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May 2021

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Abstract

The fast-moving coronavirus disease 2019 (COVID-19) called for a rapid response to slowing down the viral spread and reduce the fatality associated to the pandemic. Policymakers have implemented a wide range of non-pharmaceutical interventions to mitigate the spread of the pandemic and reduce burdens on healthcare systems. An efficient response of healthcare systems is crucial to handle a health crisis. Understanding how non-pharmaceutical interventions have contributed to slowing down contagions and how healthcare systems have impacted on fatality associated with health crisis is of utmost importance to learn from the COVID-19 pandemic. We investigated these dynamics in Italy at the regional level. We found that the simultaneous introduction of a variety of measures to increase social distance is associated with an important decrease in the number of new infected patients detected daily. Contagion reduces by 1% with the introduction of lockdowns in an increasing number of regions. We also found that a robust healthcare system is crucial for containing fatality associated with COVID-19. Also, proper diagnosis strategies are determinant to mitigate the severity of the health outcomes. The preparedness is the only way to successfully adopt efficient measures in response of unexpected emerging pandemics.

Keywords: Health outcome; Lockdown; Social distancing; Policy response.

Disclaimer: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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A revised version of the present paper has been accepted for publication in Health Policy. Please cite as: Santeramo, F., Tappi, M, Lamonaca, E. (2021) On the management of COVID-19 pandemic in Italy. Health Policy. *Forthcoming*.

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1. Introduction

The coronavirus disease 2019 (COVID-19) has spread quite rapidly. Emerged in the city of Wuhan (China) in December 2019, the new infectious agent, a severe acute respiratory syndrome (SARS-CoV-2), propagated mainly through person-to-person contact (Chan et al., 2020; Forman et al., 2020). On January 30, 2020, the World Health Organisation (WHO) declared COVID-19 a Public Health Emergency of International Concern (WHO, 2020) and, within a few months since its recognition, COVID-19 has reached more than 200 countries. The COVID-19 outbreak has become one of the worst global pandemics (Fang et al., 2020), with more than 128 million people infected and nearly 3 million of deaths claimed as of March 31, 2021. The economic impacts of the pandemic are enormous, especially due to business closures imposed to limit the contagions: the IMF (2020) has estimated that that global economy, in 2020, had acontraction equal to 3%: in Europe this tendency is observed on every month with business closures (Goodman-Bacon and Marcus, 2020).

The pandemic has called for a rapid international response to slow down the transmission of contagions and reduce the fatality rates associated with COVID-19. High pressure on healthcare systems, due to peak load hospitalisations and critical care requirements, tend to worsen the consequences of the health crisis (Rampini, 2020). Due the lack of vaccines or specific therapies to combat the COVID-19 during the first wave, policymakers, in different regions of the world, have proposed non-pharmaceutical interventions, such as lockdown and social distancing measures (Goodman-Bacon and Marcus, 2020; OECD, 2021). Understanding the effectiveness of these interventions has become an important goal to help containing the pandemic, especially in regions where the healthcare is weaker, and thus the fatality rates tend to be higher (Ji et al., 2020). Limiting interactions reduces contagions, at a high cost for the economic activities, despite massive policy interventions to mitigate the economic crisis (Wieck et al., 2020): according to the IMF, among advanced economies, Australia, Japan, UK, and US have allocated more than 15% of their GDP to interventions related to the pandemic, whereas China and Italy (the first countries hit by COVID-19) have allocated, respectively, 4.7% and 6.8% of their GDP; also low-income countries (e.g., African countries) have devoted few percentage points (about 2.5%) of their GDPs(see figure A.1 in the Appendix A.1).

However, the policy measures need to be transitory interventions, unsustainable in the long-run, and without plans to flatten the contagion curve, and to reduce the deaths due to COVID-19. We investigate and quantify the efficacy of non-pharmaceutical interventions, such as lockdown and social distancing policies in reducing contagions. Second, we analyse how differences in the management of the epidemic relates to the (regionally) heterogeneous impacts of the pandemic.

We focus on the Italian case: according to data from the Italian Department of Civil Protection on the first wave, there have been, on average and on a daily basis, 1.3% new infected patients and a fatality rate close to 42.2%. Marked differences have been observed across regions: for instance, during the first wave, several Northern regions have been more affected than the Southern and Central regions. The Italian case study is important also for another reason: in Europe, Italy has been the first country to implement non-pharmaceutical interventions (Flaxman et al., 2020). The Italian government declared the state of emergency on January 31, 2020,introduced measures for social distancing on February 23, and started the on March 09 (until May 03): the longest quarantine in the history of the country (Flaxman et al., 2020). The Italian case study is also very informative because the National Health Care System provides complimentary universal coverage for comprehensive and essential health services, with regional differences in processes (i.e., appropriateness in the use of the resources) and outcomes(Nuti and Seghieri, 2014).

We complement the analysis provide by Becchetti et al. (2020), who have also investigated the Italian case (see section A.2 of the appendix for a detailed comparison). Differently from Becchetti et al. (2020), we deepen more on the interventions to enhancesocial distancing, disinfection of public transports, and on regional differences in healthcare systems management.

The next sections review the studies on interventions during pandemics, describe the empirical approach to model the spread of contagion and the fatality rates, and provide elements for the debate. We conclude with reflections on policy implications.

2. Existing studies on interventions during pandemics

Managing the spread of infectious diseases, and pandemics, is very complex (Krumkamp et al., 2009), especially when vaccines are not available (Ferguson et al., 2020) and the herd immunity is hard to be reached (Kwok et al., 2020). The non-pharmaceutical interventions to increase social distance, may help reducing contagions (Ferguson et al., 2006), as it has been evident for the influenza pandemic in 1918 (Hatchett et al., 2007), for the severe acute respiratory syndrome (SARS) in 2003 (Bell, 2004; James et al., 2006), and for the influenza A in 2009 (H1N1) (Lai and Tan, 2012). . Social distancing and lockdown policies seem to be effective also for the COVID-19 pandemic (e.g., Fang et al., 2020; Flaxman et al., 2020). Details are provided in section A.3 of the Appendix.

The role of healthcare systems, in improving and maintaining population health, and ensuring equitable access to healthcare, has also been investigated so (e.g., Reibling, 2013; Nuti and Seghieri, 2014). Nixon and Ulmann (2006) found that highly efficient healthcare systems reduce with the fatality rates, but also the availability of resource (Ji et al., 2020) and a timely supply of medical resources (Zhang et al., 2020) matter.. A limitation of these analyses relies on their explorative (qualitative) nature that prevent a quantification of the effects.

3. Materials and methods

3.1. Contagions

We study the daily region-specific growth of COVID-19 cases (G_{it}) as ratio of daily change in new infected patients in each region ($A_{it} - A_{it-1}$) over the number of swabs in that region (S_{it}):

$$G_{it} = \frac{A_{it} - A_{it-1}}{S_{it}} \tag{1}$$

where the subscript *i* indicates regions and varies from 1 to 21 (i.e., Piemonte, Valle d'Aosta, Liguria, Lombardia, Trentino-Alto Adige –divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento–, Veneto, Friuli-Venezia Giulia, Emilia-Romagna, Toscana, Umbria, Marche, Lazio, Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna) and the subscript *t* indicates time (days), from 1 (February 24, 2020) to 70 (May 3, 2020). By normalizing for the number of swabs we control for different regional approaches (i.e., pro-swabs vs. no-swabs) and for region-specific capabilities in processing swabs.

The timing of the policy interventions varies across regions. We estimate a linear panel data model . We include regional dummies ($\boldsymbol{\alpha}_i$), time trend and time dummies ($\boldsymbol{\alpha}_t$) to control for spatial and temporal unobserved heterogeneities (de Janvry and Sadoulet, 2015):

$$G_{it} = \alpha + \boldsymbol{\alpha}_i + \boldsymbol{\alpha}_t + \boldsymbol{\beta P}_{it-14} + \gamma \Delta R_{it} + \upsilon_{it} \tag{2}$$

where the regional daily evolution of contagions (*cfr*. equation 1) is function of the date of entry into force of policy interventions, delayed by 14 days ($\boldsymbol{P}_{it-14}$). We control crowding effects (Acemoglu et al., 2020) with the changes in number of recovered patients (ΔR_{it}). The terms $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ stand for the vectors of parameters, while α and υ_{it} are, respectively, the constant and the error term. We consider policy interventions such as measures of lockdown, disinfection of public transports and social distancing (include.g. suspensions of events and teaching activities, closures of fitness and wellness activities, of retail business parks, and industries). Following Acemoglu et al. (2020), these policy interventions variables range from 0 to 1, being 0 for regions under no lockdown and 1 for regions implementing a full lockdown: intermediate values account for partial regional lockdowns, occurring when lockdowns are limited to some of the regional provinces.

We test the robustness of our findings by controlling for regional characteristics such as the yearly mean values of PM10, the population density, and the distance from the main locus of the Italian epidemic, Lombardia.

In short, the equation (2) models the infectiousness and its relationships with policy interventions, level of pollution (proxied by the level of PM10) and population density. The standard errors are geographically clustered (around Italian macro-regions) to limit potential errors correlation across within each macro-region (North West, North East, Centre, South).

3.2. Fatality ratios

We compute the fatality ratio (F_{it}) as ratio of number of deaths for COVID-19 over deaths for COVID-19 plus recoveries from COVID-19, as suggested by Ghani et al. (2005):

$$F_{it} = \frac{D_{it}}{D_{it} + R_{it}} \tag{3}$$

where D_{it} and R_{it} are the cumulative daily numbers of deaths and recoveries in the region i (from 1 to 21) at a given time *t* (from 1 to 70). The indicator does not disentangles the fatality ratios for the hospitalised and the non-hospitalised patients (Ghani et al., 2005).

