One year of COVID-19 in Italy: are containment policies enough to shape the pandemic pattern?

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Abstract A successful fight against COVID-19 greatly depends on citizens' adherence to the restrictive measures, which may not suffice alone. Making use of a containment index, data on sanctions, and Google's movement trends across Italian provinces, complemented by other sources, we investigate the extent to which compliance with the mobility limitations has affected the number of infections and deaths over time, for the period running from 24 February 2020 to 23 February 2021. We find proof of a deterrent effect on mobility given by the increase in sanction rate and positivity rate among the population. We also show how the pandemic dynamics have changed between the first and the second wave of the emergency. Lots of people could be spared by incorporating greater interventions and many more are at stake, despite the recent boost in vaccinations. Informing citizens about the effects and purposes of the restrictive measures has become increasingly important throughout the various phases of the pandemic.

Keywords COVID-19 lockdown stringency; First and second wave; Google Community Mobility Reports; Italian provinces and regions; Reopening of schools; Social distancing compliance.

1. Introduction

The Coronavirus disease 2019 (COVID-19), caused by the SARS-CoV-2 virus, was first identified in Wuhan, China, in December 2019. On the last day of the year, the Wuhan Municipal Health Commission released a briefing on its website about a pneumonia of unknown cause, with 27 confirmed cases; the World Health Organization's Western Pacific Regional Office was promptly notified by the WHO's Country Office in the People's Republic of China, which had picked up the media statement from the website[1]. In the following days, the disease quickly spread to the rest of China and Asia, being also detected in Beijing, Shanghai, and Shenzhen, as well as in Japan, Thailand, and South Korea[2]. The city of Wuhan implemented a travel ban for its citizens on the 23rd of January, as an attempt to curb the epidemic within the city (Chinazzi et al., 2020; Huang et al., 2020). The rest of the world was silently observing the evolution of the epidemic, staying on the alert. The World Health Organization finally declared the outbreak a Public Health Emergency of International Concern on 30th January 2020 (Brodeur et al., 2020). Just one day later, Italy observed two confirmed cases: a couple of tourists from China[2]. On the 1st of February, Italy suspended the issue of visas to Chinese citizens and banned all direct flights from China[2].

On 21st February 2020, an Italian citizen who had not been to China was diagnosed with SARS-CoV-2 in the Italian region of Lombardy[2]. On the same day, in the afternoon, Codogno – the town in which the hospital was located – was put into quarantine by order of the Mayor[2]; a few hours later, the first Italian citizen, an elderly person from Veneto, died from the infection[3]. One day later, the list of quarantined Municipalities in Northern Italy expanded to 11, with about 50,000 people affected[4]; on

[1] https://www.reuters.com/article/us-china-health-pneumonia-idUSKBN1YZ0GP; https://www.who.int/news/item/29-06-2020-covidtimeline
[2] https://www.agi.it/cronaca/news/2020-02-23/coronavirus-italia-morti-7175602/
[3] https://www.corriere.it/cronache/20_febbraio_21/coronavirus-muore-uomo-77-anni-monselice-dac529f6-54f9-11ea-9196-da7d305401b7.shtml
[4] https://www.ilsole24ore.com/art/un-mese-coronavirus-italia-paziente-1-militari-strada-ADQZqnE

the 25th of February, additional restrictive measures were imposed in six out of seven Northern Italian regions[4]. New cases kept being reported throughout Italy, which soon became the country with the highest number of COVID-19 infections outside Asia. Schools and universities were ordered to shut down in the whole country since the 5th of March and, on the 8th of March, the Lombardy region and 14 more provinces in Northern Italy were put into quarantine, involving about 16 million citizens and causing a night escape of thousands of people to other regions[4]. Just a short while later, the rising number of infections caused the imposition of the "most drastic public health measures ever seen in a democracy"[5]: the whole nation was sent into a severe lockdown since the 10th of March, with heavy fines – and even imprisonment – planned for anyone leaving home unauthorised[6].

The disease was ultimately declared a pandemic by the WHO on 11th March 2020 (Ocampo and Yamagishi, 2020). Other Western countries soon followed Italy in implementing social distancing measures (Kupferschmidt and Cohen, 2020): indeed, while the disease was largely unknown and no vaccine was readily available, putting restrictions on people's movements was commonly seen as the only feasible strategy to keep the number of infections below a critical threshold (Anderson et al., 2020; Bushman et al., 2020; Lipsitch et al., 2020). On the 19th of March, Italy finally overtook China as the country with the highest number of reported deaths caused by COVID-19 (JHU CSSE, 2021; see Dong et al., 2020). The active centre of the pandemic had moved from Asia to Europe, while China successfully managed to contain the spread of the virus, finally putting the quarantine in Wuhan to an end on the 8th of April (Brodeur et al., 2020). Italy ultimately emerged from the lockdown on the 4th of May, slowly starting to reopen its economic activities (Buonomo and Della Marca, 2020).

[5] https://www.theglobeandmail.com/canada/article-make-no-mistake-italy-is-not-an-outlier-in-this-global-pandemic/
[6] https://www.salute.gov.it/portale/nuovocoronavirus/dettaglioNotizieNuovoCoronavirus.jsp?id=4184

While the lockdown conveyed a message of danger, the reopening might have led citizens to perceive that the threat had come to an end (Reinders Folmer et al., 2020b). Moreover, people are shown to be less likely to comply with the restrictive measures when their duration is longer than they expect (Briscese et al., 2020). During the lockdown, inhabitants were obliged to confine themselves under severe penalties; after that, the issue was confidently put into citizens' hands, who were now able to choose how much they were willing to cooperate, mostly based on their level of concern about the health crisis, their practical capacity to adhere to the measures, their social norms, and their level of confidence in the authorities (Lalot et al., 2020; Nivette et al., 2020; Reinders Folmer et al., 2020a; Shao and Hao, 2020). Indeed, an effective response to the pandemic strongly relies on citizens' compliance with the restrictive measures put in place to halt the spread of COVID-19 (Islam et al., 2020; May, 2020; Sobol et al., 2020; West et al., 2020), ultimately reducing the number of deaths.

With this paper, we aim at offering new insights into how citizens' compliance with the restrictions – measured through longitudinal data on sanctions and movement trends – has affected the number of infections and deaths over time.

The remainder of the article is organised as follows. The next Section (2) presents a description of the data employed in the analyses; Section 3 depicts the adopted methodology; Section 4 shows the main results; finally, in Section 5, we discuss the relevant implications of our findings, along with some concluding remarks.

2. Data

Our data come from several sources of information. First, we collected the daily distribution of COVID-19 positive cases in the 107 Italian second-level institutional bodies (i.e., provinces) and of performed swabs and recorded deaths in the country's 19 regions and 2 Autonomous provinces, provided by the Italian Civil Protection (Dipartimento della Protezione Civile, 2021). Furtherly, we make use of the Containment and Health Index, developed by the University of Oxford's Blavatnik School of Government (Hale et al., 2021), tracing the government response to the pandemic outbreak over time. Moreover, we gathered the number of daily controls and fines imposed on citizens due to disrespecting the restrictive measures aimed at containing the Coronavirus spread, made available by the Italian Ministry of the Interior (Ministero dell'Interno, 2021). Plus, we employ Google's Community Mobility Reports, capturing movement trends across different categories of places at the province level (Google LLC, 2021). Additionally, we include the regional-level scores of bonding and bridging social capital (Sabatini, 2005), which may play a role in explaining citizens' compliance. Lastly, we complement these sources with a number of variables describing the demographic characteristics of the analysed provinces (i.e., activity rate, density, population, ratio of over-65s to the total population), taken from the Italian National Institute of Statistics (Istat). Some dummies portraying the restrictions adopted in particular periods (i.e., lockdown, red and orange zones) are also computed.

For each time-varying variable, we collected 366 daily observations, pertaining to the period running from the 24th of February 2020 to the 23rd of February 2021 (one year). All these data are publicly available. However, for the sake of transparency and reproducibility, as well as to help further research on the field, we provide the ready-to-use dataset and modelling codes (Panarello and Tassinari, 2021).

Descriptive statistics of the implemented variables are shown in Table 1.

Table 1 – Descriptive statistics, computed for the sample that is not missing for any of the variables (common observations).

