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

(Article begins on next page)

31 July 2024

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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.

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

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[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).

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[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

62 While the lockdown conveyed a message of danger, the reopening might have led citizens to perceive

63 that the threat had come to an end (Reinders Folmer et al., 2020b). Moreover, people are shown to

64 be less likely to comply with the restrictive measures when their duration is longer than they expect

65 (Briscese et al., 2020). During the lockdown, inhabitants were obliged to confine themselves under

66 severe penalties; after that, the issue was confidently put into citizens' hands, who were now able to

67 choose how much they were willing to cooperate, mostly based on their level of concern about the

68 health crisis, their practical capacity to adhere to the measures, their social norms, and their level of

69 confidence in the authorities (Lalot et al., 2020; Nivette et al., 2020; Reinders Folmer et al., 2020a;

70 Shao and Hao, 2020). Indeed, an effective response to the pandemic strongly relies on citizens'

71 compliance with the restrictive measures put in place to halt the spread of COVID-19 (Islam et al.,

72 2020; May, 2020; Sobol et al., 2020; West et al., 2020), ultimately reducing the number of deaths.

73 With this paper, we aim at offering new insights into how citizens' compliance with the restrictions –

74 measured through longitudinal data on sanctions and movement trends – has affected the number of

75 infections and deaths over time.

76 The remainder of the article is organised as follows. The next Section (2) presents a description of the

77 data employed in the analyses; Section 3 depicts the adopted methodology; Section 4 shows the main

78 results; finally, in Section 5, we discuss the relevant implications of our findings, along with some

79 concluding remarks.

80

81 **2. Data**

82 Our data come from several sources of information. First, we collected the daily distribution of

83 COVID-19 positive cases in the 107 Italian second-level institutional bodies (i.e., provinces) and of

84 performed swabs and recorded deaths in the country's 19 regions and 2 Autonomous provinces,

85 provided by the Italian Civil Protection (Dipartimento della Protezione Civile, 2021). Furtherly, we

86 make use of the Containment and Health Index, developed by the University of Oxford's Blavatnik

87 School of Government (Hale et al., 2021), tracing the government response to the pandemic outbreak

88 over time. Moreover, we gathered the number of daily controls and fines imposed on citizens due to

89 disrespecting the restrictive measures aimed at containing the Coronavirus spread, made available by

90 the Italian Ministry of the Interior (Ministero dell'Interno, 2021). Plus, we employ Google's

91 Community Mobility Reports, capturing movement trends across different categories of places at the

92 province level (Google LLC, 2021). Additionally, we include the regional-level scores of bonding and

93 bridging social capital (Sabatini, 2005), which may play a role in explaining citizens' compliance. Lastly,

94 we complement these sources with a number of variables describing the demographic characteristics

95 of the analysed provinces (i.e., activity rate, density, population, ratio of over-65s to the total

96 population), taken from the Italian National Institute of Statistics (Istat). Some dummies portraying

97 the restrictions adopted in particular periods (i.e., lockdown, red and orange zones) are also computed.

98 For each time-varying variable, we collected 366 daily observations, pertaining to the period running

99 from the 24th of February 2020 to the 23rd of February 2021 (one year). All these data are publicly

100 available. However, for the sake of transparency and reproducibility, as well as to help further research

101 on the field, we provide the ready-to-use dataset and modelling codes (Panarello and Tassinari, 2021).

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

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

108 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

109

110   Concerning the distribution of daily positive cases, swabs, and deaths (Dipartimento della Protezione
111   Civile, 2021), the Italian Civil Protection provides complete data at the regional level; only cases are
112   also provided at the province level. With a view to obtaining the number of swabs at the province
113   level, we weigh the regional values by the population in each province. Positivity rate is the ratio of
114   positive cases to the total number of tests performed on a given day. As there are recurrent
115   inconsistencies and delays in reporting such data, a modest number of days is characterised by negative
116   values of positive cases, swabs, and deaths: this happens when, on a particular day, the count gets
117   corrected downwards after having been overestimated on the day before – e.g., due to erroneously
118   counting duplicate data. Therefore, we correct the single negative values by means of an equally-

119 weighted seven-period two-sided moving average approach, until achieving a positive value for each

120 anomalous observation. In addition, we aggregate the data weekly, by computing equally-weighted

121 seven-period two-sided moving averages for the whole set of observations, using the transformed

122 variable in lieu of the original one in some of the models. This strategy lets us control for the effect

123 produced by the daily variations in the number of swabs on a given week: much fewer tests are usually

124 performed during weekends (Ruiu and Ruiu, 2020), causing grossly underestimated reported figures

125 from Sundays to Tuesdays each week (once swabs collected on weekends ultimately get analysed and

126 reported). Data on deaths are also difficult to assess. Indeed, daily reported figures often come as the

127 result of backlogs; moreover, each region adopts a different – and sometimes not consistent – count.

128 However, during the pandemic, the number of victims has never dropped below a certain threshold.

129 We plot daily tests (in thousands), positive cases (in hundreds), and deaths in Figure 1. The number

130 of tests, which was remarkably low at the beginning of the pandemic, shows a major increase since

131 summer 2020. At this point, the deaths line starts keeping pace with the swabs one, so that the number

132 of deaths becomes close to 1 per 100 positive cases: indeed, the apparent lethality rate approaches a

133 more realistic threshold than the one observed in the first period. As a matter of fact, the apparent

134 lethality rate (Case Fatality Rate, CFR) – calculated by dividing the number of deaths by the number

135 of confirmed COVID-19 cases – is strictly dependent on the testing policy and potentially much

136 different from the real one (Infection Fatality Rate, IFR). An early analysis (Verity et al., 2020)

137 estimated the IFR for China at 0.66% and several other studies from a wide range of countries

138 demonstrate a point estimate of IFR of about 0.68% (Meyerowitz-Katz and Merone, 2020). However,

139 as the disease is lethal especially for older people, who represent a much more substantial strand of

140 the population in Italy than in many other countries, the Italian IFR could well be slightly higher than

141 1% (see Rinaldi and Paradisi, 2020). This said, when the deaths line in Figure 1 is just marginally distant

142 than the positive cases line, contagions are likely estimated with greater accuracy and CFR could be

143 considered a realistic index of COVID-19 lethality, which was utterly overestimated in the first period

144 of the pandemic due to a very low number of daily tests.