We model the virulence (i.e., the deadliness associated with SARS-CoV-2[1]), paying attention to the healthcare system management. In line with Nixon and Ulmann (2006), and Reibling (2013), we consider health outcomes as outputs of the healthcare systems, depending on the management of inputs (e.g., medical care resources). We control for social factors (Reibling, 2013):

$$F_{it} = \lambda + \boldsymbol{\lambda}_i + \boldsymbol{\lambda}_t + \boldsymbol{\psi}\boldsymbol{M}_{it} + \omega\Delta G_{it} + \nu_{it} \tag{4}$$

where the term $\boldsymbol{M}_{it}$ collects variables related to the epidemic management and ΔG_{it} controls for the growth of contagions, that may challenge the efficiency of the healthcare systems in managing epidemics (Ji et al., 2020). The vector $\boldsymbol{M}_{it}$ includes the number of swabs per total population, the number of patients hospitalised for COVID-19 over the number of swabs, the number of patients confined with COVID-19 symptoms over the number of swabs. These variables explain the time-varying regional differences of fatality rates. . We control for the regional unobserved heterogeneity ($\boldsymbol{\lambda}_i$) and for time effects ($\boldsymbol{\lambda}_t$). Our estimates, through least squares, report standard errors geographically clustered.

The robustness of our findings is tested with different sets of controls: region-specific time-invariant determinants such as the percentage of hospital beds in intensive care wards, the percentage of hospital beds in infectious disease wards, the number of physicians per total hospital beds, the health expenditure per total population, in log We also control for life-style (i.e. percentage of smokers over total population) and environmental characteristics (i.e. percentage of males over total population, old-age rate, death rate)..

[1] COVID-19 is the main cause of death in infected patients. The analysis of the medical records conducted by National Institute of Statistics on a sample of 4,942 infected patients shows that COVID-19 is the underlying cause of death in 89% of cases and a contributory cause or deaths in the remaining 11% of cases (National Institute of Statistics, 2020). Before the COVID-19 pandemic, among infectious diseases, seasonal influenza is the third leading cause of death in Italy and may cause from 250,000 to 500,000 deaths worldwide (Bertolani et al., 2018).

3.3. Data and descriptive analysis

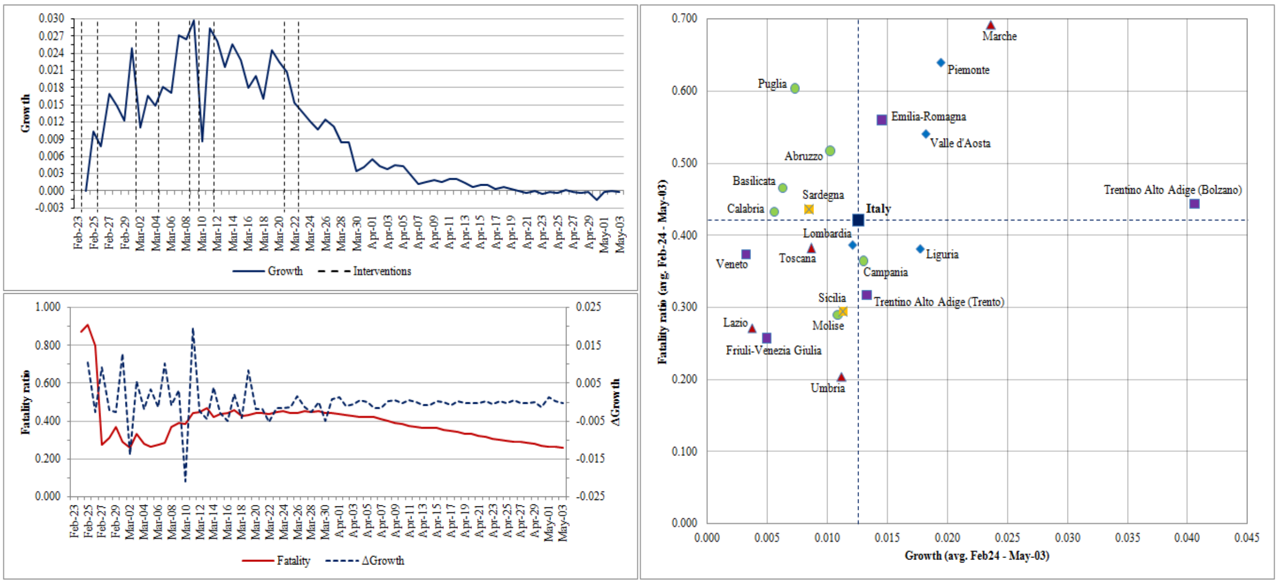
The daily evolution of the first wave of the COVID-19 epidemic in Italy, in terms of contagion and fatality rates is described in the Appendix (section A.4). We cover the period from February 24, 2020 (when the first COVID-19 case was detected in Italy) to May 3, 2020 (the last day of lockdown in Italy). In order to compute G_{it} (see equation 1) and F_{it} (see equation 3), we collected from the Italian Department of Civil Protection[2] the region-specific daily data on the number of new infected patients, swabs, deaths and recoveries.

When the growth in contagions approached zero, the fatality ratio started to decline (figure 1, left downward panel): this event occurred about three weeks after the implementation of very restrictive interventions, on March 22 (figure 1, left upward panel).

We collected information on policy interventions, whose timeline is reported in figure 1 (left upward panel), from the Decrees of the President of the Council of Ministers (named DPCM) which are published on the Italian Official Gazette and on the official website of the Italian Government. Italy has implemented more and more stringent measures, reaching the full lockdown within two weeks since the establishment, on February 23, of the first "red area" in some municipalities of the Lodi and Padova provinces, respectively in Lombardia and Veneto. Sporting events started to be suspended on February 25, followed by teaching, wellness, and fitness activities, on March 1. These measures have been extended to all regions on March 4. In addition, the disinfection of public transports became compulsory since March 1. On March 8 several new "red areas" were identified in Lombardia, Emilia-Romagna, Piemonte and Veneto. The DPCM dated March 9 has extended the lockdown to all Italian regions. Further measures of social distancing imposed the closure of business (March 11), parks (March 20), and industries (March 22) in all regions. The DPCM dated April 26 has fixed on May 4 the starting date for the "phase 2", the progressive reopening of selected activities. A detailed description of policy interventions is available in the section A.5 of the Appendix.

[2] Data available at: https://github.com/pcm-dpc/COVID-19.

Figure 1. Daily evolution of COVID-19 contagion and fatality (left panels) and positioning of Italian regions (right panel).



Source: elaboration on data of the Italian Department of Civil Protection.

Notes: In the left upward panel, policy interventions (dashed lines) plan partial lockdown in Lombardia and Veneto regions (Feb-23); suspension of events in Emilia-Romagna, Friuli-Venezia Giulia, Liguria, Lombardia, Piemonte, Veneto regions (Feb-25); suspension of events and teaching activities in Emilia-Romagna, Liguria, Lombardia, Marche, Veneto regions, closure of fitness and wellness in Emilia-Romagna and Lombardia regions, disinfection of public transports in all regions (Mar-01); suspension of events and teaching activities in all regions (Mar-04); partial lockdown in Emilia-Romagna, Lombardia, Marche, Piemonte, Veneto regions (Mar-08); lockdown in all regions (Mar-09); closure of business retails in all regions (Mar-11); closure of parks in all regions (Mar-20); closures of industries in all regions (Mar-22). In the right panel, north-western regions are in blue, north-eastern regions are in violet, central regions are in red, southern regions are in green, main islands are in orange. The positioning of regions is determined according to the average COVID-19 contagion and fatality over the period Feb-24 – May-03.

The right panel of figure 1 clusters regions according to the first-wave contagions and fatality rates. The average daily growth rate of new infected patients is 1.3%; the average fatality rate is 42.2%. The Northern regions, and the Marche region, have been the most affected in terms of contagions and fatality rates: the highest fatality has been observed in Marche (69.3%); the contagions grew the most in Trentino Alto Adige. The Southern regions reported high fatality rates, despite a lower diffusion of contagions: Puglia had an average 0.7% growth in contagions, coupled with a 60.4% fatality rate, followed by Abruzzo (1.0% and 51.7%), Basilicata (0.6% and 46.6%) and Calabria (0.6% and 43.3%).

Table 1. Descriptive statistics of key variables.

Variable	Type	Mean	Std. Dev.	Min	Max
Growth of contagions	Continuous	0.01	0.05	-0.20	1.00
Fatality rate	Continuous	0.42	0.25	0.00	1.00
Lockdown	Continuous	0.79	0.40	0	1
Social distancing (events, teaching activities)	Continuous	0.91	0.29	0	1
Social distancing (fitness and wellness)	Dummy	0.78	0.42	0	1
Social distancing (retail business)	Dummy	0.76	0.42	0	1
Social distancing (parks)	Dummy	0.64	0.48	0	1
Social distancing (industries)	Dummy	0.60	0.49	0	1
Disinfection of public transports	Dummy	0.95	0.22	0	1
Swabs per population	Continuous	1.23	1.57	0.00	8.33
Hospitalised per swabs	Continuous	0.04	0.06	0.00	1.00
Confined with symptoms per swabs	Continuous	0.07	0.06	0.00	0.84

To examine the effects of the healthcare systems, we control for several factors, collecting, from the Italian Department of Civil Protection, the daily region-specific data on the number of swabs per popuation[3] (2.7 in Trentino-Alto Adige and Veneto, 1.9 in Valle d'Aosta, 1.8 in Friuli-Venezia Giulia, 1.4 in Emilia-Romagna and Lombardia as compared to 0.4 in Campania, 0.5 in Puglia, Sicilia and Sardegna), patients hospitalised for COVID-19[4] (about 4%) or confined with COVID-19 symptoms (about 7%) (*cfr.* table 1).

4. Results and discussion

4.1. The effects of policy interventions on contagions

The results of our estimates on the contagions model are reported in table 2. Findings are robust to specifications with different variables to control for observed (columns 1, 2, 3 of table 2) and unobserved

[3] Information on the number of swabs, collected from the Department of Civil Protection, are based on data from the National Institute of Health and Regional Department of Health. Data include also swabs repeated on the same person in different time periods.

[4] The analysis of medical records conducted by National Institute of Health on a sample of about 100,000 patients hospitalised for COVID-19 shows that about 90% of hospitalisations have been caused by the COVID-19.

