becomes more relevant to them, people likely feel more pressure to comply with stringency measures themselves. In turn, the knowledge of the pandemic might matter more in economic and political environments with *low* levels of governance quality, whereas citizens do not necessarily trust the appropriateness of government interventions and/or news about those interventions. To explore this facet of the issue, we consider the quality of institutions (*Rule of law*[19]), citizens' ability to participate in selecting their government (*Voice & Accountability*[20]), and the state interference in communication and expression (*Media repression*).[21] The values of the indices for *Rule of law* and *Voice & Accountability* range from zero to 100, where zero corresponds to the country being in the lowest rank among all countries covered by the aggregate indicator and 100 to the highest rank. The *Media repression* index is composed of numerical ratings where zero is the best possible score and 100 is the worst. Furthermore, another important determinant of citizens' active pursuit to understand the seriousness of the pandemic might be their level of education[22] (*Education*): when citizens have a *low* level of education, they might be more prone to be influenced by Covid searches. The *Education* index counts the average total years of schooling for adult population over 25 year old and in our dataset its values range from 1.5 to 13.4. We create dummies for Rule of Law, Voice & Accountability, and Media Repression which are equal to one if a given country is above the median level in our sample for that variable, and zero otherwise. We also create a Low Education dummy which is equal to one if a given country is below the median level of Education in our sample. We interact these dummies with our baseline interaction between *Stringency Index* and *Covid searches*, to obtain a triple interaction term.

To compute the implied interaction term for countries whose level of Rule of Law is above the median, we sum the coefficient on the triple interaction (*Stringency Index*Covid searches*Rule of Law dummy)* with the coefficient on the baseline interaction term (*Stringency Index*Covid searches)*: this sum is statistically indistinguishable from zero at ordinary confidence levels. On the other hand, the coefficient on *Stringency Index*Covid searches* -which captures the implied interaction term for countries with below the median Rule of Law- is equal to -0.004 and statistically significant at the 1% level (Column 1 of Table 2). We find very similar results in the case of

[18] This is the case, because the marginal effect of *lockdown fatigue* on mobility is estimated as follows: -0.225+2*(0.0012)*lockdown fatigue*.

[19] As in Kaufman *et al.* (2010): "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."

[20] As in Kaufman *et al.* (2010): "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. […]

[21] Freedom House. Data refers to the last available year (2014).

[22] Human Development Report (2018). Data refers to the last available year (2017).