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

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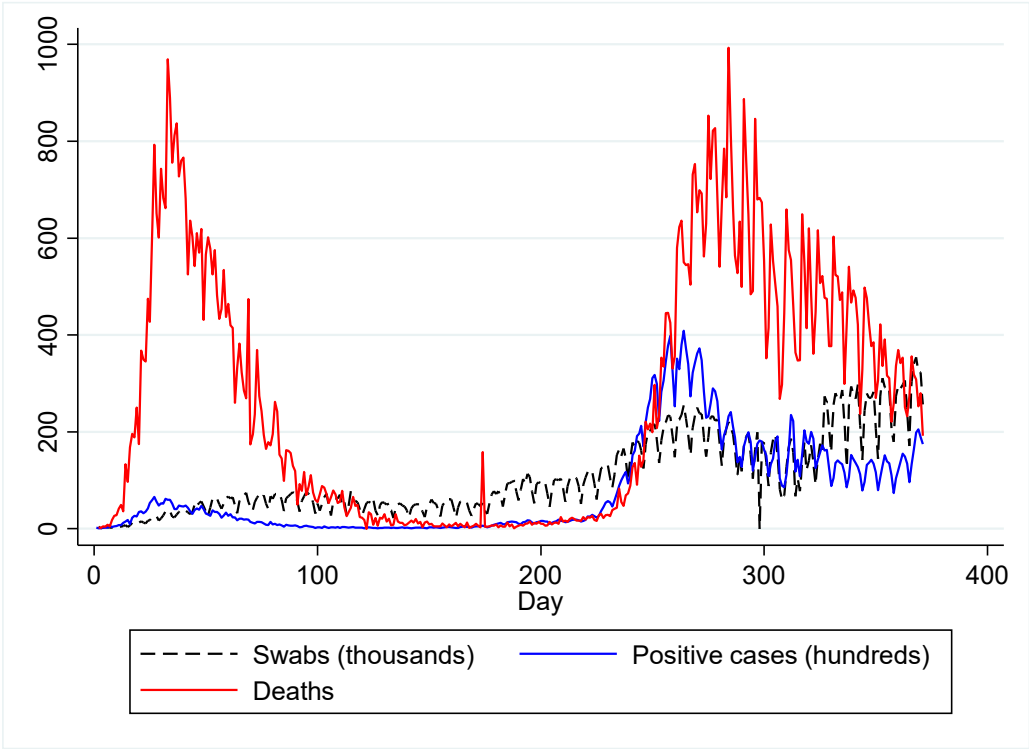
149 Figure 2 shows the ratio of positive cases to the total number of tests performed on each day. This

150 ratio – also known as positivity rate – was very high at the beginning of the pandemic, due to a low

151 number of performed daily tests, which were only used to confirm severely symptomatic cases. Indeed,

152 when an infected person is found, a good practice would be to buffer all the people that the individual

153 had recently been in contact with, even if they do not show any apparent symptom attributable to the

154 disease. On the other hand, when the number of performable tests is limited, only the most serious

155 cases (i.e., severely symptomatic individuals) are expected to be tested and, therefore, a very high

156 proportion of swabs would give positive results (Busetta et al., 2020). The positivity rate decreases in

157 summer, when the real number of infected people was lower and it was easier to trace them more

158 accurately, then starts increasing again in autumn, along with the "second wave" of the pandemic.

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160 Figure 2 – Positivity rate over time.

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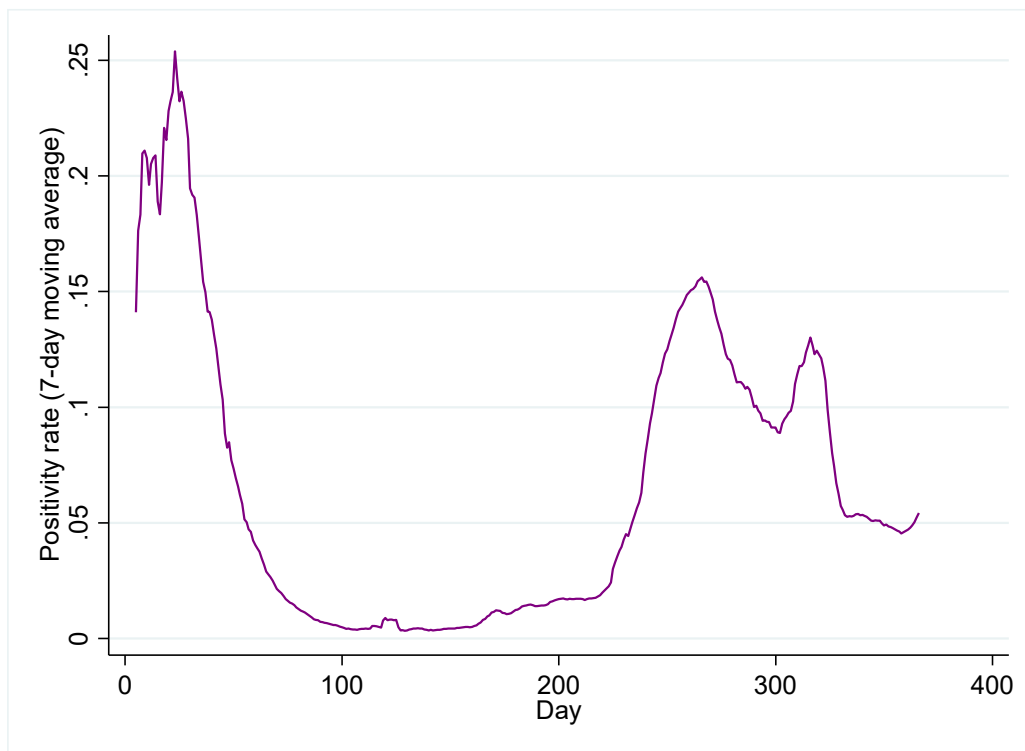
163 As regards the spatial distribution of infections over the year, we divide the count of positive cases

164 and the positivity rate into deciles and present them in four choropleth maps of Italy, at the NUTS-3

165 level of detail (provinces). Specifically, Figure 3 shows the cumulative number of positive cases

166 detected in the period 24 February 2020 – 13 September 2020, while Figure 4 refers to the period 14

167 September 2020 – 23 February 2021. Then, we display the average positivity rate determined over the

168 same two periods in Figures 5 and 6, respectively. As the maps show, infections were mostly

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169   concentrated in the northern Italian provinces during the first wave of the pandemic, becoming

170   widespread throughout the country in the second period, in which both the cumulative number of

171   cases and the positivity rate are considerably higher.