(columns 4, 5, 6 of table 2) heterogeneities. In line with Acemoglu et al. (2020), the greater the number of new recovered patients, the lower the number of new contagions.

The measures implemented to contain contagions (lockdown and the closure of parks and industries) are negatively correlated with the number of new infected patients.

Our results on the lockdown are in line with Fang et al. (2020), who found the same for the COVID epidemic in Wuhan. The daily growth of COVID-19 cases has been reduced by 1% due to the introduction of lockdowns. We found that the effects are evident about 14 days after the entry into force of the restriction, as also suggested by Becchetti et al. (2020). The closure of industries contributed to a 0.5-0.8% reduction in the daily growth of COVID-19 cases, results that are in line with Milne et al. (2008), who conclude that workplace nonattendance reduced contagions during the epidemic. The Singapore's experiences with SARS and H1NI suggest that the social distancing measures are effective only when more partners work together; single or unilateral interventions are less effective than multiple containment measures (Bell (2004; Lai and Tan, 2012). We confirm these evidences for the COVID-19 pandemic.

Table 2. Policy interventions and COVID-19 contagions.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	-0.0125***	-0.0127***	-0.0141*	-0.0120***	-0.0121***	-0.0115
	(0.0027)	(0.0027)	(0.0082)	(0.0029)	(0.0029)	(0.0074)
Social distancing (events, teaching activities)	0.0027	0.0026	0.0039	0.0013	0.0012	0.0019
	(0.0066)	(0.0065)	(0.0097)	(0.0073)	(0.0073)	(0.0104)
Social distancing (fitness and wellness)	0.0026	0.0025	0.0050	0.0026	0.0025	0.0050
	(0.0054)	(0.0054)	(0.0044)	(0.0054)	(0.0054)	(0.0044)
Social distancing (retail business)	-0.0058	-0.0055	-0.0189	-0.0057	-0.0055	-0.0186
	(0.0047)	(0.0048)	(0.0118)	(0.0048)	(0.0048)	(0.0115)
Social distancing (parks)	-0.0029***	-0.0020*	0.0031**	-0.0033***	-0.0025**	0.0018
	(0.0011)	(0.0012)	(0.0015)	(0.0010)	(0.0011)	(0.0012)
Social distancing (industries)	-0.0049***	-0.0051***	-0.0080***	-0.0046***	-0.0048***	-0.0069***
	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0008)
Disinfection of public transports	-0.0235	-0.0236	-0.0233	-0.0226	-0.0227	-0.0227
	(0.0201)	(0.0201)	(0.0173)	(0.0199)	(0.0199)	(0.0173)
Recovery (delta)	-0.00001**	-0.00001**	-0.00001**	-0.00001**	-0.00001***	-0.00001***
	(0.000005)	(0.000005)	(0.000005)	(0.000005)	(0.000005)	(0.000004)
Regional control factors	Yes	Yes	Yes	No	No	No
Region dummies	No	No	No	Yes	Yes	Yes
Time trend	No	Yes	No	No	Yes	No
Time dummies	No	No	Yes	No	No	Yes
Observations	1,134	1,134	1,134	1,134	1,134	1,134
Number of ID	21	21	21	21	21	21
R-squared						
within	0.1757	0.1758	0.1952	0.1756	0.1757	0.1951
between	0.4920	0.4940	0.5018	0.8470	0.8473	0.8449
overall	0.1876	0.1877	0.2067	0.2009	0.2010	0.2196

Notes: The dependent variable is the growth of contagions computed as in equation (1). Policy variables are observed with a 14-days delay. Specifications (1), (2), (3) control for observed heterogeneity across regions (i.e., PM10 levels, density, distance from main locus); specifications (4), (5), (6) control for unobserved heterogeneity across regions (i.e., region dummies). Time trend included in specifications (2) and (5); time dummies included in specifications (3) and (6). ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

We disentangle the impacts of non-pharmaceutical measures using different lags: i.e., 0-days, 7-days, and 14-days of delay. The results of this sensitivity analysis, omitted for brevity and reported in the Appendix (section A.6), show that a higher number of days of delay corresponds to a more robust effect. The effects of policy interventions are effective about 14-days later (table 2), due to the incubation period of the virus, as also documented by Goodman-Bacon and Marcus (2020) and by Flaxman et al. (2020). Lauer et al. (2020),report an incubation period for the SARS-CoV-2 of 5.1 days, with detection of symptoms within 11.5 days of infection in 97.5% of cases, and within 14 days for the remaining cases. According to our analysis, the different timing in the implementation of the policy interventions across regions have affected the spread of contagions (Goodman-Bacon and Jan Marcus, 2020). The results are robust to several sensitivity analyses to control for macro-regional heterogeneities, differences in income levels, and potential neighbour-contagion effects (results, omitted for brevity, are reported in the section A.7 of the Appendix).

4.2. The effects of epidemic management on fatality ratios

We evaluated how the management of the healthcare systems influenced the fatality ratios. Our findings (table 3) are robust to different specifications, controlling for regional characteristics, time effects, and for alternative control factors.

Table 3. Managerial choices and variation in COVID-19 fatality.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Swabs per population	-0.0258**	-0.0260**	-0.0153	-0.0303***	-0.0305***	-0.0051
	(0.0119)	(0.0120)	(0.0147)	(0.0113)	(0.0116)	(0.0162)
Hospitalised per swabs	1.7091***	1.7070***	1.3768***	1.9836***	1.7984***	1.1637*
	(0.4354)	(0.4245)	(0.4892)	(0.3312)	(0.3457)	(0.6342)
Confined with symptoms per swabs	1.9368***	1.9399***	1.6377***	1.6144**	1.6394**	1.3010***
	(0.5944)	(0.6030)	(0.3429)	(0.6432)	(0.6408)	(0.3687)
Growth of contagions (delta)	0.0164	0.0162	0.0184	0.0187	0.0170	0.0209
	(0.0293)	(0.0290)	(0.0142)	(0.0281)	(0.0287)	(0.0159)
Regional control factors	Yes	Yes	Yes	No	No	No
Region dummies	No	No	No	Yes	Yes	Yes
Time trend	No	Yes	No	No	Yes	No
Time dummies	No	No	Yes	No	No	Yes
Observations	1,083	1,083	1,083	1,083	1,083	1,083
Number of ID	21	21	21	21	21	21
R-squared						
within	0.5774	0.5776	0.5890	0.5700	0.5734	0.5844
between	0.5155	0.5156	0.5264	0.8689	0.8715	0.9167
overall	0.5567	0.5568	0.5726	0.6460	0.6493	0.6711

Notes: The dependent variable is the fatality ratio computed as in equation (3). Growth of contagions (delta) is observed with a 14-days delay. Specifications (1), (2), (3) control for observed heterogeneity across regions (i.e., hospital beds in intensive care wards, hospital beds in infectious diseases wards, physicians per total hospital beds, healthcare expenditure per population, percentage of males, old-age rate, percentage of smokers, death rate); specifications (4), (5), (6) control for unobserved heterogeneity across regions (i.e., region dummies). Time trend included in specifications (2) and (5); time dummies included in specifications (3) and (6). ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

We find that the larger the number of infected patients hospitalised for COVID-19 or confined with COVID-19 symptoms, the higher the fatality ratios. The rationale is that a pressing demand on the healthcare system (i.e. peak load hospitalisations and critical care requirements) the heavier the healthcare burden (Ji et al., 2020), and the lower the efficiency (Rampini, 2020). Our results are also consistent with Zhang et al. (2020), who found similar evidence in the early stage of the outbreak in Wuhan in China, due to the shortage of beds.

An opposite effect is found for the number of swabs per population. The greater the numbers of swabs per population, the lower the fatality ratios. As suggested in Zhang et al. (2020), improved and optimised diagnoses (via swabs) are crucial for saving severe and critical patients.

Our results are robust to the inclusion of control factors proxying healthcare inputs (table 3, columns 1, 2, 3) or the addition of new intensive care units to face the epidemic (see section A.7 of the Appendix). Our findings are also robust in sensitivity analyses that control for macro-region heterogeneities, differences in income levels, and air pollution (results, omitted for brevity, are reported in the section A.7 of the Appendix).

5. Discussion

We show that the effects of the interventions (e.g., lockdowns) are relevant only after a couple of weeks from their implementation. However, the anticipation (through announcements) of new closures (e.g. retail business and parks) has rapid effects. Put differently, anticipated policy interventions tend impact prior of their implementation. As for the closure of industries and parks, measures that have been introduced after other stringent measures (e.g. lockdowns), the effects are likely to be due to a synergic effect with the previously adopted policies, as suggested by German et al. (2006) and Hatchett et al. (2007). Thus combining different social distancing measures, in a holistic approach, rather than relying on a single action, seem an effective approach.

The delayed effects of the measures suggest the need of acting timely and of a maintaining the containment measures for a longer time before ascertaining their effectiveness (Flaxman et al., 2020). Policy decisions should be not only timely, but also "forward-looking". Moreover, attention should be also paid to the communication of planned policy interventions, in order to amplify their effects.

Consistently with the literature, we also found that a proper healthcare system management of epidemics may sensibly reduce the mortality rates (e.g., Nixon and Ulmann, 2006). In our specific analysis we show that an advanced diagnosis would reduce the fatality ratio, that may be further reduced by specific treatment strategies (e.g. intensive care units). The Italian healthcare system has been recently improved accordingly: on May 19, 2020, , the Legislation Decree no. 34/2020 “Decreto Rilancio” has largely increased the intensive care units in orderto reduce the pressure on the healthcare system.

In short, we conclude that the pandemic may be slowed down through a synergic approach, made of several interventions to increase the social distance, and to avoid contacts. In addition. a robust healthcare system may help mitigating the negative effects, but its proper management is crucial to decrease the number of deaths.