Variable	**Total Obs.**	**Common Obs.**	**1st percentile**	**25th percentile**	**Median**	**75th percentile**	**99th percentile**	**Mean**	**Standard Deviation**
Regional positive cases	39162	34686	0	21	157	729	5173	606.63	1112.42
Regional swabs	39055	34686	126	1806	4296	10703	41260	7821.55	8793.77
Regional deaths	39055	34686	0	1	6	26	241	22.38	46.16
Provincial positive cases	39055	34686	0	2	17	77	845	80.26	201.80
Provincial swabs	39055	34686	29.58	246.59	566.18	1238.56	9075.67	1088.87	1738.37
Provincial positivity rate	38645	34686	0.000	0.005	0.030	0.088	0.500	0.068	0.137
Provincial positivity rate (7-day moving average)	38734	34686	0.000	0.007	0.036	0.091	0.375	0.063	0.085
Containment and Health Index	39162	34686	53.87	61.01	68.15	78.75	85.42	69.97	9.94
Closures and containment Index	39162	34686	37.50	50.00	62.50	77.08	92.71	65.53	17.40
Health measures Index	39162	34686	61.11	75.69	75.69	75.69	82.36	75.89	4.79
Red zone	39162	34686	0	0	0	0	1	0.070	0.255
Orange zone	39162	34686	0	0	0	0	1	0.106	0.308
Compliance rate	37450	34686	93.80	98.53	99.17	99.84	99.97	98.86	1.28
Google Mobility: Retail and recreation	39027	34686	-95	-55	-28	-12	40	-33.47	30.98
Google Mobility: Grocery and pharmacy	38945	34686	-94	-26	-9	0	40	-14.52	24.96

Google Mobility: Parks	36987	34686	-89	-41	-6	36	368	11.16	87.72
Google Mobility: Transit stations	37925	34686	-88	-56	-36	-18	65	-35.28	31.36
Google Mobility: Workplaces	39116	34686	-81	-39	-26	-19	15	-30.10	19.64
Google Mobility: Residential	39067	34686	-7	4	9	16	36	11.14	10.10
Bridging social capital	39162	34686	-4.34	-1.69	-0.36	1.64	3.93	0.07	2.34
Bonding social capital	39162	34686	-5.9	-2.82	-0.53	2.67	5.39	-0.20	3.18
Activity rate	39162	34686	37.46	45.78	50.89	54.48	60.63	49.60	5.80
Density (pop. per sq. km)	39162	34686	38	106	184	286	2615	277.85	392.44
Percentage of over-65s to total population	39162	34686	18.2	22.4	23.9	25.6	29.2	24.10	2.35

Concerning the distribution of daily positive cases, swabs, and deaths (Dipartimento della Protezione Civile, 2021), the Italian Civil Protection provides complete data at the regional level; only cases are also provided at the province level. With a view to obtaining the number of swabs at the province level, we weigh the regional values by the population in each province. Positivity rate is the ratio of positive cases to the total number of tests performed on a given day. As there are recurrent inconsistencies and delays in reporting such data, a modest number of days is characterised by negative values of positive cases, swabs, and deaths: this happens when, on a particular day, the count gets corrected downwards after having been overestimated on the day before – e.g., due to erroneously counting duplicate data. Therefore, we correct the single negative values by means of an equally-weighted seven-period two-sided moving average approach, until achieving a positive value for each anomalous observation. In addition, we aggregate the data weekly, by computing equally-weighted seven-period two-sided moving averages for the whole set of observations, using the transformed variable in lieu of the original one in some of the models. This strategy lets us control for the effect produced by the daily variations in the number of swabs on a given week: much fewer tests are usually performed during weekends (Ruiu and Ruiu, 2020), causing grossly underestimated reported figures from Sundays to Tuesdays each week (once swabs collected on weekends ultimately get analysed and reported). Data on deaths are also difficult to assess. Indeed, daily reported figures often come as the result of backlogs; moreover, each region adopts a different – and sometimes not consistent – count. However, during the pandemic, the number of victims has never dropped below a certain threshold.

We plot daily tests (in thousands), positive cases (in hundreds), and deaths in Figure 1. The number of tests, which was remarkably low at the beginning of the pandemic, shows a major increase since summer 2020. At this point, the deaths line starts keeping pace with the swabs one, so that the number of deaths becomes close to 1 per 100 positive cases: indeed, the apparent lethality rate approaches a more realistic threshold than the one observed in the first period. As a matter of fact, the apparent lethality rate (Case Fatality Rate, CFR) – calculated by dividing the number of deaths by the number of confirmed COVID-19 cases – is strictly dependent on the testing policy and potentially much different from the real one (Infection Fatality Rate, IFR). An early analysis (Verity et al., 2020) estimated the IFR for China at 0.66% and several other studies from a wide range of countries demonstrate a point estimate of IFR of about 0.68% (Meyerowitz-Katz and Merone, 2020). However, as the disease is lethal especially for older people, who represent a much more substantial strand of the population in Italy than in many other countries, the Italian IFR could well be slightly higher than 1% (see Rinaldi and Paradisi, 2020). This said, when the deaths line in Figure 1 is just marginally distant than the positive cases line, contagions are likely estimated with greater accuracy and CFR could be considered a realistic index of COVID-19 lethality, which was utterly overestimated in the first period of the pandemic due to a very low number of daily tests.

Figure 1 – Number of swabs, positive cases and deaths over time.

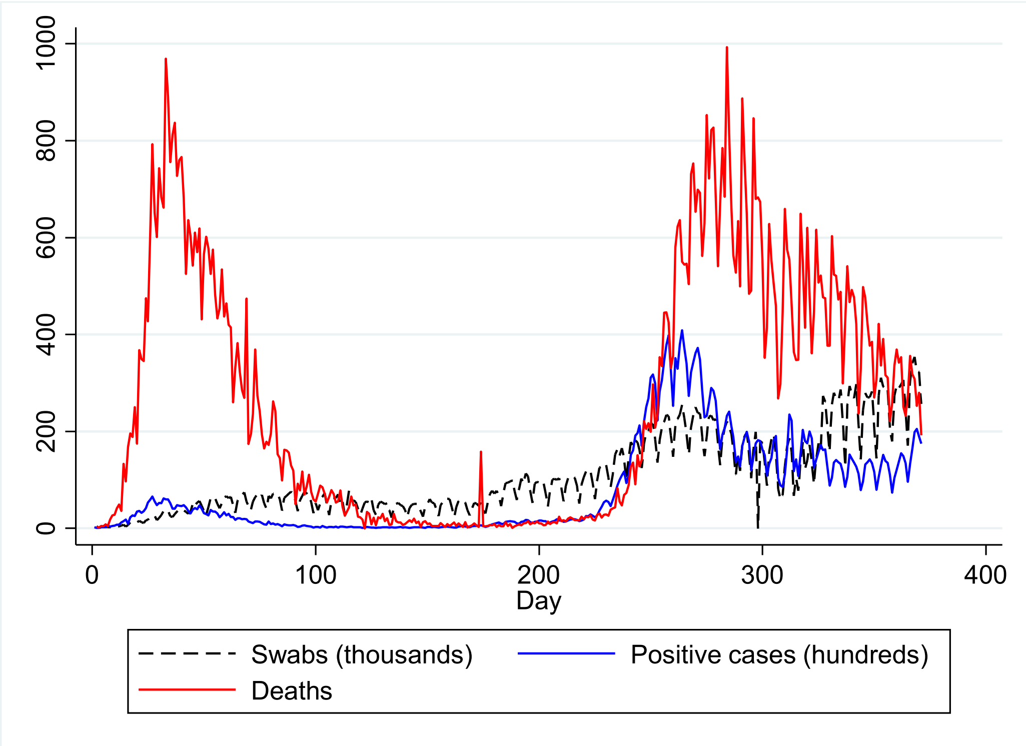
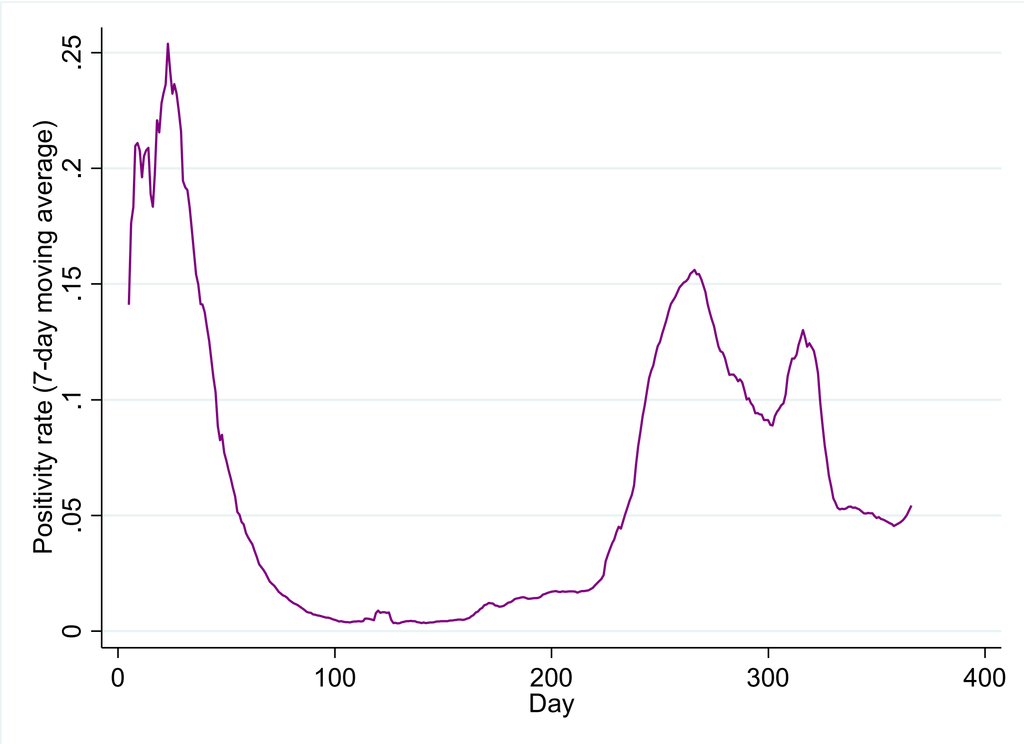