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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.
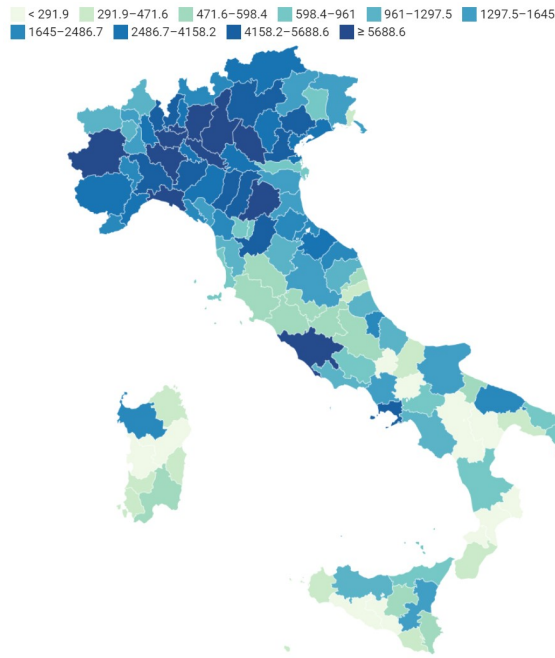
Figure 4 – Cumulative number of positive cases in the period 14 September 2020 – 23 February 2021, divided into deciles, at the Italian NUTS-3 level.
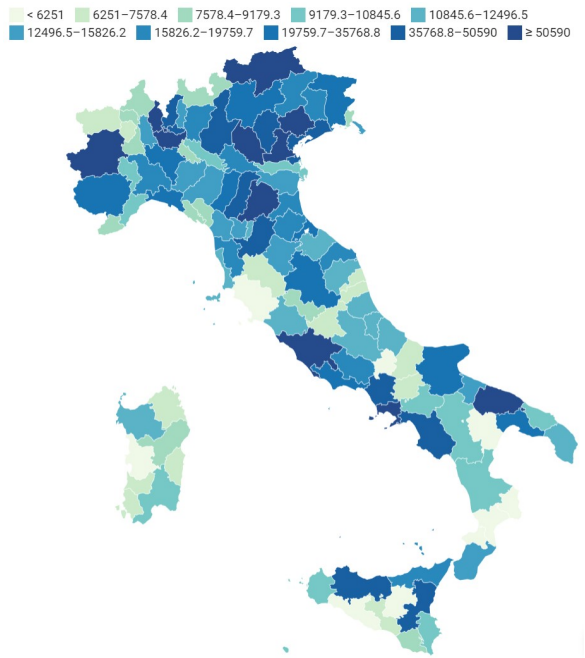
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Figure 5 – Average positivity rate in the period 24 February 2020 – 13 September 2020, divided into deciles, at the Italian NUTS-3 level.
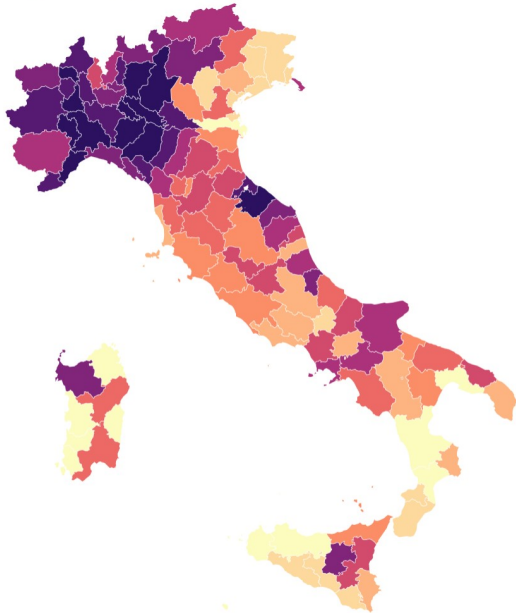
Figure 6 – Average positivity rate in the period 14 September 2020 – 23 February 2021, divided into deciles, at the Italian NUTS-3 level.

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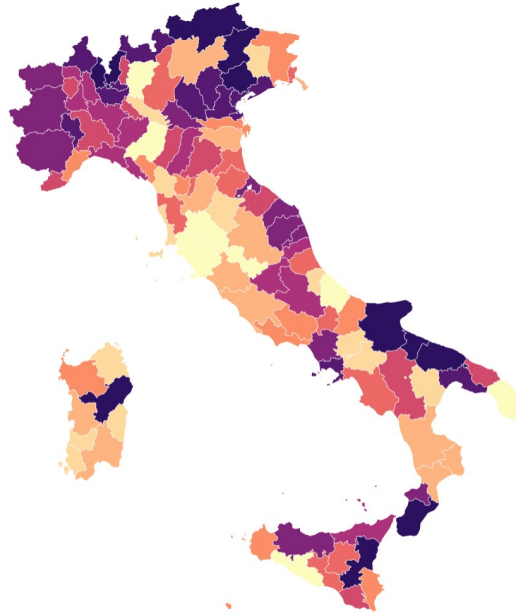
The Containment and Health Index (Hale et al., 2021) was developed to measure the evolution of government responses to the pandemic over time. It is a composite index made up of 14 indicators, each ranging between 0 and 100, aggregated with no weighting. Deeply, the adopted indicators refer to country-level 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.

189   Figure 7 – Containment and Health Index over time.

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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
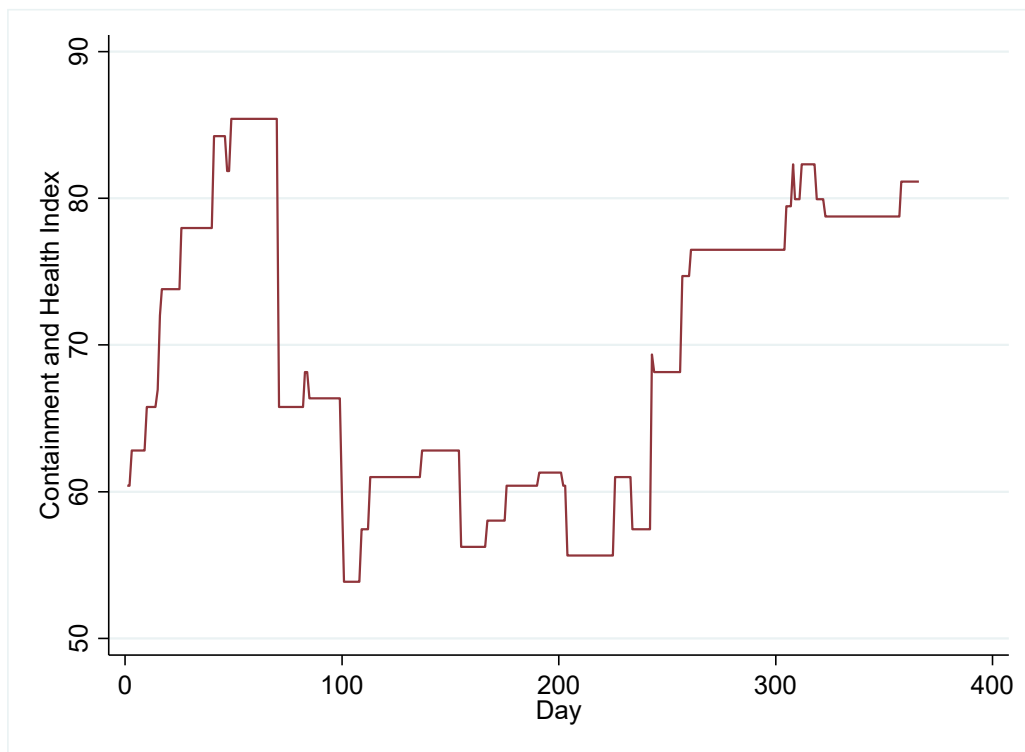
fines and the number of people who were controlled on a given day (Ruiu and Ruiu, 2020); the one's