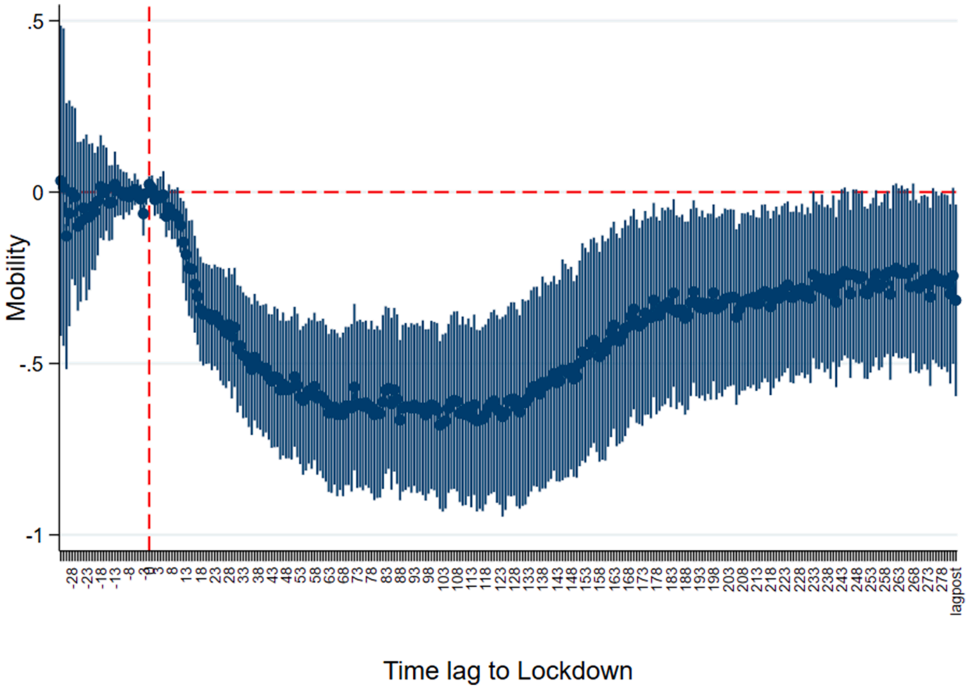

Fig. 3. Autor test estimates.
Notes: Plots of estimates β from Eq. (3), with their respective pointwise 90% confidence intervals. The plotted estimated coefficient is the interaction between the leads and lags and the mean of the Stringency Index for each country during the entire time period. The dependent variable is the Mobility Index. The day before the start of the lockdown is omitted, so the estimates are normalized to zero in that day. The model also includes country and daily fixed effects, temperatures, and confirmed cases per capita as covariates. Errors are clustered at country level. The sample includes 35 countries observed over 315 days.

countries above and below the median values of *Voice & Accountability* (Column 2): thus, in countries with lower institutional quality (as measured by Rule of Law and by Voice & Accountability) knowledge about the pandemic apparently makes containment measures effective in reducing mobility, while this knowledge is not relevant in countries with higher institutional quality.

An opposite pattern does emerge in the case of Media Repression and Low Education (Columns 3 and 4 in Table 2, respectively). For Media Repression, the sum of the estimated coefficient on the triple interaction (*Stringency Index*Covid searches* Media Repression dummy)* with the coefficient on *Stringency Index*Covid searches* is -0.004 and 1% significant, while the coefficient on the double interaction (*Stringency Index*Covid searches*) is not statistically significant (Column 3). In the case of Low Education, the sum of the estimated coefficients on *Stringency Index*Covid searches*Low Education dummy* with the coefficient on *Stringency Index*Covid searches* is -0.005 and 5% significant, while the coefficient on *Stringency Index*Covid searches* is not statistically significant (Column 4).

These results indicate that transparency of institutions, citizens' confidence in the rules of society, low level of media repression and high level of education narrow down the effect of citizens' knowledge, as measured by the volume of Covid searches: when people are more likely to trust institutions, abide by the law, receive fair information and be properly informed because of their high level of education, Covid searches do not amplify or diminish the effects of stringency measures.

4.3. Autor test

The key identifying assumption for DiD estimates is that the variation in mobility in countries belonging to the control group 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. In line with Autor (2003), we create a dummy variable which takes on the value of one on the first day of the *Stringency Index* greater than zero, 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[23] (one for each day after the lockdown

[23] 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 *mean stringency*.

Table 3
Regression explaining Covid searches.

Dependent Variable: Covid searches	(1)	(2)	(3)
Difference in number of confirmed cases with neighbors	0.426***	0.367***	0.257**
	(0.100)	(0.106)	(0.123)
Stringency Index (SI)	-	0.304***	0.351***
		(0.092)	(0.090)
SI * Low Education	-	-	-0.311*
			(0.104)
Temperatures	-	-	-0.025
			(0.029)
Constant	40.27 ***	23.93***	34.02***
	(0.06)	(4.94)	(7.62)
Observations	11,025	11,025	11,025
R-squared	0.68	0.70	0.71
Country FE	YES	YES	YES
Daily FE	YES	YES	YES
Country specific trend	YES	YES	YES

Notes: The difference in number of confirmed cases with neighbors is the difference between the 7-days moving average of confirmed cases in country i and the mean of the 7-days moving average of confirmed cases in the four closest neighbouring countries. The dataset includes 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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:

$$mobility_{cd} = \alpha + \sum_{\pi=-32}^{-2} \beta_\pi first\ day_{c(d+\pi)} * Mean\ stringency_c + \sum_{\tau=0}^{283} \beta_\tau first\ day_{c(d+\tau)} * Mean\ stringency_c + \gamma X_{cd} + f_c + f_d + u_{cd} \tag{3}$$