Our analysis is not exempt from limitations. First, the quality of data is affected by different registration approaches at the regional level and across time. For instance, the swabs have been often performed on patients with severe symptoms and with previous contacts with positive cases, but not on the asymptomatic but potential positive patients. This may lead to underestimate the COVID-19 cases. This concern has been partially mitigated by the normalization (through the number of swabs) we have performed on the the dependent variable of the model of contagion. On the other hand, relying on the official data makes our analysis reliable and comparable with the existing studies.

Second, our empirical models do not control for potential effects due to intra-regional and inter-regional mobility. These dynamics, partially controlled by regional, macro-regional, and time fixed effects, are beyond the scope of this analysis and left for future research.

Third, our empirical models has a strong validity in detecting correlations between contagions, fatality, policy interventions and management strategies, but should be cautiously taken before concluding on causality relationships. Future research should investigate these dynamics with counterfactuals, and experimental methods, if feasible.

6. Conclusions

The rapid evolution of the COVID-19 pandemic reached more than 200 countries, and called for a timely response to slow down the number of contagions and deaths (Forman et al., 2020). Policymakers have implemented a wide range of non-pharmaceutical interventions, such as lockdown and social distancing measures, to mitigate the spread of the pandemic (Goodman-Bacon and Marcus, 2020) and the burdens on healthcare systems (Ferguson et al., 2006). Efficient responses of the healthcare systems are crucial to handle the health crisis and mitigate the severity of health outcomes (Quah, 2007), thus measuring the effectiveness of the policy interventions is of utmost importance to learn lessons from the COVID-19 pandemic. We derive a lesson from the first-wave epidemic evolution of COVID-19 in Italy.

We found that the sequential introduction of measures to increase social distance has been associated with an important decrease in the daily number of new infected patients. Our findings, in line with previous studies on other pandemics (e.g., Bell, 2004; Ferguson et al., 2006) and on the COVID-19 (e.g., Becchetti et al., 2020; Fang et al., 2020) suggest that the impact of lockdowns is more effective if coupled with other containment measures.

We also show that a robust and well managed healthcare system is crucial for containing the negative health outcomes associated with COVID-19.

The preparedness of the healthcare system does not only depend on the resources availability, but also by the capability of promptly and efficiently react to in the insurgence of health crises. In other terms, the resilience of the system heavily depends on the management of resources. In addition, it is advisable for policymakers to engage in synergic actions to develop a coherent, unified strategy to mitigate both the transmission of contagions and the cumulative number of deaths associated with the health crisis.

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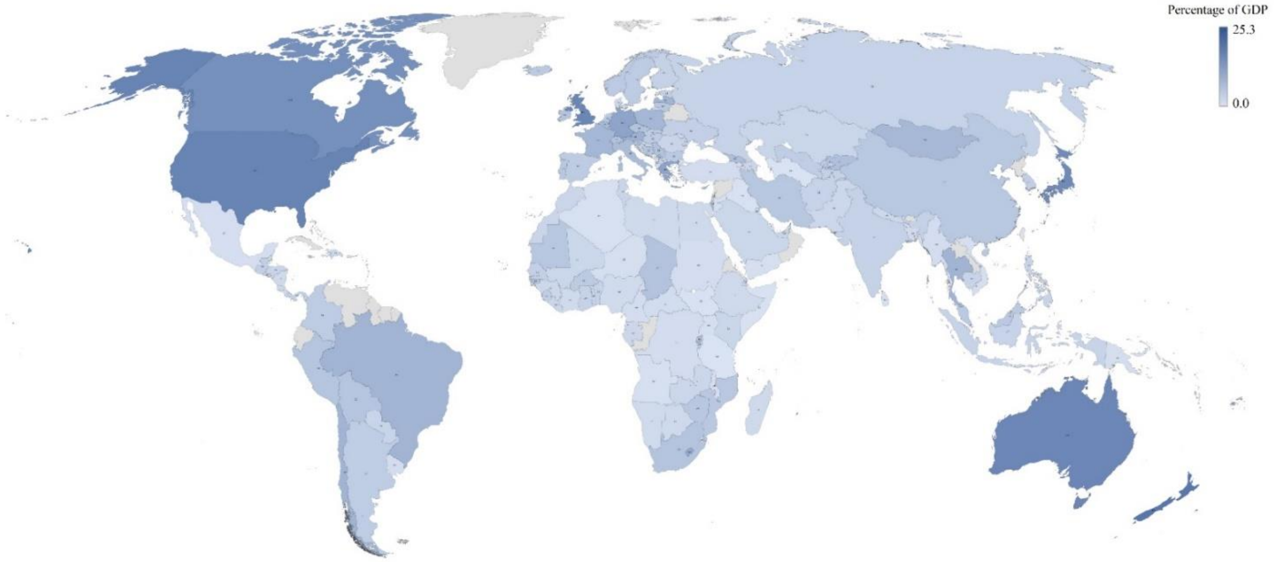
A. Methodological Appendix

A.1 An outline of previous studies on the role of non-pharmaceutical interventions in containing pandemics

Figure A.1. Budgetary fiscal support in response to the COVID-19 pandemic.



Source: elaboration on data from IMF's Fiscal Policies Database in Response to COVID-19.

A.2 A comparison with Becchetti et al. (2020)

A recent article by Becchetti et al. (2020) investigates the determinants of variations in the new positive cases and number of deaths in Italy. Both their article and our investigation start from the observation of the uneven distribution of contagions and fatality across Italian regions. However, while Becchetti et al. (2020) indicate that potential drivers of COVID-19 contagions and fatality are lockdown decisions, economic activity, frequency of people interactions, pollution and weather conditions, our analysis discriminates between determinants of COVID-19 contagions and fatality. In particular, we explain variations in contagions through a set of policy interventions: Becchetti et al. (2020) test if lockdown measure proved effective in limiting deceases and contagion, whereas our study considers the impact of all non-pharmaceutical interventions progressively introduced during the lockdown phase (i.e. lockdown, suspension of events and teaching activities, closure of fitness and wellness, retail business, parks and industries, disinfection of public transports). More importantly, our analysis explains cross-regional differences in fatality associated with COVID-19 pandemic as a function of management of the epidemic. The table A.2 provides a detailed comparison between Becchetti et al. (2020) and our analysis.

Table A.1. Differences with Becchetti et al. (2020).

	Becchetti et al. (2020)	Our analysis
Unit of observation	Provinces	Regions
Timeframe	February 24t – April 06, 2020	February 24t – May 03, 2020
Empirical model	Fixed effects OLS	Dummy-fixed effects OLS
Model of contagions		
Dependent variable	Number of daily new COVID-19 cases over total population, per 1,000 inhabitants	$G_{it} = \frac{A_{it} - A_{it-1}}{S_{it}}$
Explanatory variables	Lockdown decisions, economic activity, frequency of people interactions, pollution and weather conditions	Non-pharmaceutical interventions, evolution in the number of patients recovered from COVID-19, regional characteristics
Policy interventions	Lockdown	Lockdown, social distancing (events, teaching activities; gyms, pools, wellness, retail business; parks, industries), Disinfection of public transports
Model of contagions		
Dependent variable	Average number of daily deaths at province level over total population, per 1,000 inhabitants	$F_{it} = \frac{D_{it}}{D_{it} + R_{it}}$
Explanatory variables	Lockdown decisions, economic activity, frequency of people interactions, pollution and weather conditions	Health inputs, epidemic management, epidemic evolution, life-style and environmental regional characteristics

Specifically, Becchetti et al. (2020, p. 8) estimate the following equation:

$$
\begin{aligned}
COV19 - Outcome_{it} &= \alpha_0 + \alpha_1 Day_t + \alpha_2 Day_t^2 + \alpha_3 PM_i + \alpha_4 DLockdown_i \\
&+ \alpha_5 DHighTemperature_i + \alpha_6 Artisan_i + \alpha_7 Density_i + \alpha_8 Income_i \\
&+ \alpha_9 Over65_i + \alpha_{10} Ventilators_i + \alpha_{11} InternalCommuting_i \\
&+ \alpha_{12} ExternalCommuting_i + \alpha_{13} PublicTransportUse_i + \varepsilon_{it}
\end{aligned} \tag{A.1}
$$

The dependent variable ($COV19 - Outcome_{it}$) is, alternatively, the daily change in contagions over local population (new cases) and the daily number of deceases over local population (deaths) in province *i* and day *t*. Regressors include a linear and a quadratic time trend (Day_t and Day_t^2), pollution variables (PM_i), that is, alternatively, average year levels of PM10 and PM2.5, a dummy variable taking value 1 from the day after the lockdown decision with 5-day lead ($DLockdown_i$), a dummy taking value 1 if the three days moving average of minimum temperature is higher than 12°C ($DHighTemperature_i$), the share of artisan firms at province level ($Artisan_i$), population density ($Density_i$), average household disposable income ($Income_i$), the share of individuals aged over 65 ($Over65_i$), the number of lung ventilators ($Ventilators_i$), a measure of internal commuting flow ($InternalCommuting_i$) and of imported commuting flow ($ExternalCommuting_i$), the number of passengers on public transport ($PublicTransportUse_i$).

In order to provide a better comparison between their analysis and our, we replicate the model in equation A.1 using as dependent variable a proxy of the daily evolution of COVID-19 contagion at the regional level (G_{it}), built as the ratio between the number of new infected patients detected each day *t* with respect to the day before *t-1* in any region *i* and the cumulative number of swabs in region *i* at any given day *t* (see table A.2). Given the availability of data, we include as regressors Day_t, Day_t^2, $DLockdown_i$, PM_i, $Density_i$, $Over65_i$, $Income_i$.

The analysis of Becchetti et al. (2020) is based on data since February 24 until April 06, 2020 at the provincial level. In our analysis, the COVID-19 outcomes are observed on a daily basis since February 24, 2020 (the day in which the first COVID-19 case was detected in Italy) until May 3, 2020 (the last day of full lockdown in Italy) in 20 Italian regions.

As in Becchetti et al. (2020), we estimate a pooled OLS and a panel fixed effect OLS: the results are reported in tables A.3 and A.4, respectively. A comparison with estimation results reported in Becchetti et al. (2020, pp. 22-24) is also provided. Findings of both models are consistent. In pooled OLS results, we find a positive correlation between the linear time trend and contagions as well as between income and contagions, and a negative effect of lockdown on the growth in contagions (table A.3). Similar effects for lockdown and income are found in the panel fixed effect OLS estimation (table A.4).