Figure 2 shows the ratio of positive cases to the total number of tests performed on each day. This ratio – also known as positivity rate – was very high at the beginning of the pandemic, due to a low number of performed daily tests, which were only used to confirm severely symptomatic cases. Indeed, when an infected person is found, a good practice would be to buffer all the people that the individual had recently been in contact with, even if they do not show any apparent symptom attributable to the disease. On the other hand, when the number of performable tests is limited, only the most serious cases (i.e., severely symptomatic individuals) are expected to be tested and, therefore, a very high proportion of swabs would give positive results (Busetta et al., 2020). The positivity rate decreases in summer, when the real number of infected people was lower and it was easier to trace them more accurately, then starts increasing again in autumn, along with the "second wave" of the pandemic.

Figure 2 – Positivity rate over time.



As regards the spatial distribution of infections over the year, we divide the count of positive cases and the positivity rate into deciles and present them in four choropleth maps of Italy, at the NUTS-3 level of detail (provinces). Specifically, Figure 3 shows the cumulative number of positive cases detected in the period 24 February 2020 – 13 September 2020, while Figure 4 refers to the period 14 September 2020 – 23 February 2021. Then, we display the average positivity rate determined over the same two periods in Figures 5 and 6, respectively. As the maps show, infections were mostly concentrated in the northern Italian provinces during the first wave of the pandemic, becoming widespread throughout the country in the second period, in which both the cumulative number of cases and the positivity rate are considerably higher.

Figure 3 – Cumulative number of positive cases in the period 24 February 2020 – 13 September 2020, divided into deciles, at the Italian NUTS-3 level.

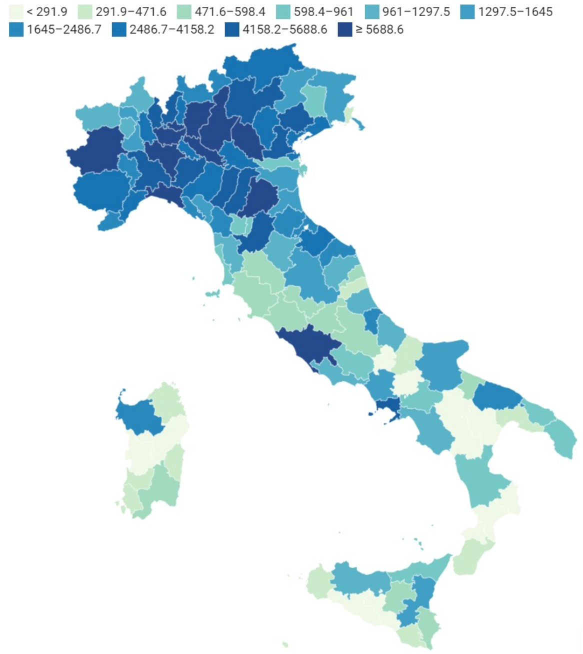


Figure 4 – Cumulative number of positive cases in the period 14 September 2020 – 23 February 2021, divided into deciles, at the Italian NUTS-3 level.

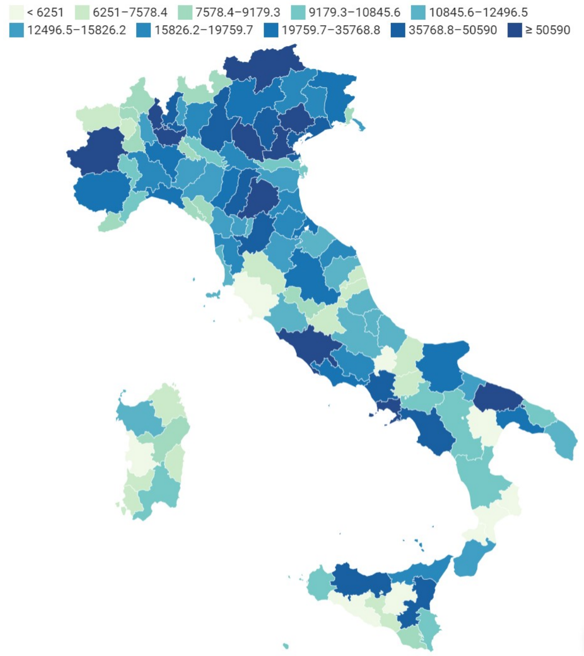


Figure 5 – Average positivity rate in the period 24 February 2020 – 13 September 2020, divided into deciles, at the Italian NUTS-3 level.

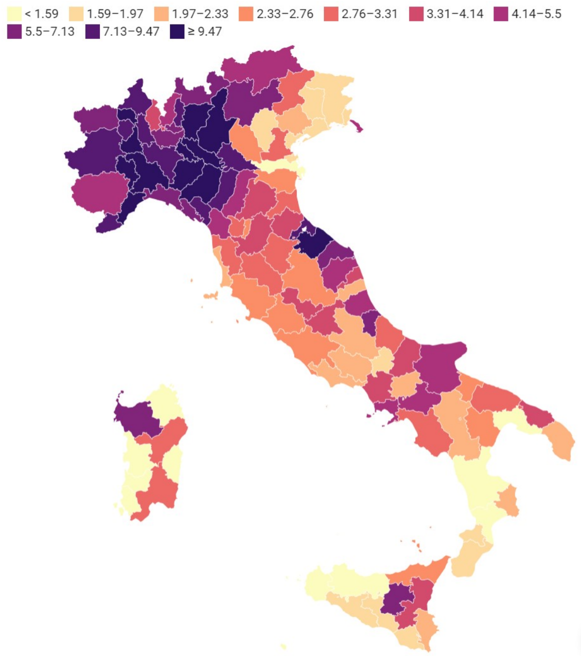
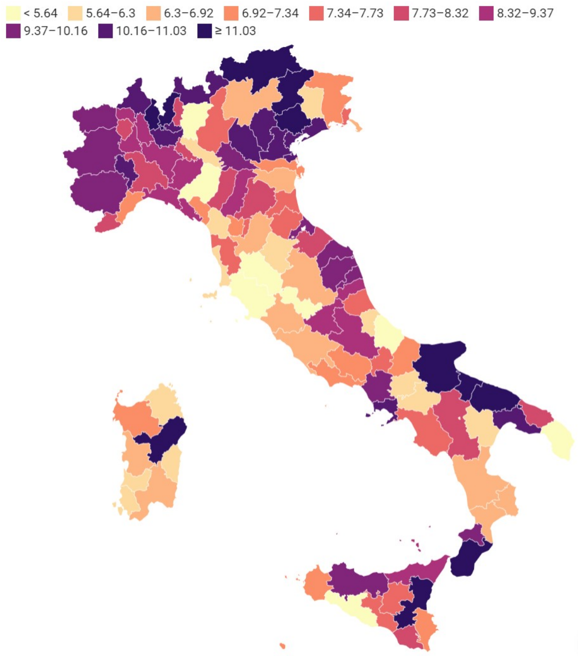
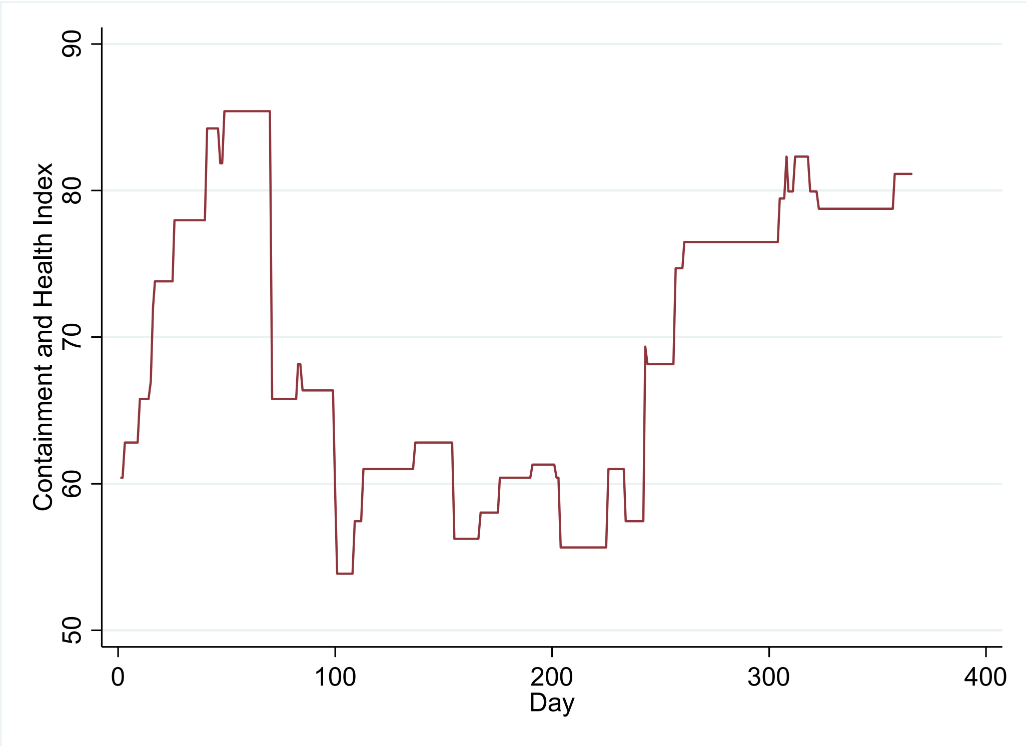