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

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202   each day. Controls were particularly tight during the lockdown, then loosened after the restrictions

203   had been gradually released.

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

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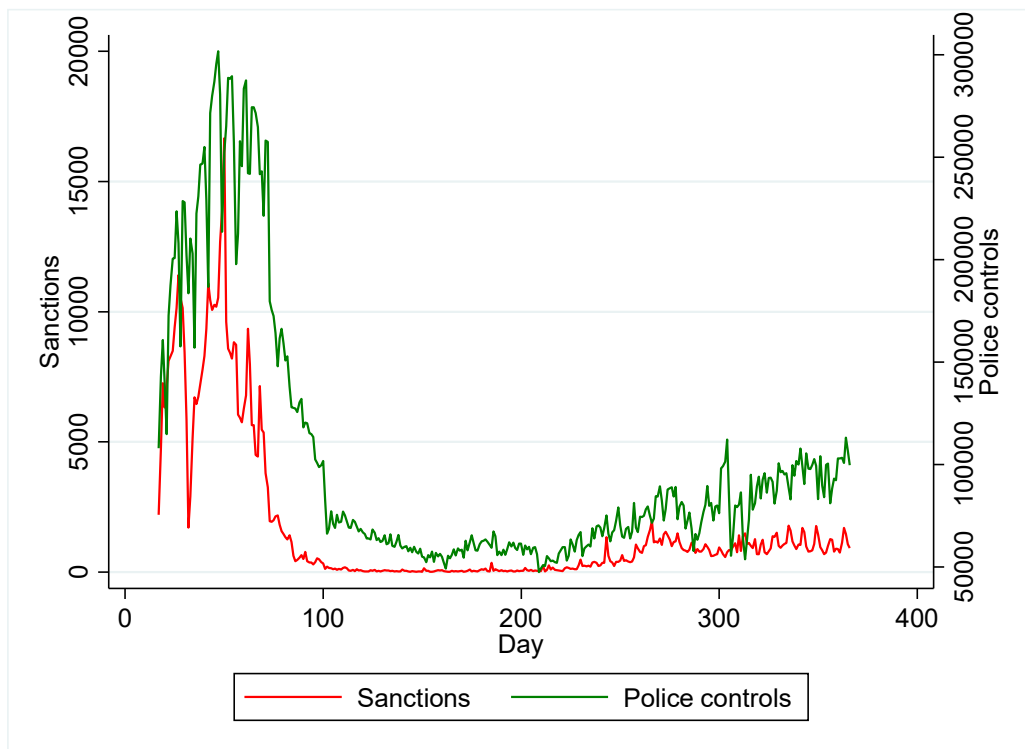
208   Figure 9 shows the evolution of Italians' compliance with COVID-19 restrictions over the considered

209   period, in percentage points. Compliance was lower during the lockdown, then increased in

210   correspondence of the easing of surveillance services. In the latest period, as individuals' response to

211   social distancing measures wanes over time (Hoeben et al., 2021; Jeffrey et al., 2020; Reinders Folmer

212   et al., 2020a), compliance looks to be on the decrease again.

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214   Figure 9 – Compliance with COVID-19 restrictions over time.
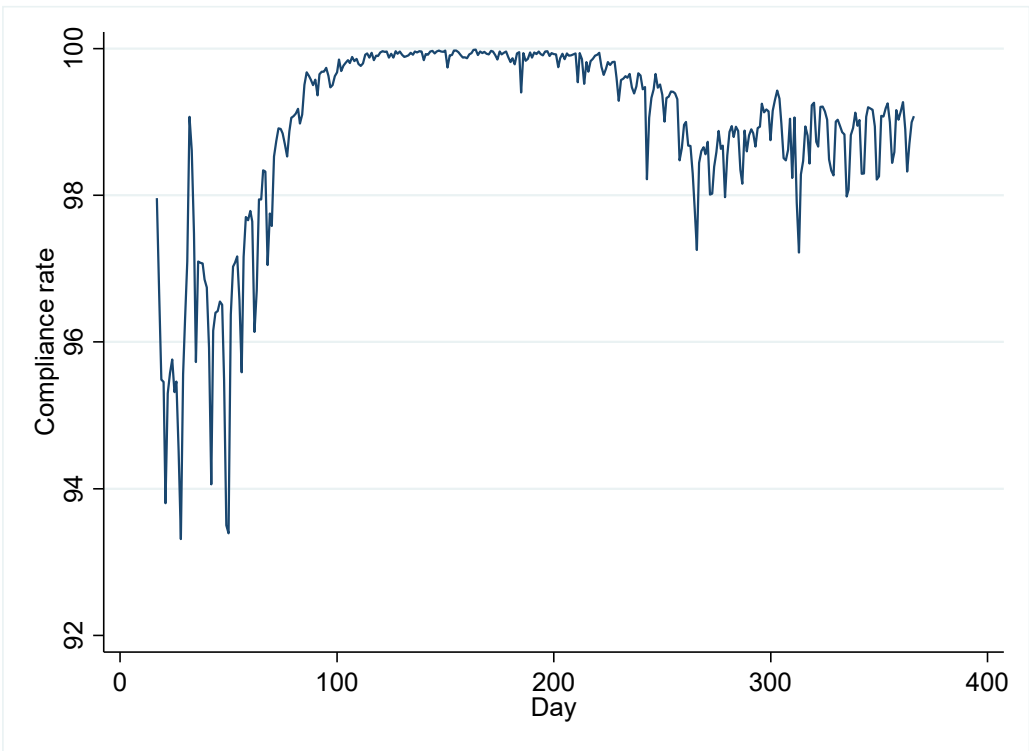
217   Moreover, we use Google's Community Mobility Reports (Google LLC, 2021), consisting in province-