Where *first day*$_{cd}$ is a dummy equal to 1 only in the day the *Stringency Index* starts being greater than zero in country c and day d. Moreover, *first day*$_{c(d+\pi)}$ is a dummy variable equal to 1 in country c and day $d+\pi$, with π going from -32 to -2: those dummies stand for the leads of the variable *first day*$_{cd}$. We also include the lags of the *first day*$_{cd}$ by building the dummies *first day*$_{c(d+\tau)}$ equal to 1 in country c and day $d+\tau$, with τ going from 1 to 283. Finally, we have *Mean stringency*$_c$ which is the mean of the *Stringency Index* in country c. All the other variables and fixed effects are defined as in Eq. (1). 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 March 9, 2020, therefore there are 13 leads and 270 lags, and the omitted day is March 8, 2020.

The estimates, together with their 90% confidence intervals, are plotted in Fig. 3. 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. 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. From the 11th day after the introduction of the stringency measures, we get a steep decrease in mobility for the following two weeks, followed by a milder decrease up to the 120th day after the introduction of the lockdown. Afterwards, the estimated coefficient starts increasing and reaches a plateau after the 160th day until the end.

5. Correlates of Covid searches

To explain and better understand the panel variation of *Covid searches* we implement a fixed effects regression analysis.

First, in Column (1) of Table 3, we show that the difference in the number of confirmed cases between country i and the average of its four closest neighbouring countries is positively and significantly correlated with Covid searches in country i, with a coefficient of 0.43 (1% confidence level). The intuition is that the search of information by citizens of a given country appears to be driven by the excess of country's own cases *vis a vis* its neighbouring -and comparable- countries.

Second, to identify other observable factors that are significantly associated with Covid searches, we include additional variables in our regressions. In Column (2) we add the Stringency Index and find that it is positively and significantly correlated with Covid searches. Citizens are significantly more interested in searching about COVID-19 when governments implement stricter containment measures. In Column (3) we also include temperature, confirmed cases per capita and the interaction between the Stringency Index and the country-specific level of education.

We find that the coefficient of the interaction of the Stringency Index and the country-specific low education level is negative and statistically significant, thus offsetting the significant positive non-interacted coefficient. In other terms, in countries with low levels of

Table 4–
Difference-in-differences estimates, using alternative specific measures of Mobility Index as dependent variables.

	(1) Mobility Index without retail & recreation	(2) Mobility Index without workplaces	(3) Mobility Index without grocery & pharmacy	(4) Mobility Index without transit stations	(5) Mobility Index without parks
Stringency Index (SI)	-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 specific trend	YES	YES	YES	YES	YES

Notes: The dependent variable is the original Mobility Index, removing one component at a time. The dataset includes 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