Figure 6 – Average positivity rate in the period 14 September 2020 – 23 February 2021, divided into deciles, at the Italian NUTS-3 level.



The Containment and Health Index (Hale et al., 2021) was developed to measure the evolution of government responses to the pandemic over time. It is a composite index made up of 14 indicators, each ranging between 0 and 100, aggregated with no weighting. Deeply, the adopted indicators refer to country-level data on closures and containment (closings of schools and universities, closing of workplaces, cancelling of public events, restrictions on private gatherings, closing of public transport, stay-at-home requirements, restrictions on internal movements, restrictions on international travel) and health measures (presence of public information campaigns, testing policy, contact tracing, facial coverings policy, vaccination policy, policies for protecting elderly people). Figure 7 plots the values taken by the index over the analysed period. Of course, the values were higher in the first period due to the heavy restrictions (i.e., lockdown) that took place from the 10th of March to the 3rd of May 2020.

Figure 7 – Containment and Health Index over time.



Starting from the 11th of March 2020 (one day after the extension of the lockdown to the whole country), the Italian Ministry of the Interior started delivering daily reports on the number of controls carried out by the police and the number of sanctions given due to violation of lockdown dispositions (Ministero dell'Interno, 2021). We can calculate the sanction rate as the ratio between the number of fines and the number of people who were controlled on a given day (Ruiu and Ruiu, 2020); the one's complement to this rate (Compliance rate) represents a proxy of citizens' degree of adhesion and consent to the COVID-19 restrictive measures, which is a determining factor in the success of lockdown policies (Li et al., 2020a). Indeed, not all individuals violating the lockdown norms had been caught by the competent authorities; nevertheless, this ratio can still provide useful information on this issue, proving its robustness in our analyses. Figure 8 shows sanctions and police controls for each day. Controls were particularly tight during the lockdown, then loosened after the restrictions had been gradually released.

Figure 8 – Number of sanctions and police controls over time.

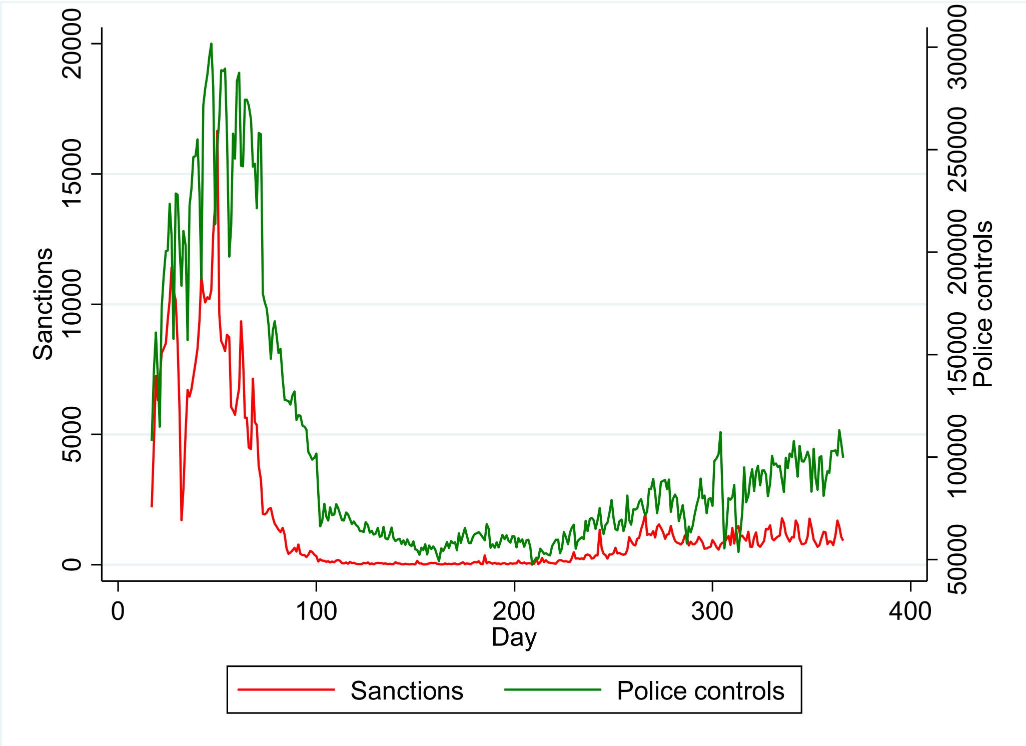
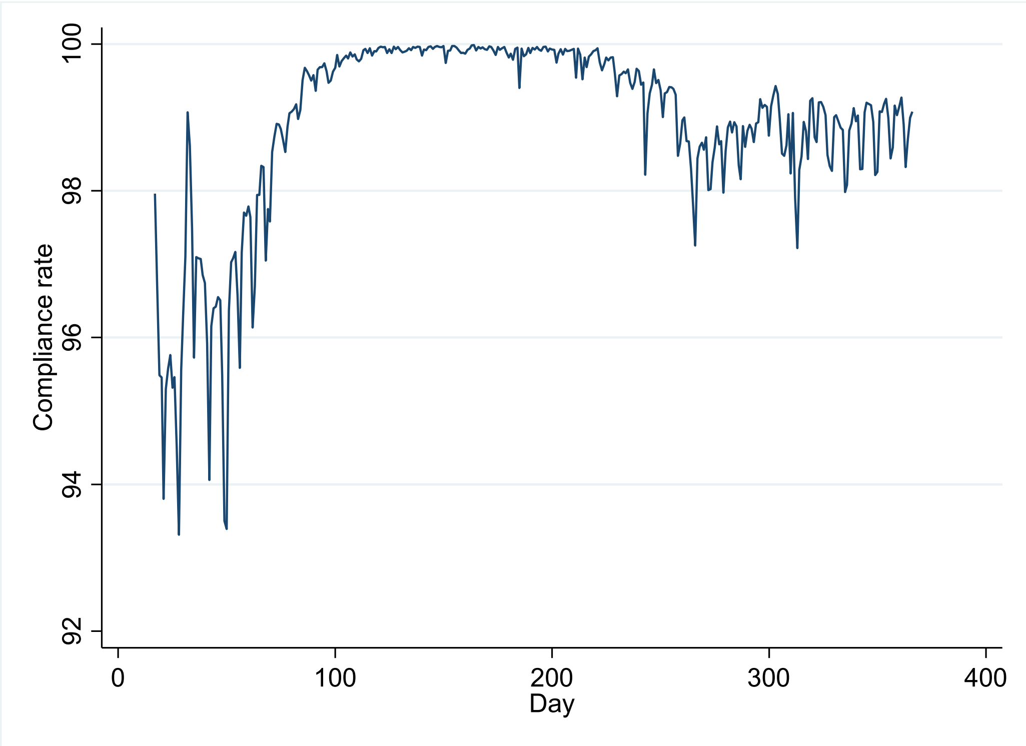


Figure 9 shows the evolution of Italians' compliance with COVID-19 restrictions over the considered period, in percentage points. Compliance was lower during the lockdown, then increased in correspondence of the easing of surveillance services. In the latest period, as individuals' response to social distancing measures wanes over time (Hoeben et al., 2021; Jeffrey et al., 2020; Reinders Folmer et al., 2020a), compliance looks to be on the decrease again.