218   level aggregated daily data on human mobility trends, grouped into six different location categories

219   (i.e., residential areas, retail stores and recreation sites, grocery stores and pharmacies, parks, transit

220   stations, and workplaces). These are anonymised sets of data passively collected from millions of users

221   who have enabled the Location History setting on their mobile devices, used in other Google's

222   products, such as Maps, to track human traffic and display popular times at various locations. Deeply,

223   these data consist in daily percentage changes from a pre-pandemic baseline, which is the median value

224   for that day of the week, pertaining to the 5-week period 3rd January – 6th February 2020. Therefore,

225   the baseline consists in 7 individual values: one for each weekday. The residential category measures

226   percentage changes in the duration of stay, while the other categories quantify variations in the number

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227 of visitors: indeed, simple information on the time a person spends out of the house is not enough

228 for predicting infections, as movements directed to high-risk locations and solitary walks would be

229 considered on equal terms (Bushman et al., 2020).

230 In the considered 366 time periods, the maximum negative baseline change at the province level was

231 100% (for transit stations), while the maximum change in the positive direction was 933% (for parks).

232 As regards mean daily percentage changes, these range from a minimum of -96% (for retail stores and

233 recreation sites) to a maximum of +263% (for parks). The residential category is the one with the

234 lowest variance, while the parks category is the one with the highest variance, considering both

235 provincial data and daily means. These variations allow us to realise how each of the six categories had

236 been affected by policy action. Moreover, as each province shows different trends, restrictions had

237 better be managed at the local level.

238 Mean daily percentage changes for the six categories are plotted in Figure 10. Indeed, data for parks

239 are peculiar: this category shows an intense growth in summer, due to seasonality. As regards

240 residential areas, since the related information consists in average lengths of stay, the possible variation

241 is bounded above: sure enough, there are only 24 hours in a day and all the people – even those who

242 only come back home for sleeping at night – already spend a good amount of time at their places of

243 residence.

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249   Figure 10 – Google Community Mobility Reports for all categories over time.
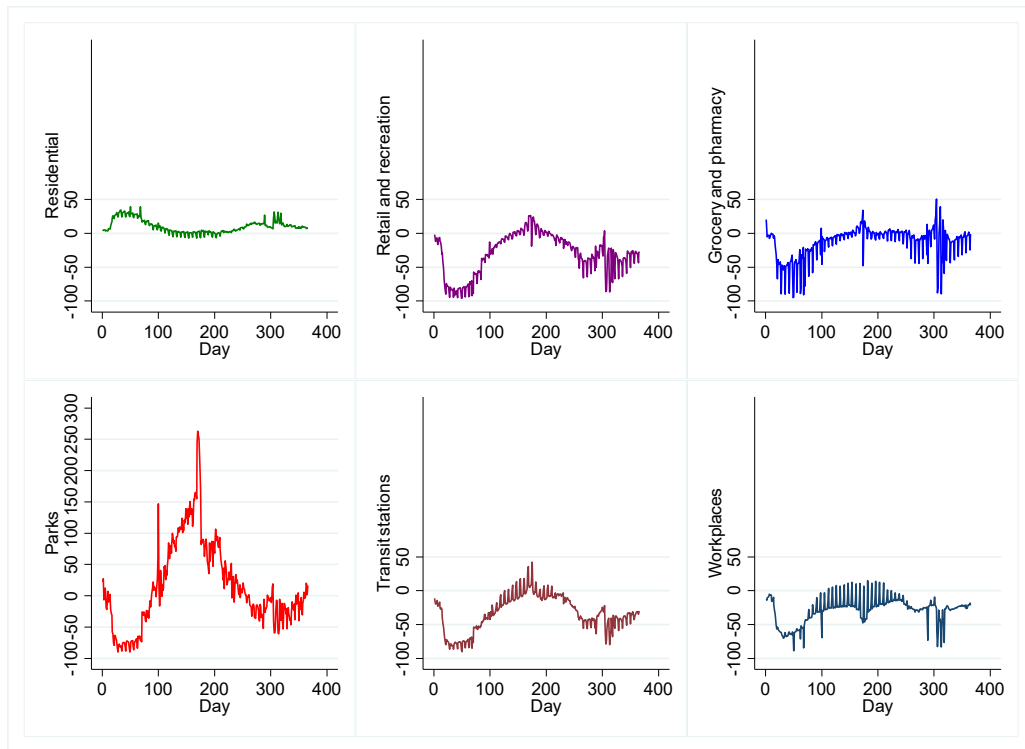
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252   A substantial stream of scientific literature has endeavoured to investigate the relationships between

253   citizens' reactions to containment policies – and, more generally, to the pandemic – by using the

254   theoretical construct of social capital (Bourdieu, 1980; Coleman, 1988; Putnam et al., 1993; Fine, 2001),

255   implemented with different operational definitions (Alfano and Ercolano, 2020a; Bartscher et al.,

256   2020; Borgonovi and Andrieu, 2020). Social interactions can reinforce the spread of infections; indeed,

257   they also determine other factors that are crucial in outlining the progress of the pandemic. In

258   particular, social capital can affect individual awareness of the costs and benefits associated with

259   behaviours that can contribute to the transmission of the SARS-CoV-2 virus. Deeply, Alfano and

260   Ercolano (2020a) employed the conceptualisations of bridging and bonding social capital (Fine, 2001;

261   Sabatini, 2005; 2009), obtaining significant coefficients in an econometric model aimed at analysing

262 the trend of COVID-19 infections in Italy. In brief, bridging social capital is based on trust between

263 heterogeneous social groups, while bonding social capital is based on kinship and family groups. We

264 expect a strong presence of bridging social capital in a particular area to have the effect of decreasing

265 the containment policies' effectiveness; conversely, bonding social capital, by conditioning people's

266 behaviour, should mitigate the spread of infections, thus strengthening the impact of the adopted

267 measures. For the operational definition of the two constructs, we followed Alfano and Ercolano

268 (2020a).