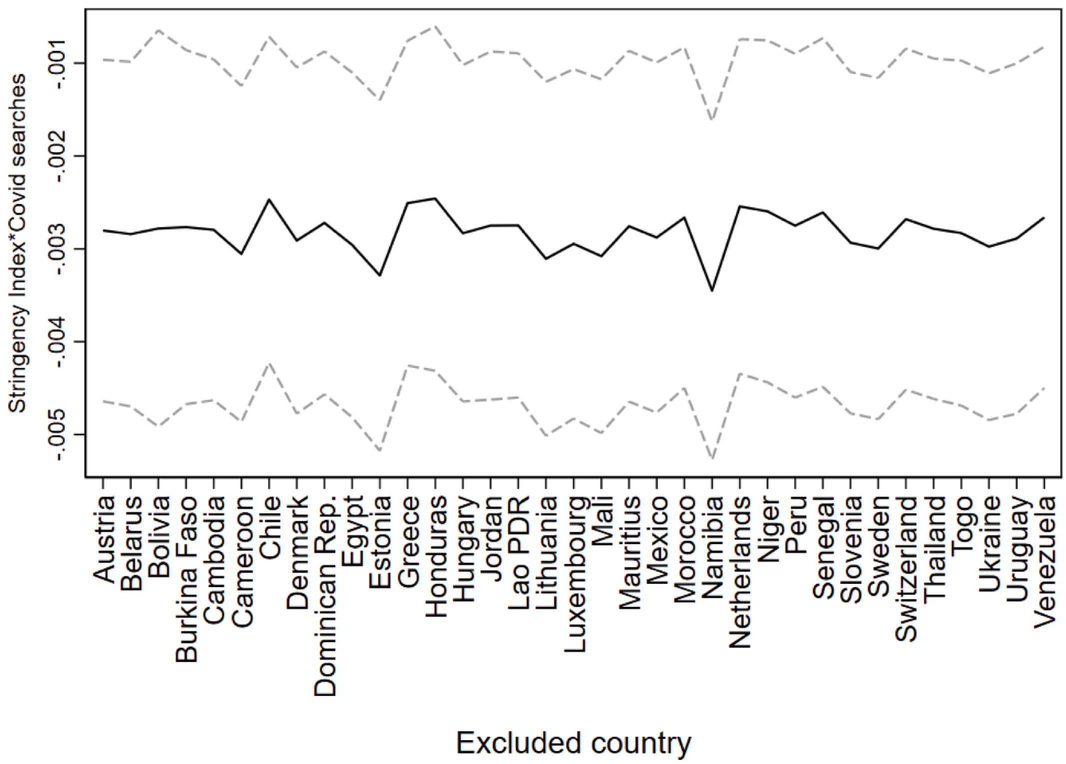

Fig. 4. Country sensitivity analysis: estimates, excluding each time one country.
Notes: Estimates of the coefficient ϑ from Eq. (2) with its 95% confidence interval, excluding from the original set of 35 countries one country at a time (reported on the x-axis). We include country, daily fixed effects and country specific trends. The dataset includes therefore 34 countries and 315 days. Robust standard errors are clustered at country level.