Figure 9 – Compliance with COVID-19 restrictions over time.

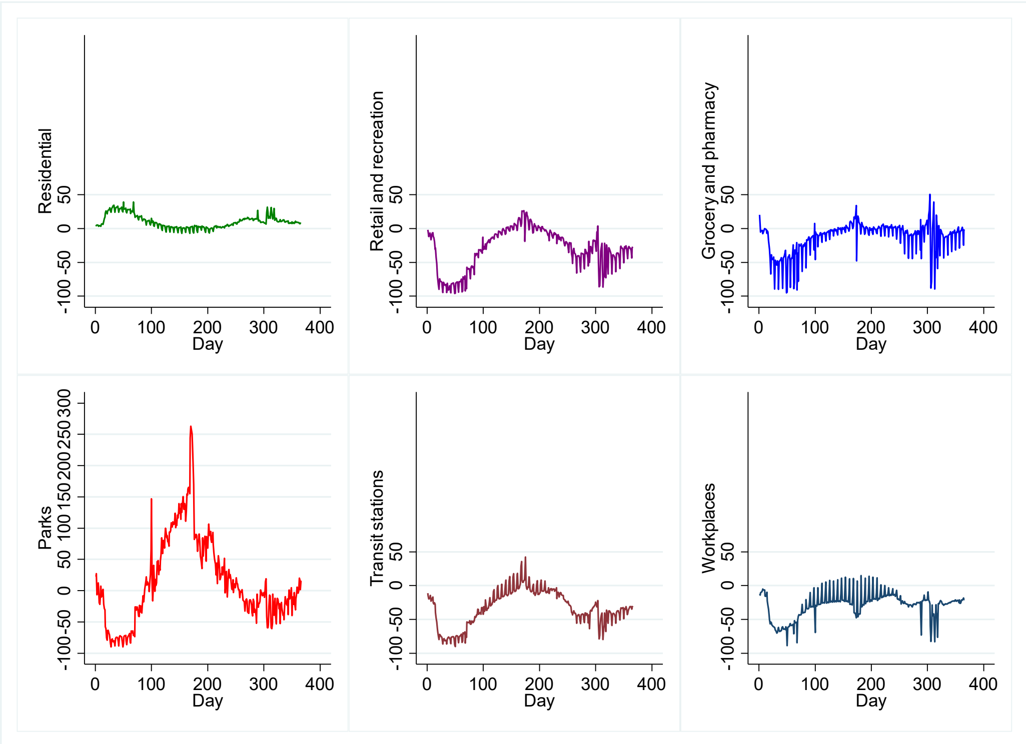


Moreover, we use Google's Community Mobility Reports (Google LLC, 2021), consisting in province-level aggregated daily data on human mobility trends, grouped into six different location categories (i.e., residential areas, retail stores and recreation sites, grocery stores and pharmacies, parks, transit stations, and workplaces). These are anonymised sets of data passively collected from millions of users who have enabled the Location History setting on their mobile devices, used in other Google's products, such as Maps, to track human traffic and display popular times at various locations. Deeply, these data consist in daily percentage changes from a pre-pandemic baseline, which is the median value for that day of the week, pertaining to the 5-week period 3rd January – 6th February 2020. Therefore, the baseline consists in 7 individual values: one for each weekday. The residential category measures percentage changes in the duration of stay, while the other categories quantify variations in the number of visitors: indeed, simple information on the time a person spends out of the house is not enough for predicting infections, as movements directed to high-risk locations and solitary walks would be considered on equal terms (Bushman et al., 2020).

In the considered 366 time periods, the maximum negative baseline change at the province level was 100% (for transit stations), while the maximum change in the positive direction was 933% (for parks). As regards mean daily percentage changes, these range from a minimum of -96% (for retail stores and recreation sites) to a maximum of +263% (for parks). The residential category is the one with the lowest variance, while the parks category is the one with the highest variance, considering both provincial data and daily means. These variations allow us to realise how each of the six categories had been affected by policy action. Moreover, as each province shows different trends, restrictions had better be managed at the local level.

Mean daily percentage changes for the six categories are plotted in Figure 10. Indeed, data for parks are peculiar: this category shows an intense growth in summer, due to seasonality. As regards residential areas, since the related information consists in average lengths of stay, the possible variation is bounded above: sure enough, there are only 24 hours in a day and all the people – even those who only come back home for sleeping at night – already spend a good amount of time at their places of residence.

Figure 10 – Google Community Mobility Reports for all categories over time.



A substantial stream of scientific literature has endeavoured to investigate the relationships between citizens' reactions to containment policies – and, more generally, to the pandemic – by using the theoretical construct of social capital (Bourdieu, 1980; Coleman, 1988; Putnam et al., 1993; Fine, 2001), implemented with different operational definitions (Alfano and Ercolano, 2020a; Bartscher et al., 2020; Borgonovi and Andrieu, 2020). Social interactions can reinforce the spread of infections; indeed, they also determine other factors that are crucial in outlining the progress of the pandemic. In particular, social capital can affect individual awareness of the costs and benefits associated with behaviours that can contribute to the transmission of the SARS-CoV-2 virus. Deeply, Alfano and Ercolano (2020a) employed the conceptualisations of bridging and bonding social capital (Fine, 2001; Sabatini, 2005; 2009), obtaining significant coefficients in an econometric model aimed at analysing the trend of COVID-19 infections in Italy. In brief, bridging social capital is based on trust between heterogeneous social groups, while bonding social capital is based on kinship and family groups. We expect a strong presence of bridging social capital in a particular area to have the effect of decreasing the containment policies' effectiveness; conversely, bonding social capital, by conditioning people's behaviour, should mitigate the spread of infections, thus strengthening the impact of the adopted measures. For the operational definition of the two constructs, we followed Alfano and Ercolano (2020a).

3. Methods

Ten models are estimated. The first three models (Models A1 to A3) are Hausman-Taylor panel regressions, in which some covariates are allowed to be correlated with the unobserved individual-level random effects (Hausman and Taylor, 1981). Indeed, one of the main drawbacks of fixed-effects models is that they cannot incorporate time-constant covariates, as they show no variability within individuals over time. On the other hand, in random-effects models, endogenous time-varying and time-constant covariates may be correlated with the unobserved panel-level random effects. The Hausman-Taylor estimator is designed to address both the time-constant issue and any potential endogeneity concerns. In these models, we use the equally-weighted seven-period two-sided moving average of provincial positivity rate for day i and province j as dependent variable. As the schools' reopening on the 14th of September 2020 is said to have been the primary cause of the resurgence of the pandemic in Italy (Sebastiani and Palù, 2020), we perform our estimations on two subsamples: until the 13th of September and since the 14th of September.

Model A1 is performed on the first subsample. It includes seven time-varying covariates: the Containment and Health Index, the Compliance rate, as well as Google's mobility data for retail and recreation, grocery and pharmacy, parks, transit stations, and workplaces. Moreover, it includes four time-constant regressors: activity rate and population density, measured at the province level, and the regional-level scores of bonding and bridging social capital. All the time-varying covariates are measured with an 8-day lag from the dependent variable. The reason behind this choice is that the mean incubation period (i.e., the time between the contact with a positive individual and the onset of symptoms) is around 5.2 days, with a mean of approximately 5 days (Li et al., 2020b; Linton et al., 2020); to these 5 days, we add the median time between the onset of symptoms and the official diagnosis, which was 2.6 days in the considered period (Istituto Superiore di Sanità, 2021). Google's mobility regressors are assumed to be endogenous, as the variations in mobility are affected by the values taken by other variables in the model. Moreover, as the dependent variable is on a different lag than the regressors in our analyses, it is assumed not to affect the independent variables, thus furtherly allowing us to control for endogeneity. Albeit we do not control for time fixed-effects, our model still allows us to manage time differences through the Containment and Health Index, measured alongside citizens' compliance.

Moving on to Model A2, as the Containment and Health Index aggregates fourteen policies, it is indeed interesting to evaluate the impact of the different indicators which it is composed of. Therefore, in this model we split the Containment and Health Index into two sub-indices: the Closures and containment Index, made up of 8 indicators, and the Health measures Index, which includes 6 indicators.