269

3. Methods

271 Ten models are estimated. The first three models (Models A1 to A3) are Hausman-Taylor panel

272 regressions, in which some covariates are allowed to be correlated with the unobserved individual-

273 level random effects (Hausman and Taylor, 1981). Indeed, one of the main drawbacks of fixed-effects

274 models is that they cannot incorporate time-constant covariates, as they show no variability within

275 individuals over time. On the other hand, in random-effects models, endogenous time-varying and

276 time-constant covariates may be correlated with the unobserved panel-level random effects. The

277 Hausman-Taylor estimator is designed to address both the time-constant issue and any potential

278 endogeneity concerns. In these models, we use the equally-weighted seven-period two-sided moving

279 average of provincial positivity rate for day i and province j as dependent variable. As the schools'

280 reopening on the 14th of September 2020 is said to have been the primary cause of the resurgence of

281 the pandemic in Italy (Sebastiani and Palù, 2020), we perform our estimations on two subsamples:

282 until the 13th of September and since the 14th of September.

283 Model A1 is performed on the first subsample. It includes seven time-varying covariates: the

284 Containment and Health Index, the Compliance rate, as well as Google's mobility data for retail and

285   recreation, grocery and pharmacy, parks, transit stations, and workplaces. Moreover, it includes four

286   time-constant regressors: activity rate and population density, measured at the province level, and the

287   regional-level scores of bonding and bridging social capital. All the time-varying covariates are

288   measured with an 8-day lag from the dependent variable. The reason behind this choice is that the

289   mean incubation period (i.e., the time between the contact with a positive individual and the onset of

290   symptoms) is around 5.2 days, with a mean of approximately 5 days (Li et al., 2020b; Linton et al.,

291   2020); to these 5 days, we add the median time between the onset of symptoms and the official

292   diagnosis, which was 2.6 days in the considered period (Istituto Superiore di Sanità, 2021). Google's

293   mobility regressors are assumed to be endogenous, as the variations in mobility are affected by the

294   values taken by other variables in the model. Moreover, as the dependent variable is on a different lag

295   than the regressors in our analyses, it is assumed not to affect the independent variables, thus furtherly

296   allowing us to control for endogeneity. Albeit we do not control for time fixed-effects, our model still

297   allows us to manage time differences through the Containment and Health Index, measured alongside

298   citizens' compliance.

299   Moving on to Model A2, as the Containment and Health Index aggregates fourteen policies, it is

300   indeed interesting to evaluate the impact of the different indicators which it is composed of. Therefore,

301   in this model we split the Containment and Health Index into two sub-indices: the Closures and

302   containment Index, made up of 8 indicators, and the Health measures Index, which includes 6

303   indicators.

304   Model A3 is performed on the second subsample (14th September 2020 – 23rd February 2021). This

305   period is characterised by a regional differentiation in the implemented containment measures: starting

306   from the 6th of November 2020, each Italian region and Autonomous province is assigned a colour

307   based on the local pandemic risk, which is updated each week. The possible colours are: white (safe);

308 yellow (low risk); orange (medium risk); and red (high risk). For each colour, specific restrictive

309 measures are foreseen. Hence, when analysing the second subsample, we replace the "Closures and

310 containment" part of the national-level Containment and Health Index with a set of dummy variables

311 indicating the pandemic-risk colour attributed to each region: deeply, we include the Health measures

312 Index along with two dichotomic variables, respectively indicating whether the region was attributed

313 a red or orange classification; when both dichotomic variables take value 0, it means that the region is

314 classified as having a low or very low pandemic risk, with mild envisaged containment policies.

315 The fourth model (Model B) is a Generalised Least Squares fixed-effects panel regression of time

316 spent in residential areas – derived from Google data – on sanction rate (measured at lag 1), moving

317 average of provincial positivity rate (lag 1), and an interaction of the extended lockdown period (10th

318 March – 2nd June) with the Containment and Health Index. Although the lockdown was lifted since

319 the 4th of May, most restrictions, such as limitations on movements outside the region, kept being

320 applied until the 2nd of June. Here, we assume that people react with fear in response to information

321 about the daily percentage of positive cases and sanctioned individuals, which would result in

322 voluntary compliance to the restrictions on the following day, thus making citizens spend more time

323 at home (see Buonomo and Della Marca, 2020; Goorah et al., 2020).

324 Models C1 to C3 are similar to Models A1 to A3 but estimated through Negative Binomial fixed-

325 effects panel regressions, to account for the discrete nature of the dependent variable. Indeed, as the

326 dependent variables in our analyses (exception made for Model B) refer to the counts of infections

327 and deaths, the correct investigation approach is given by regression models based on the Negative

328 Binomial distribution, which has been employed in several COVID-19-related studies (e.g., Allel et

329 al., 2020; Basellini et al., 2021; Chaudhry et al., 2020; Pan et al., 2020; Piovani et al., 2021; Woody et

330 al., 2020). Compared to other count regression models such as Poisson, the Negative Binomial has

331   the further advantage of being explicitly able to keep the variability of the data under control by

332   considering overdispersion (i.e., variance being larger than the mean), which is common for

333   epidemiological data (Endo et al., 2020; Lee et al., 2012). This may lead to improved efficiency in

334   estimation: as demonstrated by Chan et al. (2021), the Negative Binomial regression corresponds to

335   the best fitting model for the analysis of COVID-19-related data. Models C1 to C3 employ the count

336   of provincial positive cases as dependent variable. Therefore, compared to the first three models,

337   which use the moving average of provincial positivity rate as response variable, we need to include

338   some additional regressors: provincial swabs, to account for the daily number of performed tests, and

339   six dummy variables indicating the day of the week (Monday to Saturday), to account for the variability

340   in the number of reported cases over the course of each calendar week.

341   Models D1 to D3 are Negative Binomial fixed-effects panel regressions of the regional deaths count,

342   estimated on the two subsamples 24th February 2020 – 13th September 2020 (Models D1 and D2) and

343   14th September 2020 – 23rd February 2021 (Model D3). The employed regressors are: regional positive

344   cases, regional swabs, Containment and Health Index (aggregated in Model D1, split into two parts in

345   Model D2, and with the "Closures and containment" part replaced by the regional-level pandemic-

346   risk colour in Model D3), Compliance rate, Google's mobility data (for retail and recreation, grocery

347   and pharmacy, parks, transit stations, and workplaces), bridging and bonding social capital scores,

348   activity rate, population density, and percentage of over-65s to the total population. Here, the time-

349   varying variables are employed with a 17-day lag from the dependent variable, as we add the median

350   time from the onset of symptoms to death, which was estimated in 12 days in Italy (Gruppo della

351   Sorveglianza COVID-19, 2021), to the 5-days mean incubation period (Li et al., 2020b; Linton et al.,

352   2020).

353

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.

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

377　average).