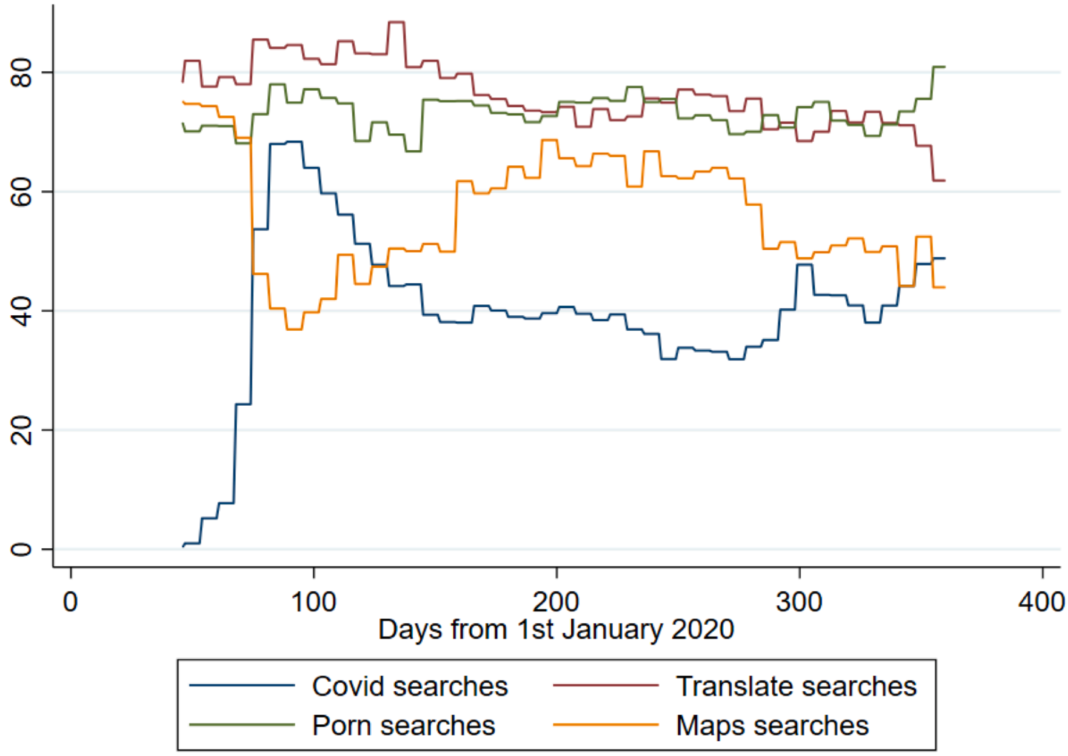

Fig. 5. Covid searches and placebo Google searches (Translate, Porn, and Maps).
Notes: Searches for Covid, Translate, Porn, and Maps over 2020, from February 15 (day 46) to December 30 (day 365). Observations for 35 countries are averaged by day. All variables vary from 0 to 100.

Table 5
Falsification test using as dependent variables Google searches for Translate, Porn and Maps.

Dependent variable: Mobility Index *Fake Google searches*	(1) *Translate*	(2) *Porn*	(3) *Maps*
Stringency Index	-0.228	-0.501***	-0.495***
	(0.161)	(0.137)	(0.096)
Fake Google searches	0.042	0.037	0.075
	(0.085)	(0.083)	(0.050)
Stringency Index*Fake Google searches	-0.003	0.001	0.001
	(0.002)	(0.002)	(0.001)
Stringency Index*Confirmed cases pc	-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 specific trend	YES	YES	YES

Notes: The dataset includes 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

education, the Stringency Index is not significantly correlated with the outcome variable, while in countries with high levels of education the Stringency Index has a positive and statistically significant correlation with Covid searches.

6. Robustness tests

In this section, we use a battery of robustness tests 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 Mobility Index; then we move to a country-sensitive test to show that the estimated effects do not depend on a specific country, and lastly, we run a falsification test, replacing the Covid searches with other relevant terms searched on Google during the same timespan.

6.1. Alternative dependent variables

The dependent variable used in the main regression (Table 1) is a composite indicator which is calculated as the daily average of the mobility for visits to the following destinations: (i) retail & recreation, (ii) workplaces, (iii) grocery & pharmacy, (iv) transit stations, and (v) parks.

To check whether results are not driven by a specific individual component of the Google mobility composite indicator, in Table 4 we exclude one component at a time from the dependent variable.[24] The coefficient on the interaction term *Stringency Index*Covid searches* remains negative and statistically significant in all specifications, which is consistent with our results not essentially depending on a particular component of the Mobility Index.

6.2. Country sensitivity analysis

We also test whether our main findings are sensitive to the exclusion of a single country. For this reason, we estimate Eq. (2), by dropping one country at a time. The estimated coefficients of the interaction term *Stringency Index*Covid searches* and their 95% confidence interval (Fig. 4) are very similar to those obtained in our baseline specification. Hence, it can be concluded that our main results are not driven by a particular country.

6.3. 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 which causes more searching activity on Google, 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 Eq. (2) by replacing Covid searches with the main three terms searched in Google in the year 2020 (Translate, Porn, and Maps). Notice, moreover, that these terms are most likely unrelated with the term Covid. The graphical analysis in Fig. 5 shows that the searches for Translate, Porn, and Maps are not correlated with the Covid searches in the timespan of our analysis.: the Pearson correlation index is respectively equal to 0.16, 0.17, and -0.09.

In Table 5, we use as explanatory variable Google searches for Translate (Column 1), Porn (Column 2), and Maps (Column 3). In all specifications we find that the coefficients on the interaction terms are statistically indistinguishable from zero: thus, Google searches different from Covid apparently do not affect the impact of stringency on mobility.