Model A3 is performed on the second subsample (14th September 2020 – 23rd February 2021). This period is characterised by a regional differentiation in the implemented containment measures: starting from the 6th of November 2020, each Italian region and Autonomous province is assigned a colour based on the local pandemic risk, which is updated each week. The possible colours are: white (safe);

yellow (low risk); orange (medium risk); and red (high risk). For each colour, specific restrictive measures are foreseen. Hence, when analysing the second subsample, we replace the "Closures and containment" part of the national-level Containment and Health Index with a set of dummy variables indicating the pandemic-risk colour attributed to each region: deeply, we include the Health measures Index along with two dichotomic variables, respectively indicating whether the region was attributed a red or orange classification; when both dichotomic variables take value 0, it means that the region is classified as having a low or very low pandemic risk, with mild envisaged containment policies.

The fourth model (Model B) is a Generalised Least Squares fixed-effects panel regression of time spent in residential areas – derived from Google data – on sanction rate (measured at lag 1), moving average of provincial positivity rate (lag 1), and an interaction of the extended lockdown period (10th March – 2nd June) with the Containment and Health Index. Although the lockdown was lifted since the 4th of May, most restrictions, such as limitations on movements outside the region, kept being applied until the 2nd of June. Here, we assume that people react with fear in response to information about the daily percentage of positive cases and sanctioned individuals, which would result in voluntary compliance to the restrictions on the following day, thus making citizens spend more time at home (see Buonomo and Della Marca, 2020; Goorah et al., 2020).

Models C1 to C3 are similar to Models A1 to A3 but estimated through Negative Binomial fixed-effects panel regressions, to account for the discrete nature of the dependent variable. Indeed, as the dependent variables in our analyses (exception made for Model B) refer to the counts of infections and deaths, the correct investigation approach is given by regression models based on the Negative Binomial distribution, which has been employed in several COVID-19-related studies (e.g., Allel et al., 2020; Basellini et al., 2021; Chaudhry et al., 2020; Pan et al., 2020; Piovani et al., 2021; Woody et al., 2020). Compared to other count regression models such as Poisson, the Negative Binomial has the further advantage of being explicitly able to keep the variability of the data under control by considering overdispersion (i.e., variance being larger than the mean), which is common for epidemiological data (Endo et al., 2020; Lee et al., 2012). This may lead to improved efficiency in estimation: as demonstrated by Chan et al. (2021), the Negative Binomial regression corresponds to the best fitting model for the analysis of COVID-19-related data. Models C1 to C3 employ the count of provincial positive cases as dependent variable. Therefore, compared to the first three models, which use the moving average of provincial positivity rate as response variable, we need to include some additional regressors: provincial swabs, to account for the daily number of performed tests, and six dummy variables indicating the day of the week (Monday to Saturday), to account for the variability in the number of reported cases over the course of each calendar week.

Models D1 to D3 are Negative Binomial fixed-effects panel regressions of the regional deaths count, estimated on the two subsamples 24th February 2020 – 13th September 2020 (Models D1 and D2) and 14th September 2020 – 23rd February 2021 (Model D3). The employed regressors are: regional positive cases, regional swabs, Containment and Health Index (aggregated in Model D1, split into two parts in Model D2, and with the "Closures and containment" part replaced by the regional-level pandemic-risk colour in Model D3), Compliance rate, Google's mobility data (for retail and recreation, grocery and pharmacy, parks, transit stations, and workplaces), bridging and bonding social capital scores, activity rate, population density, and percentage of over-65s to the total population. Here, the time-varying variables are employed with a 17-day lag from the dependent variable, as we add the median time from the onset of symptoms to death, which was estimated in 12 days in Italy (Gruppo della Sorveglianza COVID-19, 2021), to the 5-days mean incubation period (Li et al., 2020b; Linton et al., 2020).

4. Results

Models A1 to A3 are Hausman-Taylor panel regressions of provincial positivity rate, the results of which are shown in Table 2. As expected, higher containment scores and citizens' compliance imply a lower positivity rate. The "Health measures" feature of the Containment and Health Index is apparently the only effective one in shaping the number of infections over time (Model A2). Moreover, unsurprisingly, red zones are more successful than orange zones in limiting the spread of the disease (Model A3). As regards mobility, a greater activity towards grocery stores is always correlated with rising positivity rates. The same effect is given by a higher percentage change in visits to parks in the first period. Indeed, as depicted in Figure 10, parks became overcrowded with joggers and walkers during spring and summer 2020, after the relaxation of the ban on outdoor exercise imposed during the lockdown (Camporesi, 2020), which may explain this positive relationship. By contrast, going to sites for retail and recreation seems to have a negative effect on the number of confirmed cases per swab, which is likely due to the correlation with the closure of such activities amidst the infection peaks. In the second period, characterised by the provision of strict safety protocols in workplaces and public means of transportation, visits to such places are correlated with a lower positivity rate. The role of bridging and bonding social capital appears to be relevant in the first period, in which more connections among people are associated with a higher positivity rate. Finally, higher activity rates in the first period seem to bring about an increase in positivity rates among the population.

Table 2 – Results from Models A1 to A3: Hausman-Taylor panel regressions of provincial positivity rate (7-day moving average).

	A1 (until 13th Sep)	**A2 (until 13th Sep)**	**A3 (since 14th Sep)**
	Coefficient (Robust Std. Err.)	**Coefficient (Robust Std. Err.)**	**Coefficient (Robust Std. Err.)**
Containment and Health Index (lag 8)	-0.003***		
	(0.0002)		
Closures and containment Index (lag 8)		-0.000	
		(0.0001)	
Health measures Index (lag 8)		-0.008***	-0.008***
		(0.0005)	(0.0006)
Red zone (lag 8)			-0.040***
			(0.0055)
Orange zone (lag 8)			-0.030***
			(0.0033)
Compliance rate (lag 8)	-0.036***	-0.018***	-0.013***
	(0.0028)	(0.0021)	(0.0025)
Google Mobility: Retail and recreation (lag 8)	-0.001***	-0.000	-0.002***
	(0.0001)	(0.0001)	(0.0002)
Google Mobility: Grocery and pharmacy (lag 8)	0.001***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)
Google Mobility: Parks (lag 8)	0.000***	0.000**	0.000
	(0.0000)	(0.0000)	(0.0000)
Google Mobility: Transit stations (lag 8)	-0.000	-0.000	-0.000***
	(0.0001)	(0.0001)	(0.0001)
Google Mobility: Workplaces (lag 8)	-0.000	0.000***	-0.000***
	(0.0001)	(0.0001)	(0.0001)
Bridging social capital	0.007***	0.007***	-0.002
	(0.0018)	(0.0018)	(0.0022)
Bonding social capital	0.002**	0.002**	-0.001
	(0.0010)	(0.0009)	(0.0009)
Activity rate	0.003***	0.003***	-0.000
	(0.0008)	(0.0008)	(0.0009)
Density (pop. per sq. km)	0.000	0.000	0.000
	(0.0000)	(0.0000)	(0.0000)
Intercept	3.583***	2.232***	1.945***
	(0.2790)	(0.2175)	(0.2766)
Observations	17197	17197	16803

Note: ** and *** stand for $p < 0.05$ and $p < 0.01$.

Model B is a Generalised Least Squares fixed-effects panel regression of time spent in residential areas. The results, shown in Table 3, highlight that the increase in time spent at home is governed by a plurality of factors. The trend of the pandemic at the provincial level, measured by the ratio of positive cases to performed tests, acts as a deterrent to mobility, while the percentage of sanctions on controlled individuals signals the effectiveness of repressive measures in hindering mobility. The Containment and Health Index confirms its effect in limiting people's movements, as was already brought to light by the results of the previous models. It is interesting to note that, with the same level of Containment and Health Index, its effect is almost doubled by interacting it with the extended lockdown (10th March – 2nd June), proving the key role played by psychological factors in governing citizens' behaviour.

Table 3 – Results from Model B: GLS fixed-effects panel regression of time spent in residential areas.

	Coefficient (Robust Std. Err.)
Sanction rate (lag 1)	1.488***
	(0.0503)
Provincial positivity rate (7-day moving average, lag 1)	16.445***
	(1.8710)
Containment and Health Index, extended lockdown=0	0.383***
	(0.0061)
Containment and Health Index, extended lockdown=1	0.511***
	(0.0054)
Intercept	-20.922***
	(0.3679)
Observations	37250
R^2 (overall)	0.780
R^2 (adjusted)	0.794

Note: *** stands for $p < 0.01$.