Table A.2. Major factors explaining variation in COVID-19 contagion (pooled OLS).

	Becchetti et al. (2020)		Our results	
Dependent variable	New cases		Growth	
Variables	(1)	(2)	(1)	(2)
Day	0.0126**	0.0133**	0.0004**	0.0004**
	(0.00473)	(0.00483)	(0.0001)	(0.0001)
Day^2	-0.000103**	-0.000109**	-0.0021	-0.0023
	(4.82e-05)	(5.00e-05)	(0.0013)	(0.0014)
Lockdown	-0.0258***	-0.0265***	-0.0186**	-0.0180**
	(0.00789)	(0.00739)	(0.0051)	(0.0057)
PM10	0.00298**		-0.0001	
	(0.00122)		(0.0008)	
PM2.5		0.00390**		-0.0005
		(0.00155)		(0.0008)
High temperature	-0.00678	0.000366	No	No
	(0.0114)	(0.0119)		
Density	-2.61e-06	-5.35e-06	-0.0153	-0.0117
	(8.29e-06)	(9.51e-06)	(0.0190)	(0.0119)
Over65	-0.000722**	-0.000808**	-0.0310	-0.0292
	(0.000288)	(0.000301)	(0.09166)	(0.0841)
Income	0.148**	0.168***	0.0007***	0.0010*
	(0.0599)	(0.0498)	(0.0001)	(0.0004)
Ventilators	-7.316	-1.922	No	No
	(20.12)	(31.64)		
Public transport use	0.0103	0.00976	No	No
	(0.0161)	(0.0181)		
Internal commuting	0.0433	-0.000811	No	No
	(0.0653)	(0.0684)		
External commuting	-0.134	-0.185	No	No
	(0.187)	(0.209)		
Artisan	0.585***	0.581***	No	No
	(0.106)	(0.106)		
Observations	3,506	2,803	1,364	1,300
R-squared	0.338	0.330	0.1109	0.1129

Notes: Robust standard errors in parentheses, clustered at regional level in Becchetti et al. (2020) and at geographical area level in Our results. ‘Lockdown’ observed with a 5-days delay. Coefficients and standard errors for variables ‘Day^2’, ‘Density’ and ‘Income’ are of the order of 10^{-3}.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table A.3. Major factors explaining variation in COVID-19 contagion (fixed effects OLS).

	Becchetti et al. (2020)		Our results	
Dependent variable	New cases		Growth	
Variables	(1)	(2)	(1)	(2)
Day	0.00211	0.00447	0.0003	0.0002
	(0.00400)	(0.00394)	(0.0006)	(0.0004)
Day^2	-0.000106**	-0.000114**	-0.0212	-0.0230
	(4.44e-05)	(4.70e-05)	(0.0132)	(0.0133)
Lockdown	-0.0274***	-0.0288***	-0.0185**	-0.0179**
	(0.00642)	(0.00639)	(0.0051)	(0.0057)
High temperature	-0.00439	-0.00327	No	No
	(0.00356)	(0.00435)		
Day*PM10	7.40e-05**		-0.0842	
	(3.14e-05)		(0.1816)	
Day*PM2.5		0.000103**		-0.1915
		(4.89e-05)		(0.1513)
Day*Density	3.21e-07	1.44e-07	-0.0044	-0.0048
	(4.40e-07)	(4.39e-07)	(0.0051)	(0.0036)
Day*Over65	-1.59e-05	-2.02e-05	-0.0010	-0.0006
	(1.54e-05)	(1.77e-05)	(0.0023)	(0.0021)
Day*Income	0.00690*	0.00855**	0.0002***	0.0002**
	(0.00342)	(0.00348)	(0.00003)	(0.0001)
Day*Ventilators	-0.370	-0.356	No	No
	(1.236)	(1.527)		
Day*Public transport use	2.04e-06	0.000404	No	No
	(0.000750)	(0.000688)		
Day*Internal commuting	0.0156*	0.0152	No	No
	(0.00841)	(0.00963)		
Day*External commuting	-0.0130	-0.0152	No	No
	(0.0113)	(0.0131)		
Day*Artisan	0.0210***	0.0192**	No	No
	(0.00534)	(0.00721)		
Observations	3,506	2,803	1,364	1,300
R-squared	0.313	0.313	0.1078	0.1090

Number of ID	95	76	21	20

Notes: Robust standard errors in parentheses, clustered at regional level in Becchetti et al. (2020) and at geographical area level in Our results. ID are provinces in Becchetti et al. (2020) and regions/autonomous provinces in Our results (Trentino Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). ‘Lockdown’ observed with a 5-days delay. Coefficients and standard errors for variables ‘Day^2’, ‘Day*PM10’, ‘Day*PM2.5’, ‘Day*Density’ and ‘Day*Income’ are of the order of 10^{-4}.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

A.3 An outline of previous studies on the role of non-pharmaceutical interventions in containing pandemics

Several studies investigate the effectiveness of non-pharmaceutical interventions in combating pandemics. The literature agrees in attributing to such interventions a significant reduction in the diffusion of contagions. Supporting evidence are found for the influenza pandemic in 1918 (Hatchett et al., 2007), the outbreak of severe acute respiratory syndrome (SARS) in 2003 (Pang et al., 2003; Bell, 2004; James et al., 2006; Lai and Tan, 2012) and novel influenza A (H1N1) in 2009 (Lai and Tan, 2012). Recent studies investigate the impact of non-pharmaceutical interventions in containing the COVID-19 pandemic (e.g., Becchetti et al., 2020; Fang et al., 2020; Ferguson et al., 2020). The table A.1 provides a synthesis of related studies.

Table A.4. Outline of main findings from literature.

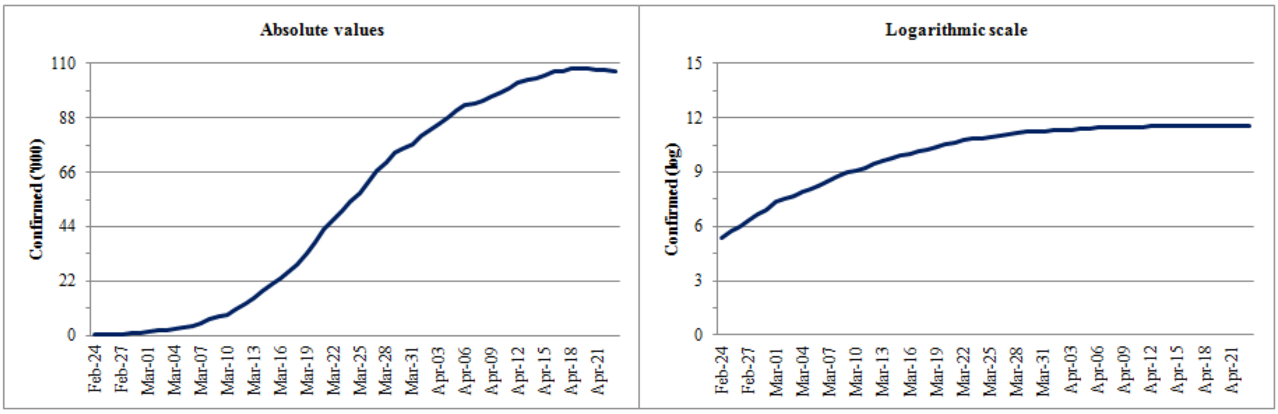
References	Main findings on pandemic containment
Lockdown	
Fang et al (2020)	Effective to reduce the total infections
Becchetti et al. (2020)	Effective to reduce contagions but not deaths
Flaxman et al. (2020)	Effective to reduce the transmission
Hatchett et al. (2007)	Effective to reduce deaths
Social distancing mesures	
Bell (2004); Germann et al. (2006); James et al. (2006); Lai & Tan (2012); Milne et al. (2008);	Effective to combat pandemic
Ferguson et al. (2006)	Effective to reduce R_0
Becchetti et al. (2020)	Effective to reduce contagions but not deaths
Fang et al (2020)	Effective to reduce the total infections
Flaxman et al. (2020); Pang et al. (2003); Riley et al. (2003); Krumkamp et al. (2009)	Effective to reduce the transmission

Ferguson et al. (2020)	Effective to reduce deaths
Halder et al. (2010)	Effective to combat pandemic (in combination with antiviral drug)
Hatchett et al. (2007)	Effective to reduce deaths
Isolating case-patients	
Bell (2004); Milne et al. (2008); Pang et al. (2003)	Effective to combat pandemic
Ferguson et al. (2020)	Effective to reduce deaths
Ferguson et al. (2006)	Effective to reduce R_0
Flaxman et al. (2020)	Effective to reduce the transmission
Wilder-Smith et al. (2020)	Effective to reduce transmission and deaths
Quarantine	
Bell (2004); James et al. (2006); Lai & Tan (2012); Pang et al. (2003)	Effective to combat pandemic
Wilder-Smith et al. (2020)	Effective to reduce transmission and deaths
Ferguson et al. (2020)	Effective to reduce deaths
Ferguson et al. (2006)	Effective to reduce R_0
Hsieh et al. (2005)	Effective to reduce infections
Krumkamp et al. (2009)	Effective to interrupt transmission chains
Travel restrictions	
Bajardi et al. (2011)	Effective to retard the peak of cases but not the spread
Camitz & Liljeros (2006)	Effective to reduce the speed and geographical spread
Ferguson et al. (2006); Germann et al. (2006)	Effective to delay the time course of the outbreak
Riley et al. (2003)	Effective to reduce the transmission

Screening of travellers	
Bajardi et al. (2011)	Effective to retard the peak of cases but not the spread
Bell (2004)	Not effective to contain pandemic