6.4. Scaled Covid searches

The variable *Covid searches* we use in our main analysis (Table 1) is a weekly intensity, which is measured as the number of weekly searches for the term, divided by the maximum number of its weekly searches over the whole time period, within each country, and scaled to 100 for easier readability.

On the other hand, *Covid searches* can be re-scaled at the aggregate level, i.e. jointly considering all sampled countries. To rescale the variable, we proceed as follows. First, we find the country with the maximum number of searches (i.e. Chile) in our sample of 35 countries. Then we collect the data from the other countries in groups of five from Google Trends, always including the leading country (Chile). Afterwards, we use the ratio between the leading country and the remaining observations of different groups to re-scale the variable. Eventually, we come up with a dataset with variables from 0 to 100, where the maximum value of 100 is only reached by Chile on April 2020 (Brodeur *et al.*, 2021).

We replicate our baseline specifications by replacing the original Google searches with the scaled version (Table A5): we find very similar results, and a negative and significant coefficient on the interaction term *Stringency Index*Scaled Covid searches*.

[24] As a robustness test, we also replace the composite Mobility Index with its individual components, namely: workplaces, parks, transit stations grocery & pharmacy, and retail & recreation. In the case of mobility to workplaces, transit grocery % pharmacy and retail & recreation we find very similar results to our baseline ones. On the other hand, the result on mobility to/from parks is slightly smaller in size and not statistically significant at ordinary confidence levels (see Table A6).

7. 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. Mobility decreases by 11.42% points when considering a shift from a country in the 25th percentile of the stringency measure and Covid searches to a country in the 75th percentile of the stringency measure and Covid searches.

Interestingly, we show that the decrease in mobility due to the implementation of lockdown measures is sensitive to citizens' knowledge about the severity of pandemic itself. We proxy this (search for) knowledge about the pandemic by using the Google search of the term "Covid". More precisely, mobility is reduced by 35.90% 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% points. The Google search interaction term would enhance the mobility reduction impact of stringency measures by about 47%.

We find that this enhancing effect of citizens' knowledge is driven by countries with low trust in institutions, low confidence in the rules of society, high level of media repression, and low level of education. In this case the adherence of people to coercive regulations ends up being guided by individual-level knowledge about the severity of the pandemic.

Therefore, the knowledge about the gravity of the pandemic appears to have been crucial in making lockdown measures effective, especially in countries with low institutional quality and low level of education. This result suggests that any lockdown measure must be accompanied by a credible communication effort, which could work as a short-medium term substitute for the quality of institutions and education. It is a challenge for nations with low institutional quality and low level of education to engage in effective communication about the development of the pandemic. An effective government communication strategy should involve clear and transparent messages (Everett *et al.*, 2020), delivered via appropriate platforms, and customized for diverse audiences (Hyland-Wood et al., 2021).[25]

Acknowledgments

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Appendix

Table A1, Table A2, Table A3, Table A4, Table A5, Table A6

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	

[25] We thank two anonymous reviewers for providing insightful comments.

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
Difference in number of conf. cases with neighbours	11,025	-0.606	10.07	-64.83	77.13
Maps searches	10,701	57.63	23.94	0	100
Mobility	11,025	84.79	24.18	6.800	175
Mobility without retail & 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 & 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
Rule of law	11,025	52.46	30.92	0	99.04
Voice & Accountability	11,025	53.89	30.23	4.43	99.01
Media repression	11,025	45.49	23.30	10	93
Education	11,025	5.87	3.45	1.5	13.4

Notes: For more details about the variables, see Section 2.

Table A3
Difference-in-differences estimates, main specification, all countries.

Dependent variable:Mobility Index	(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	0.745	0.769	0.771	0.775	0.803	0.8041
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: The dataset includes 109 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A4

Difference-in-differences estimates, confirmed deaths per caputa in place of confirmed cases per capita.