Table 4 shows the results from Models C1 to C3, which employ the count of provincial cases as dependent variable. The analysis of infections by means of Negative Binomial models (our favourite specification) confirms the results obtained through the Hausman-Taylor panel regressions. Here, the count of provincial swabs and six dummies indicating the day of the week are added to the regressors already appearing in Models A1 to A3. The particularly high value of the Compliance rate coefficient highlights the importance of citizens' cooperation to keep down the number of infections: for a one per cent increase in this rate, the difference in the logs of expected infections is likely to decrease by about 0.21 – 0.37 units, given that the other regressors are held constant. Concerning parks, while the first period is characterised by a positive correlation with the number of infections (as already seen in Models A1 to A3), the second period – in which mobility data do not exhibit the exceptionally high peaks experienced right after the lockdown – displays a negative relationship. Undeniably, outdoor environments, when not overcrowded, are associated with a lower likelihood of airborne droplet transmission and, thus, reduced risk of infection, due to lower density of people and lower stability of the virus in the air (Morawska and Cao, 2020; Setti et al., 2020).

Table 4 – Results from Models C1 to C3: Negative Binomial fixed-effects panel regressions of provincial cases.

	C1 (until 13th Sep)	**C2 (until 13th Sep)**	**C3 (since 14th Sep)**
	Coefficient (Std. Err.)	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Provincial swabs	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)
Containment and Health Index (lag 8)	-0.017***		
	(0.0014)		
Closures and containment Index (lag 8)		0.011***	
		(0.0010)	
Health measures Index (lag 8)		-0.061***	-0.069***
		(0.0014)	(0.0018)
Red zone (lag 8)			-0.553***

			(0.0215)
Orange zone (lag 8)			-0.383***
			(0.0159)
Compliance rate (lag 8)	-0.369***	-0.209***	-0.346***
	(0.0084)	(0.0080)	(0.0155)
Google Mobility: Retail and recreation (lag 8)	-0.018***	-0.005***	-0.029***
	(0.0009)	(0.0010)	(0.0010)
Google Mobility: Grocery and pharmacy (lag 8)	0.017***	0.009***	0.015***
	(0.0007)	(0.0008)	(0.0005)
Google Mobility: Parks (lag 8)	0.001***	0.001***	-0.001***
	(0.0002)	(0.0002)	(0.0003)
Google Mobility: Transit stations (lag 8)	0.004***	0.004***	-0.001
	(0.0008)	(0.0008)	(0.0007)
Google Mobility: Workplaces (lag 8)	-0.015***	-0.013***	0.006***
	(0.0011)	(0.0010)	(0.0006)
Bridging social capital	0.074***	0.045***	-0.073***
	(0.0119)	(0.0122)	(0.0097)
Bonding social capital	0.002	-0.005	-0.020***
	(0.0053)	(0.0053)	(0.0044)
Activity rate	0.093***	0.088***	-0.012***
	(0.0053)	(0.0054)	(0.0040)
Density (pop. per sq. km)	0.000***	0.000***	-0.000***
	(0.0000)	(0.0000)	(0.0000)
Monday dummy	-0.094***	-0.111***	-0.244***
	(0.0361)	(0.0347)	(0.0226)
Tuesday dummy	-0.243***	-0.264***	0.357***
	(0.0313)	(0.0300)	(0.0218)
Wednesday dummy	-0.003	-0.120***	0.526***
	(0.0309)	(0.0293)	(0.0216)
Thursday dummy	0.160***	0.013	0.546***
	(0.0298)	(0.0283)	(0.0210)
Friday dummy	0.103***	-0.024	0.491***
	(0.0300)	(0.0286)	(0.0209)
Saturday dummy	0.013	-0.079***	0.337***
	(0.0302)	(0.0285)	(0.0199)
Intercept	31.325***	18.995***	39.863***
	(0.8962)	(0.8188)	(1.5481)
Observations	17197	17197	16803
Log-likelihood	-44450	-43598	-89541

Note: *** stands for $p < 0.01$.

Table 5 displays the results from Models D1 to D3. As regards the number of deaths (similarly analysed through Negative Binomial fixed-effects panel regression models), the involved variables are the same that were identified for the number of infections, to which is added, among the structural variables, the provincial percentage of over-65s, which turns out to be significant and positively correlated with the deaths count only in the first period. Indeed, this shows that the demographic dynamics of the pandemic have changed compared to the beginning, embracing the whole population, and that the elderly might have become more cautious in the second phase of the pandemic.

Table 5 – Results from Models D1 to D3: Negative Binomial fixed-effects panel regressions of regional deaths.

	D1 (until 13th Sep)	**D2 (until 13th Sep)**	**D3 (since 14th Sep)**
	Coefficient	**Coefficient**	**Coefficient**
	(Std. Err.)	**(Std. Err.)**	**(Std. Err.)**
Regional positive cases (lag 17)	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)
Regional swabs (lag 17)	-0.000***	-0.000***	-0.000
	(0.0000)	(0.0000)	(0.0000)
Containment and Health Index (lag 17)	-0.016***		
	(0.0012)		
Closures and containment Index (lag 17)		0.012***	
		(0.0009)	
Health measures Index (lag 17)		-0.042***	-0.035***
		(0.0010)	(0.0017)
Red zone (lag 17)			-0.486***
			(0.0187)
Orange zone (lag 17)			-0.273***
			(0.0138)
Compliance rate (lag 17)	-0.187***	-0.133***	-0.294***
	(0.0061)	(0.0056)	(0.0125)
Google Mobility: Retail and recreation (lag 17)	-0.039***	-0.027***	-0.028***
	(0.0009)	(0.0010)	(0.0009)
Google Mobility: Grocery and pharmacy (lag 17)	0.019***	0.014***	0.016***
	(0.0007)	(0.0007)	(0.0004)
Google Mobility: Parks (lag 17)	0.003***	0.002***	-0.002***
	(0.0003)	(0.0003)	(0.0002)

Google Mobility: Transit stations (lag 17)	-0.016***	-0.013***	-0.007***
	(0.0011)	(0.0010)	(0.0006)
Google Mobility: Workplaces (lag 17)	0.006***	0.010***	0.009***
	(0.0011)	(0.0011)	(0.0006)
Bridging social capital	0.048**	0.048**	0.036***
	(0.0205)	(0.0212)	(0.0132)
Bonding social capital	0.056***	0.067***	0.029***
	(0.0100)	(0.0105)	(0.0073)
Activity rate	0.024***	0.010	-0.036***
	(0.0090)	(0.0094)	(0.0055)
Density (pop. per sq. km)	-0.000	-0.000	-0.000***
	(0.0000)	(0.0000)	(0.0000)
Percentage of over-65s to total population	0.059***	0.062***	0.003
	(0.0122)	(0.0126)	(0.0087)
Monday dummy	0.063***	0.066***	0.031*
	(0.0214)	(0.0203)	(0.0174)
Tuesday dummy	0.042*	0.119***	0.034*
	(0.0237)	(0.0228)	(0.0184)
Wednesday dummy	-0.079**	-0.017	-0.060**
	(0.0398)	(0.0388)	(0.0238)
Thursday dummy	0.163***	0.249***	0.558***
	(0.0231)	(0.0218)	(0.0174)
Friday dummy	0.224***	0.263***	0.489***
	(0.0218)	(0.0207)	(0.0169)
Saturday dummy	0.252***	0.245***	0.324***
	(0.0215)	(0.0203)	(0.0170)
Intercept	15.551***	12.773***	33.748***
	(0.8867)	(0.8537)	(1.2912)
Observations	16900	16900	16150
Log-likelihood	-34414	-33633	-56937

Note: *, ** and *** stand for $p < 0.10$, $p < 0.05$ and $p < 0.01$.

As regards potential collinearity issues, after examining the correlation between regression coefficients, we did not detect any worrying values. Moreover, in our estimates, most coefficients appear to be significant and we obtain satisfactory standard errors as well as confidence intervals (Giacalone et al., 2018).

The days with the highest number of nationally reported deaths are the 3rd of December 2020, with 993 lost lives, and the 27th of March 2020, in which the number of registered fatalities amounted to 969. As people's mobility 17 days before these peaks may have elicited such extraordinary numbers, we present two choropleth maps of Italy that portray the spatial distribution of the percentage changes in time spent in residential areas on 10th March 2020 (Figure 11) and 16th November 2020 (Figure 12). In the two selected dates, the median percentage change turns out to be the same, while the variability between provinces is higher in November compared to the 10th of March (which is also the first day of the national lockdown). Territorial differences in Italy are well-known (e.g., Aiello and Scoppa, 2000; Ercolano, 2012) and are also reflected in the dynamics of the COVID-19 pandemic. The highest decile largely embraces the provinces with the highest population (Rome, Turin, and most of the Lombardy region in the first period; the Campania region in the second period), indicating that citizens living in such provinces have considerably altered their mobility habits compared to the pre-pandemic period. The islands of Sicily and Sardinia appear to be closer to pre-pandemic mobility values in the second period compared to the first one, while a large share of provinces maintained a similar level of commitment with the mobility restrictions in the two periods.