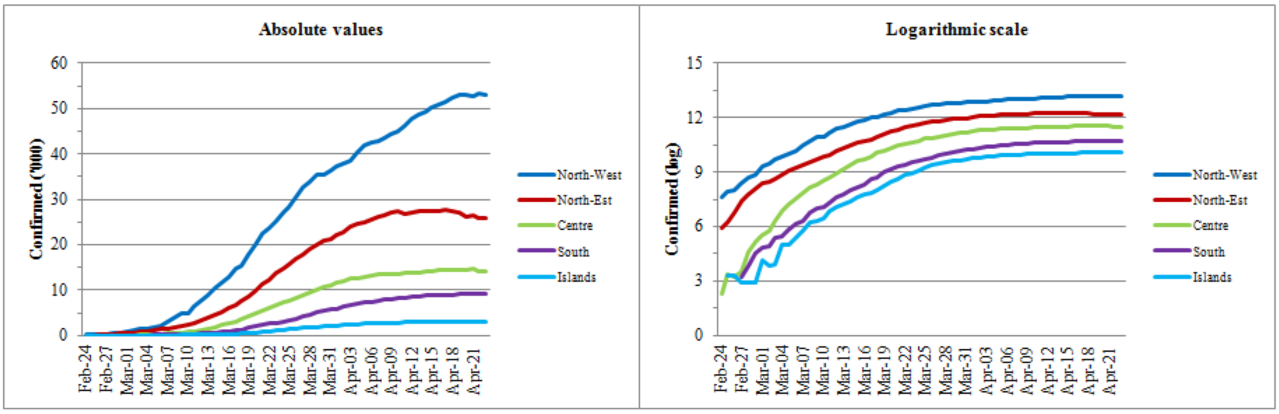
A.4 Daily evolution of COVID-19 contagion and fatality in Italy

Figure A.2. Daily evolution of confirmed COVID-19 cases in Italy, Feb 24 – Apr 23, 2020.



Source: elaboration on data of the Italian Department of Civil Protection.

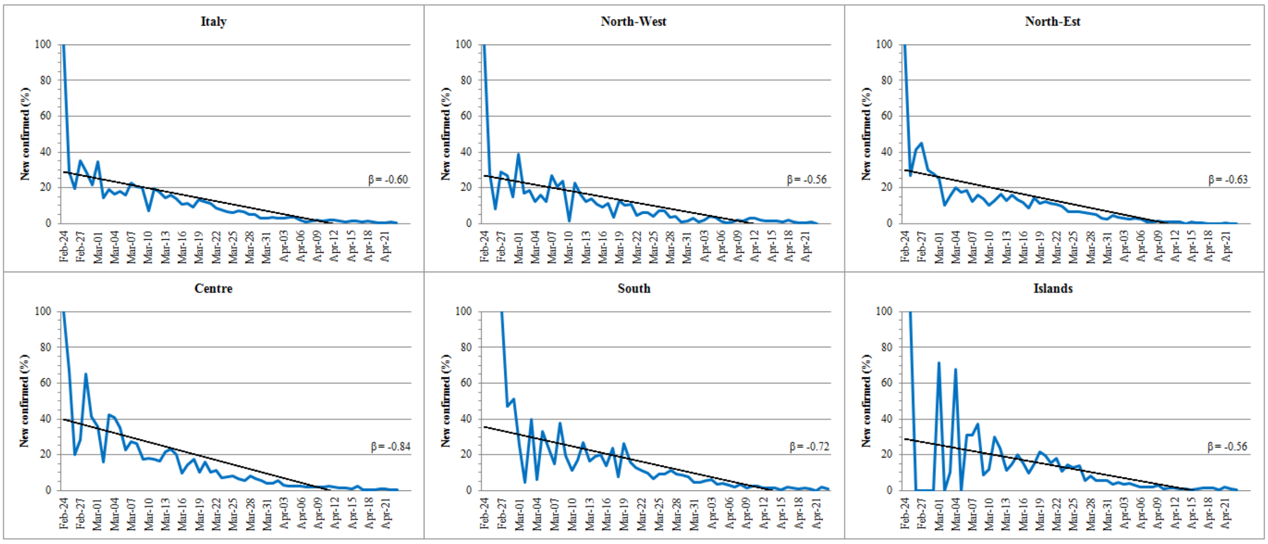
Figure A.3. Daily evolution of confirmed COVID-19 cases by area, Feb 24 – Apr 23, 2020.



Source: elaboration on data of the Italian Department of Civil Protection.

Notes: North-West includes Piemonte, Valle d'Aosta, Liguria, Lombardia; North-Est includes Trentino Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna; Centre includes Toscana, Umbria, Marche, Lazio; South includes Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria; Islands include Sicilia, Sardegna.

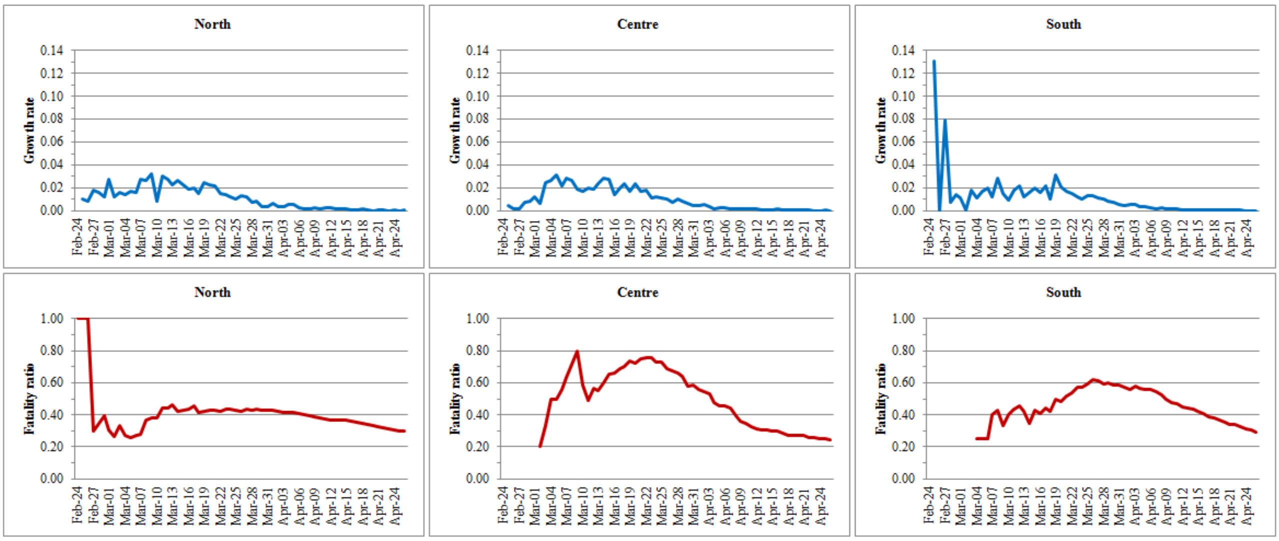
Figure A.4. Daily evolution of new confirmed COVID-19 cases in Italy and by area, Feb 24 – Apr 23, 2020.



Source: elaboration on data of the Italian Department of Civil Protection.

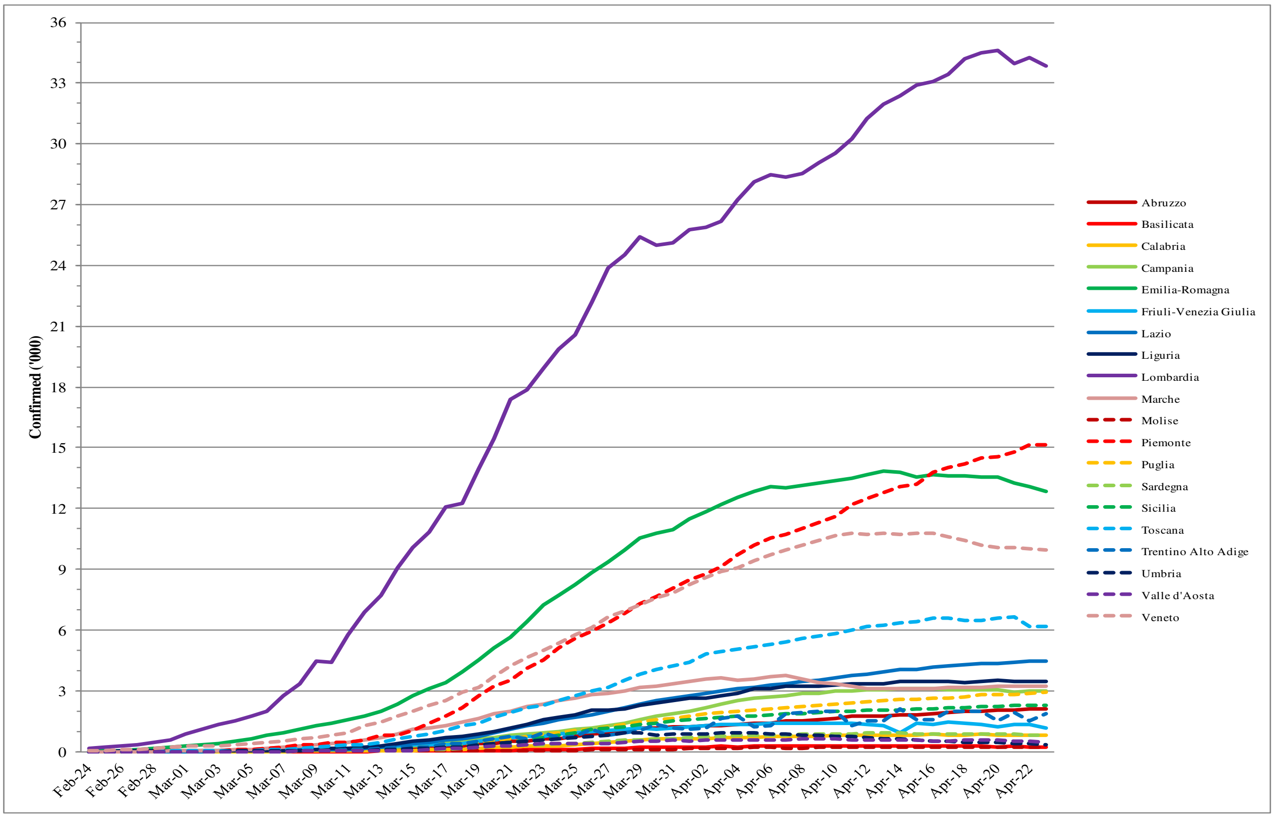
Notes: North-West includes Piemonte, Valle d'Aosta, Liguria, Lombardia; North-Est includes Trentino Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna; Centre includes Toscana, Umbria, Marche, Lazio; South includes Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria; Islands include Sicilia, Sardegna.