	A1 (until 13th Sep)	A2 (until 13th Sep)	A3 (since 14th Sep)
	Coefficient	Coefficient	Coefficient
	(Robust Std. Err.)	(Robust Std. Err.)	(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

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

379

23

380   Model B is a Generalised Least Squares fixed-effects panel regression of time spent in residential areas.

381   The results, shown in Table 3, highlight that the increase in time spent at home is governed by a

382   plurality of factors. The trend of the pandemic at the provincial level, measured by the ratio of positive

383   cases to performed tests, acts as a deterrent to mobility, while the percentage of sanctions on

384   controlled individuals signals the effectiveness of repressive measures in hindering mobility. The

385   Containment and Health Index confirms its effect in limiting people's movements, as was already

386   brought to light by the results of the previous models. It is interesting to note that, with the same level

387   of Containment and Health Index, its effect is almost doubled by interacting it with the extended

388   lockdown (10th March – 2nd June), proving the key role played by psychological factors in governing

389   citizens' behaviour.

390

391   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

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

393

394   Table 4 shows the results from Models C1 to C3, which employ the count of provincial cases as

395   dependent variable. The analysis of infections by means of Negative Binomial models (our favourite

396   specification) confirms the results obtained through the Hausman-Taylor panel regressions. Here, the

397   count of provincial swabs and six dummies indicating the day of the week are added to the regressors

398   already appearing in Models A1 to A3. The particularly high value of the Compliance rate coefficient

399   highlights the importance of citizens' cooperation to keep down the number of infections: for a one

400   per cent increase in this rate, the difference in the logs of expected infections is likely to decrease by

401   about $0.21 - 0.37$ units, given that the other regressors are held constant. Concerning parks, while the

402   first period is characterised by a positive correlation with the number of infections (as already seen in

403   Models A1 to A3), the second period – in which mobility data do not exhibit the exceptionally high

404   peaks experienced right after the lockdown – displays a negative relationship. Undeniably, outdoor

405   environments, when not overcrowded, are associated with a lower likelihood of airborne droplet

406   transmission and, thus, reduced risk of infection, due to lower density of people and lower stability of

407   the virus in the air (Morawska and Cao, 2020; Setti et al., 2020).

408

409   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	Coefficient	Coefficient
	(Std. Err.)	(Std. Err.)	(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 $p < 0.01$.

412   Table 5 displays the results from Models D1 to D3. As regards the number of deaths (similarly

413   analysed through Negative Binomial fixed-effects panel regression models), the involved variables are

414   the same that were identified for the number of infections, to which is added, among the structural

415   variables, the provincial percentage of over-65s, which turns out to be significant and positively

416   correlated with the deaths count only in the first period. Indeed, this shows that the demographic

417   dynamics of the pandemic have changed compared to the beginning, embracing the whole population,

418   and that the elderly might have become more cautious in the second phase of the pandemic.

419

420   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

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

422

423   As regards potential collinearity issues, after examining the correlation between regression coefficients,

424   we did not detect any worrying values. Moreover, in our estimates, most coefficients appear to be

425   significant and we obtain satisfactory standard errors as well as confidence intervals (Giacalone et al.,

426   2018).

427   The days with the highest number of nationally reported deaths are the 3rd of December 2020, with

428   993 lost lives, and the 27th of March 2020, in which the number of registered fatalities amounted to

429   969. As people's mobility 17 days before these peaks may have elicited such extraordinary numbers,

430   we present two choropleth maps of Italy that portray the spatial distribution of the percentage changes

431   in time spent in residential areas on 10th March 2020 (Figure 11) and 16th November 2020 (Figure 12).

432   In the two selected dates, the median percentage change turns out to be the same, while the variability

433   between provinces is higher in November compared to the 10th of March (which is also the first day

434   of the national lockdown). Territorial differences in Italy are well-known (e.g., Aiello and Scoppa,

435   2000; Ercolano, 2012) and are also reflected in the dynamics of the COVID-19 pandemic. The highest

436   decile largely embraces the provinces with the highest population (Rome, Turin, and most of the

437   Lombardy region in the first period; the Campania region in the second period), indicating that citizens

438   living in such provinces have considerably altered their mobility habits compared to the pre-pandemic

439   period. The islands of Sicily and Sardinia appear to be closer to pre-pandemic mobility values in the

440   second period compared to the first one, while a large share of provinces maintained a similar level of

441   commitment with the mobility restrictions in the two periods.

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Figure 11 – Time spent in residential areas (percentage changes from baseline) on 10th March 2020, divided into deciles, at the Italian NUTS-3 level.
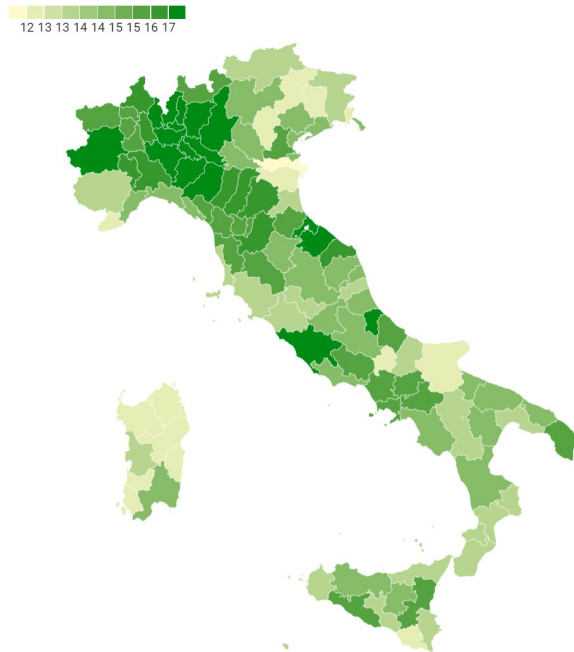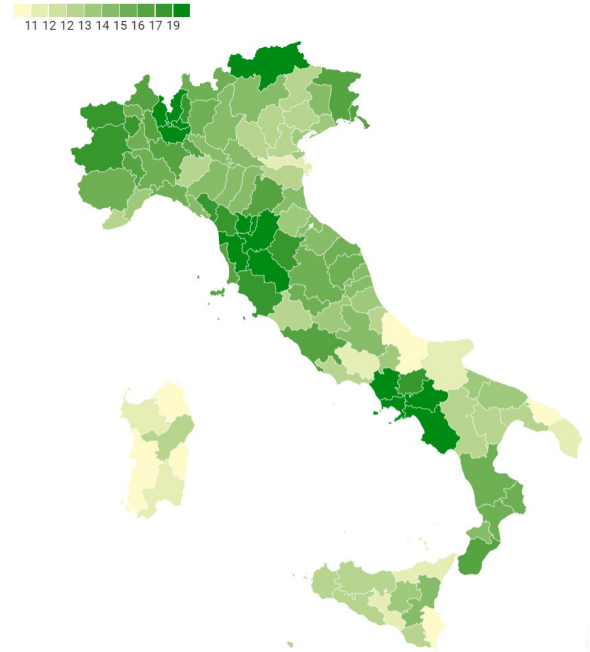
Figure 12 – Time spent in residential areas (percentage changes from baseline) on 16th November 2020, divided into deciles, at the Italian NUTS-3 level.