Figure 11 – Time spent in residential areas (percentage changes from baseline) on 10th March 2020, divided into deciles, at the Italian NUTS-3 level.

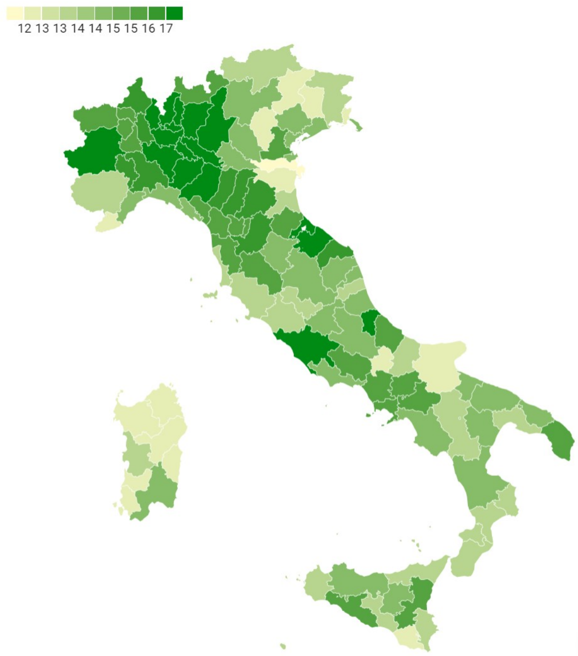
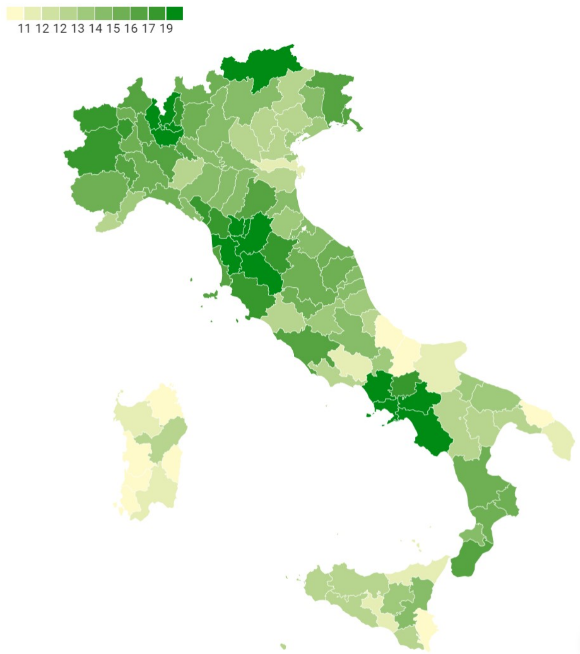


Figure 12 – Time spent in residential areas (percentage changes from baseline) on 16th November 2020, divided into deciles, at the Italian NUTS-3 level.



5. Discussion and conclusions

Our results confirm that the containment policies have had a beneficial impact on the pandemic, having been able to reduce the amount of infections and deaths caused by COVID-19. This corroborates the findings of a considerable number of studies (e.g., Alfano and Ercolano, 2020b; Alfano and Ercolano, 2021; Balmford et al., 2020; Caselli et al., 2021; Dergiades et al., 2020; Ghosh et al., 2020; Pasdar et al., 2020).

Our outcomes concerning infections are comparable when using either the Hausman-Taylor or the Negative Binomial model. However, the latter is our preferred specification, being the ideal approach for COVID-19 data modelling, in line with the model comparison results presented and discussed by Chan et al. (2021). The number of infections exhibits a negative relationship with the Containment and Health Index and the Compliance rate, proving that the degree of agreement to the restrictive measures and the awareness of their necessity represents the greatest leverage to limit the spread of the pandemic. Therefore, great attention must be paid by the Government and the other authorities in informing citizens about the motives and consequences of the restrictive measures. This result is already present in the literature (Baldwin and Di Mauro, 2020; Bargain and Aminjonov, 2020; Lalot et al., 2020; McKenzie and Adams, 2020). Our results highlight the paramount importance of social capital in determining the trend of the pandemic. Following Alfano and Ercolano (2020a), we distinguished between bridging and bonding social capital: as regards the former, the signs of the estimated coefficients are aligned with what was expected; conversely, the estimates pertaining to bonding social capital also show positive signs. Indeed, the presence of a high level of bonding social capital could be read as a sign of a "closed" society, which would hinder the pandemic by reducing contacts between strangers. Our contrary evidence can be rationalised in light of the fact that family clusters of COVID-19 are shown to have played a dominant role in the transmission of the disease (Liu et al., 2020); moreover, particularly intense outbreaks in Italy occurred in "closed" – if not segregated – social contexts, such as prisons (Cingolani et al., 2021) and residential care homes (Ventura et al., 2021).

Some structural features of the Italian provinces help explain the number of infections experienced during the first wave. Activity rate reveals a direct relationship with positive cases in the first period, as a stronger productive fabric causes more contacts, therefore facilitating infections, and the same effect is attributable to population density.

It is remarkable that the reduction in mobility, as represented by the trend concerning time spent in residential places, obtained from Google data, is also due to psychological factors. On the one hand, we have the effect of the provincial positivity rate, whereby citizens reduce their mobility as a consequence of its increase, which we might call the "prudence effect". On the other hand, we have the deterrent effect expressed by the sanction rate and the Containment and Health Index. It should also be noted that the effect given by the Containment and Health Index is, at the same level, stronger during the lockdown period, confirming its psychological impact on citizens' compliance level: undeniably, the lockdown conveyed a message of danger, which calls for the mobilisation of individual behaviours to contain the pandemic.

In relation to the model concerning the number of deaths, we estimated three distinct models, differentiating the study period in order to separately analyse the different "waves" of the pandemic (Table 5). The variables that show a significant impact are the same ones that were significant in the model concerning infections, to which the regional number of cases and the number of performed tests are added, with the first one showing a positive impact on the dependent variable. Among the structural variables, the share of population aged 65 or more is added to population density and activity rate, with a positive sign, which reflects the known situation of higher lethality characterising the elderly population (Rinaldi and Paradisi, 2020). Nevertheless, some regressors change their sign from one period to the other: mobility towards parks is positive in the first period, but negative in the second one, and the same goes for activity rate. Moreover, the magnitude of some coefficients changes considerably. In particular, the coefficient for Compliance rate in the second period is noticeably higher than that of the first period; additionally, the set of coefficients pertaining to containment measures shows a large increase, although not being straightly comparable due to the introduction of red and orange zones in the second period. This means that the importance of the restrictive measures and of citizens' accord on their abidance has greatly increased since the end of the summer, also because the stringency level of such measures – as we have already seen – has critically declined, which was preparatory to the formation of the "second wave" of the pandemic. Finally, the coefficient regarding the share of over-65s to the total population is only significant in the first period, which indicates that the pandemic has extended to all age groups.

Trying to sum up our achieved outcomes, the restrictions represented by the Containment and Health Index appear essential to contain the pandemic until the vaccination campaign produces the so-called herd immunity. However, we have highlighted that such restrictions are not sufficient when they are not accompanied by citizens' consent, which translates into adherence to the mobility restrictions, detected through the reduction in Google's mobility indices: indeed, it is unrealistic to think that repressive actions are enough to enforce compliance with the new mobility rules.

If the goal is to "bend the curve", it must be borne in mind that this is a collective operation: therefore, all institutional actors should better manage communication to motivate the citizens and avoid contradictory behaviours that confuse the population. It may seem like a paradox, but COVID-19 shall be defeated in people's minds first.

But it is not just a psychological and political communication problem. The role played by the closure of workplaces, except for essential activities, should also be kept in mind. The relevant contribution of workplaces-related mobility to the deaths count throughout the pandemic leads us to question whether there has been some hesitation in taking more incisive measures, such as the partial closure of productive activities. With no additional interventions, the number of daily lives lost can eventually become much greater than that suffered in the very first period of the pandemic (Vollmer et al., 2020). Moreover, timeliness in introducing further restrictive measures is crucial in order to strongly reduce their required duration (Chang et al., 2020).

Some countries are going further than others in the way they deal with this unprecedented emergency; hopefully, we will not be found wanting.

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