Figure 2. Daily evolution of COVID-19 contagion and fatality by geographical area in Italy.



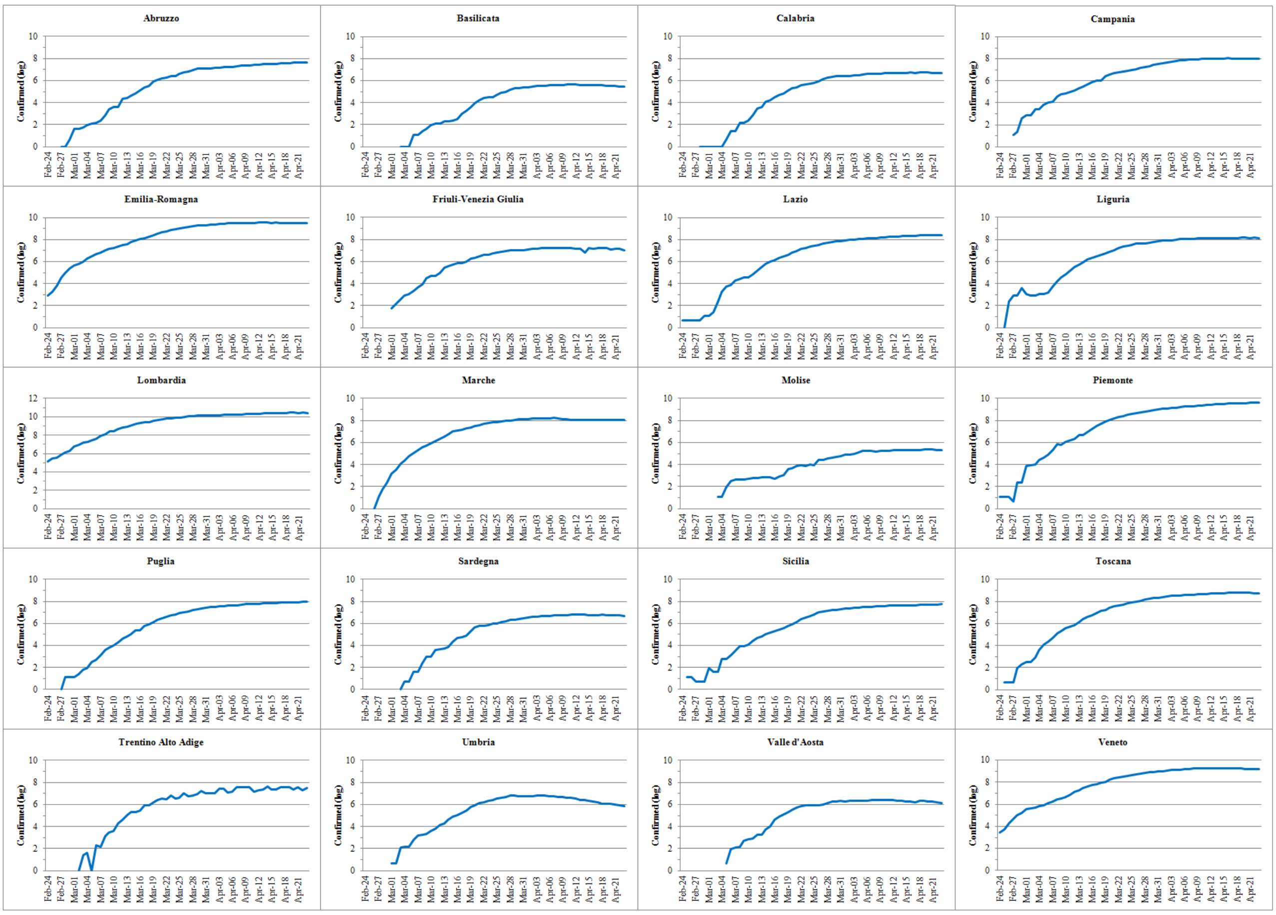
Source: elaboration on data of the Italian Department of Civil Protection.

Figure A.5. Daily evolution of confirmed COVID-19 cases by region, Feb 24 – Apr 23, 2020.



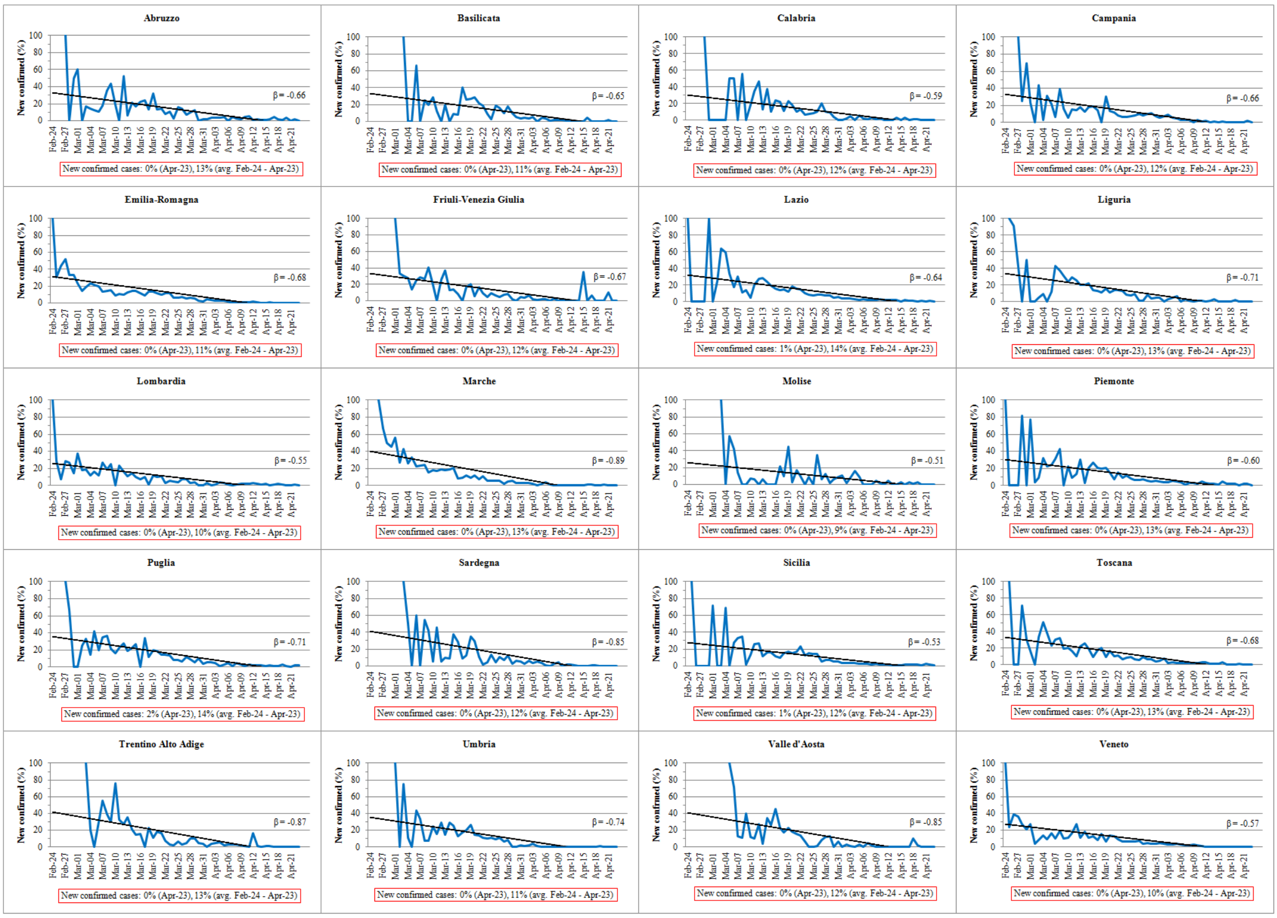
Source: elaboration on data of the Italian Department of Civil Protection.

Figure A.6. Daily evolution of confirmed COVID-19 cases by region, Feb 24 – Apr 23, 2020.