449

5. Discussion and conclusions

451 Our results confirm that the containment policies have had a beneficial impact on the pandemic,

452 having been able to reduce the amount of infections and deaths caused by COVID-19. This

453 corroborates the findings of a considerable number of studies (e.g., Alfano and Ercolano, 2020b;

454 Alfano and Ercolano, 2021; Balmford et al., 2020; Caselli et al., 2021; Dergiades et al., 2020; Ghosh et

455 al., 2020; Pasdar et al., 2020).

456 Our outcomes concerning infections are comparable when using either the Hausman-Taylor or the

457 Negative Binomial model. However, the latter is our preferred specification, being the ideal approach

458 for COVID-19 data modelling, in line with the model comparison results presented and discussed by

459 Chan et al. (2021). The number of infections exhibits a negative relationship with the Containment

460 and Health Index and the Compliance rate, proving that the degree of agreement to the restrictive

461 measures and the awareness of their necessity represents the greatest leverage to limit the spread of

462 the pandemic. Therefore, great attention must be paid by the Government and the other authorities

463 in informing citizens about the motives and consequences of the restrictive measures. This result is

464 already present in the literature (Baldwin and Di Mauro, 2020; Bargain and Aminjonov, 2020; Lalot et

465 al., 2020; McKenzie and Adams, 2020). Our results highlight the paramount importance of social

466 capital in determining the trend of the pandemic. Following Alfano and Ercolano (2020a), we

467 distinguished between bridging and bonding social capital: as regards the former, the signs of the

468 estimated coefficients are aligned with what was expected; conversely, the estimates pertaining to

469 bonding social capital also show positive signs. Indeed, the presence of a high level of bonding social

470 capital could be read as a sign of a "closed" society, which would hinder the pandemic by reducing

471 contacts between strangers. Our contrary evidence can be rationalised in light of the fact that family

472 clusters of COVID-19 are shown to have played a dominant role in the transmission of the disease

473 (Liu et al., 2020); moreover, particularly intense outbreaks in Italy occurred in "closed" – if not

474 segregated – social contexts, such as prisons (Cingolani et al., 2021) and residential care homes

475 (Ventura et al., 2021).

476 Some structural features of the Italian provinces help explain the number of infections experienced

477 during the first wave. Activity rate reveals a direct relationship with positive cases in the first period,

478 as a stronger productive fabric causes more contacts, therefore facilitating infections, and the same

479 effect is attributable to population density.

480 It is remarkable that the reduction in mobility, as represented by the trend concerning time spent in

481 residential places, obtained from Google data, is also due to psychological factors. On the one hand,

482 we have the effect of the provincial positivity rate, whereby citizens reduce their mobility as a

483 consequence of its increase, which we might call the "prudence effect". On the other hand, we have

484 the deterrent effect expressed by the sanction rate and the Containment and Health Index. It should

485 also be noted that the effect given by the Containment and Health Index is, at the same level, stronger

486 during the lockdown period, confirming its psychological impact on citizens' compliance level:

487 undeniably, the lockdown conveyed a message of danger, which calls for the mobilisation of individual

488 behaviours to contain the pandemic.

489 In relation to the model concerning the number of deaths, we estimated three distinct models,

490 differentiating the study period in order to separately analyse the different "waves" of the pandemic

491 (Table 5). The variables that show a significant impact are the same ones that were significant in the

492 model concerning infections, to which the regional number of cases and the number of performed

493 tests are added, with the first one showing a positive impact on the dependent variable. Among the

494 structural variables, the share of population aged 65 or more is added to population density and activity

495 rate, with a positive sign, which reflects the known situation of higher lethality characterising the

496 elderly population (Rinaldi and Paradisi, 2020). Nevertheless, some regressors change their sign from

497 one period to the other: mobility towards parks is positive in the first period, but negative in the

498 second one, and the same goes for activity rate. Moreover, the magnitude of some coefficients changes

499 considerably. In particular, the coefficient for Compliance rate in the second period is noticeably

500 higher than that of the first period; additionally, the set of coefficients pertaining to containment

501 measures shows a large increase, although not being straightly comparable due to the introduction of

502 red and orange zones in the second period. This means that the importance of the restrictive measures

503 and of citizens' accord on their abidance has greatly increased since the end of the summer, also

504 because the stringency level of such measures – as we have already seen – has critically declined, which

505 was preparatory to the formation of the "second wave" of the pandemic. Finally, the coefficient

506   regarding the share of over-65s to the total population is only significant in the first period, which

507   indicates that the pandemic has extended to all age groups.

508   Trying to sum up our achieved outcomes, the restrictions represented by the Containment and Health

509   Index appear essential to contain the pandemic until the vaccination campaign produces the so-called

510   herd immunity. However, we have highlighted that such restrictions are not sufficient when they are

511   not accompanied by citizens' consent, which translates into adherence to the mobility restrictions,

512   detected through the reduction in Google's mobility indices: indeed, it is unrealistic to think that

513   repressive actions are enough to enforce compliance with the new mobility rules.

514   If the goal is to "bend the curve", it must be borne in mind that this is a collective operation: therefore,

515   all institutional actors should better manage communication to motivate the citizens and avoid

516   contradictory behaviours that confuse the population. It may seem like a paradox, but COVID-19

517   shall be defeated in people's minds first.

518   But it is not just a psychological and political communication problem. The role played by the closure

519   of workplaces, except for essential activities, should also be kept in mind. The relevant contribution

520   of workplaces-related mobility to the deaths count throughout the pandemic leads us to question

521   whether there has been some hesitation in taking more incisive measures, such as the partial closure

522   of productive activities. With no additional interventions, the number of daily lives lost can eventually

523   become much greater than that suffered in the very first period of the pandemic (Vollmer et al., 2020).

524   Moreover, timeliness in introducing further restrictive measures is crucial in order to strongly reduce

525   their required duration (Chang et al., 2020).

526   Some countries are going further than others in the way they deal with this unprecedented emergency;

527   hopefully, we will not be found wanting.

528

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