Dependent variable:Mobility Index	(1)	(2)	(3)	(4)	(5)	(6)
Stringency Index	-0.537***	-0.443***	-0.412***	-0.289***	-0.345***	-0.340***
	(0.056)	(0.053)	(0.056)	(0.061)	(0.069)	(0.069)
Confirmed deaths pc	-6.23***	-3.494***	-2.012	-1.739	-2.304	-14.520
	(1.93)	(1.636)	(1.519)	(1.467)	(1.578)	(9.200)
Temperatures	-	0.126***	0.128***	0.125***	0.118***	0.124***
		(0.018)	(0.019)	(0.018)	(0.020)	(0.020)
Covid searches	-	-	-0.100**	0.100	0.126	0.108
			(0.039)	(0.086)	(0.020)	(0.082)
Stringency Index*Covid searches	-	-	-	-0.003***	-0.003**	-0.003**
				(0.001)	(0.001)	(0.001)
Stringency Index*Confirmed deaths pc	-	-	-	-	-	0.158
						(0.113)
Observations	10,675	10,675	10,675	10,675	10,675	10,675
R-squared	0.753	0.793	0.798	0.801	0.821	0.822
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: The dataset includes 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A5

Difference-in-differences estimates, with Scaled Covid searches.

Dependent variable:Mobility Index	(1)	(2)	(3)	(4)	(5)	(6)
Stringency Index	-0.489***	-0.412***	-0.405***	-0.289***	-0.367***	-0.368***
	(0.059)	(0.055)	(0.055)	(0.064)	(0.063)	(0.062)
Confirmed cases per capita	-0.345***	-0.246***	-0.198**	-0.198**	-0.196*	-0.261
	(0.100)	(0.088)	(0.088)	(0.088)	(0.098)	(0.306)
Temperatures	-	0.118***	0.120***	0.121***	0.119***	0.119***
		(0.017)	(0.017)	(0.016)	(0.020)	(0.020)
Scaled Covid searches	-	-	-0.210***	0.458***	0.334**	0.349**
			(0.086)	(0.111)	(0.128)	(0.150)
Stringency Index*Scaled Covid searches	-	-	-	-0.008***	-0.006**	-0.006**
				(0.002)	(0.002)	(0.002)
Stringency Index*Confirmed cases pc	-	-	-	-	-	0.0001
						(0.0038)
Observations	11,025	11,025	11,025	11,025	11,025	11,025
R-squared	0.755	0.789	0.791	0.797	0.8174	0.8174
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: The dataset includes 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A6
Difference-in-differences estimates, separate components of the dependent variable.

Dependent variable: Mobility Index	(1) Workplaces	(2) Parks	(3) Transit stations	(4) Retail & recreation	(5) Grocery & pharmacy
Stringency Index	-0.270***	-0.395**	-0.383***	-0.352***	-0.262***
	(0.085)	(0.183)	(0.066)	(0.076)	(0.082)
Confirmed cases per capita	-0.008	-1.306	-0.277	-0.194	-0.198
	(0.155)	(1.021)	(0.229)	(0.179)	(0.136)
Temperatures	-0.011	0.433***	0.059***	0.060***	0.047***
	(0.012)	(0.074)	(0.015)	(0.013)	(0.012)
Covid searches	0.183*	0.097	-0.063	0.134	0.095
	(0.094)	(0.198)	(0.065)	(0.083)	(0.090)
Stringency Index*Covid searches	-0.003**	-0.004	-0.002*	-0.003**	-0.003*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Stringency Index*Confirmed cases pc	-0.002	0.012	0.001	-0.006**	0.003
	(0.002)	(0.014)	(0.003)	(0.002)	(0.002)
Observations	11,022	10,839	10,900	10,972	10,997
R-squared	0.720	0.773	0.863	0.839	0.707
Country FE	YES	YES	YES	YES	YES
Daily FE	YES	YES	YES	YES	YES
Country specific trend	YES	YES	YES	YES	YES

Notes: Columns (1) to (5) use as dependent variable separate components of the mobility index: workplaces, parks, transit stations, retail & recreation, and grocery & pharmacy. The dataset includes 35 countries and 315 days. Robust standard errors are clustered at country level (and shown in parentheses). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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