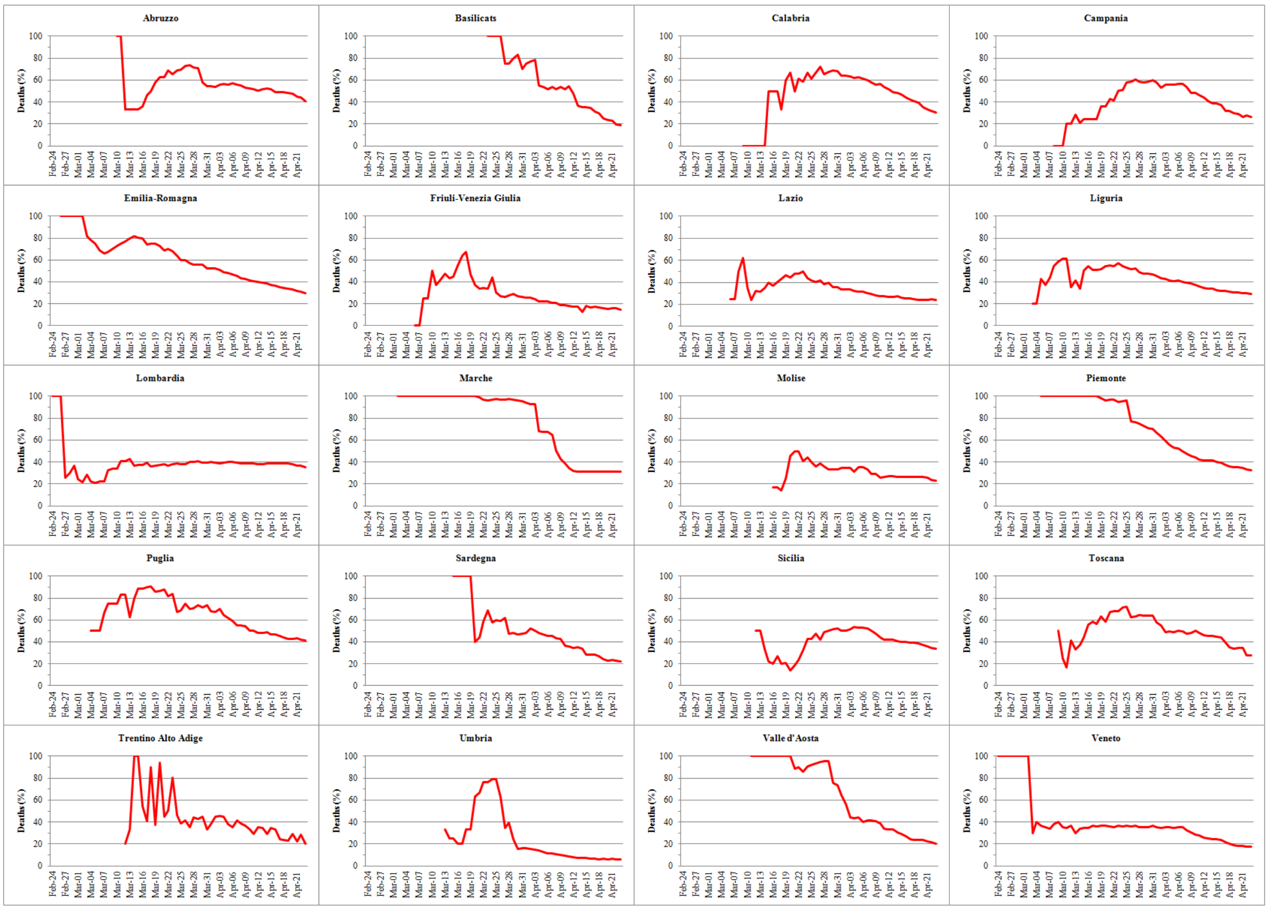
Source: elaboration on data of the Italian Department of Civil Protection.

Figure A.7. Daily evolution of new confirmed COVID-19 cases by region, Feb 24 – Apr 23, 2020.



Source: elaboration on data of the Italian Department of Civil Protection.

Figure A.8. Daily evolution of COVID-19 deaths by region, Feb 24 – Apr 23, 2020.



Source: elaboration on data of the Italian Department of Civil Protection.

A.5 Policy interventions adopted by the Italian government to combat COVID-19 pandemic

Table A.5 provides the detailed coverage of measures implemented to contain the COVID-19 contagions. Policy interventions implemented until March 8, 2020 are region-specific, whereas the measures adopted after this date are implemented at the national level.

Table A.5. Policy interventions.

Date	Intervention	Region	Province	Municipality
February 23	Lockdown	Lombardia	Lodi	Bertonico, Casalpusterlengo, Castelgerundo, Castiglione d’Adda, Codogno, Fombio, Maleo, San Fiorano, Somaglia, Terranova dei Passerini
		Veneto	Padova	Vo’
	Home-confinement and quarantine	Italy		
February 25	Suspension events	Emilia-Romagna, Friuli-Venezia Giulia, Lombardia, Veneto, Liguria, Piemonte		
March 01	Suspension events, teaching activities	Emilia-Romagna, Lombardia, Veneto		
		Marche	Pesaro e Urbino	
		Liguria	Savona	
	Closing fitness and wellness	Lombardia		
		Emilia-Romagna	Piacenza	
	Closing retail business	Lombardia	Bergamo, Cremona, Lodi	
		Emilia-Romagna	Piacenza	
	Disinfection of public transports	Italy		
March 04	Suspension events, teaching activities	Italy		

		Lombardia	
		Emilia-Romagna	Modena, Parma, Piacenza, Reggio nell'Emilia, Rimini
March 08	Lockdown	Marche	Pesaro e Urbino
		Piemonte	Alessandria, Asti, Novara, Verbano-Cusio-Ossola, Vercelli
		Veneto	Padova, Treviso, Venezia
March 09	Lockdown	Italy	
March 11	Closing retail business	Italy	
March 20	Closing parks	Italy	
March 22	Closing industries	Italy	

Source: elaboration on Decrees by the President of the Council of Ministers (DPCM) published in the Italian Official Gazette and the official website of the Italian Government.

A.6 Delayed effects of policy interventions on COVID-19 contagion

A.6.1 Empirical model

Following the approach used in Becchetti et al. (2020), we run the following OLS panel fixed-effects model to explain the delayed effects of policy interventions on variation in COVID-19 contagion:

$$G_{it} = \alpha + \boldsymbol{\beta P}_{it-k} + \boldsymbol{\delta X}_i + \boldsymbol{\zeta T}_t + v_{it} \qquad \text{(A.2)}$$

The dependent variable (G_{it}), a proxy of the daily evolution of COVID-19 contagion at the regional level, is built as the ratio between the number of new infected patients detected each day *t* with respect to the day before *t-1* in any region i ($A_{it} - A_{it-1}$) and the cumulative number of swabs in region *i* at any given day *t* (S_{it}):

$$G_{it} = \frac{A_{it} - A_{it-1}}{S_{it}} \tag{A.3}$$

The vector of policy intervention variables ($\boldsymbol{P}_{it-k}$), observed with a k-days delay, $k = \{0, 7, 14\}$, includes proxies for lockdown and social distancing measures, as well as disinfection of public transports that are likely to affect the rate of transmission of infections. Social distancing measures refer to different behaviour and policies as well (i.e., suspension of events and teaching activities, closure of fitness and wellness activities, closure of retail business, closure of parks, closure of industries). The policy intervention variables are built following an approach similar to Acemoglu et al. (2020) and ranges from 0 to 1; for instance, the lockdown variable assumes the value 0 if a certain region i is no under lockdown at any given day *t-k*, and the value 1 if that region is under a full lockdown; intermediate values represent less extreme situations in which only some of the provinces of the region are under a full lockdown.

As discussed in Goodman-Bacon and Jan Marcus (2020), policies that limit exposure are likely to have a delayed effect on recorded infection rates. For instance, Lauer et al. (2020), who estimate the length of the incubation period of SARS-CoV-2, report a median incubation period of 5.1 days, with symptoms developed within 11.5 days of infection in 97.5% of cases and after 14 days of active monitoring or quarantine for remaining cases. The use of different lags for policy variables (i.e., $k = \{0, 7, 14\}$) allows us to disentangle short- and long-run effects of non-pharmaceutical interventions on the containment of COVID-19 contagion.

The vector $\boldsymbol{X}_i$ includes a set of time-invariant characteristics of regions: i.e., the population density at the regional level ($Density_i$), the distance from the main locus –Lombardia region– ($Distance_i$), the pollution variable (average year levels of PM10 –$PM10_i$– or PM2.5 –$PM2.5_i$–, alternatively). Since in OLS panel fixed-effects models the intercept absorbs time-invariant controls, we interact the time variable (Day_t) with each time-invariant control. This approach allows us to account for delayed effects of time-invariant characteristics of regions (Becchetti et al., 2020).

The distance from the main locus, $Distance_i$, is obtained using the haversine formula:

$$Distance_i = 2r \cdot arcsin\left(\sqrt{\sin^2\left(\frac{lat_i - lat_{Lombardia}}{2}\right) + \cos(lat_{Lombardia})\cos(lat_i)\sin^2\left(\frac{lon_i - lon_{Lombardia}}{2}\right)}\right) \tag{A.4}$$

where r is the radius of the sphere, lat_i and lon_i are latitude and longitude of region i, $lat_{Lomberdia}$ and $lon_{Lombardia}$ are latitude and longitude of Lombardia region.

The inclusion of pollution variables in the equation A.2 is supported by several epidemiological studies that report an increase of diseases (e.g., chronic obstructive pulmonary disease and pneumonia, ischemic health disease, cardiopulmonary disease and mortality), hospital admissions and mortality associated with exposures to poor air quality (e.g., Schwartz and Morris, 1995; Medina-Ramon et al., 2006; Pope III, 2006). As argued in Becchetti et al. (2020), individuals living in highly polluted areas have weaker lungs and reduced capacity to react to respiratory diseases or pneumonias; thus, the historical levels of particulate matter (i.e., PM2.5 and PM10) may be correlated with the increase in COVID-19 cases. Following this hypothesis, we control, alternatively, for average year levels of PM10 and PM2.5 (both interacted with the time variable). However, recent studies demonstrate that also the current levels of pollution are correlated with the evolution of COVID-19 contagion. For instance, Wu et al. (2020) report a 15% increase in COVID-19 death rate with 1 μg/m^3 increase in PM2.5. In addition, Magazzino et al. (2020) find an increase of COVID-19 cases with an exposure to PM10 exceeding legal limits. Consolidated evidence suggest that viruses are carried by airborne particles and transmitted by aerosols (e.g., Alonso et al., 2015; Herfst et al., 2012). Aerosols contribute to the survivability of viruses (Zuo et al., 2013) and carry them over large distances (Tellier, 2006) leaving room for increasing potential contagions; thus, the airborne transmission of SARS-CoV-2 is plausible (van Doremale et al., 2020). In order to test this hypothesis, we also control for the effect of the current levels of PM10 and consider the daily number of provinces in a region with PM10 levels over allowed limits ($PM10over_{it}$). The variable $PM10over_{it}$ is built following the same approach used for policy variables. Thus, $PM10over_{it}$ assumes the value 0 if a certain region never exceeds legal limits of PM10, the value 1 if all the provinces of that region exceed legal limits of PM10, intermediate values if only some of the provinces of the region exceed legal limits of PM10. The variable $PM10over_{it}$ varies on day-by-day basis and is introduced in the model without the interaction with the time trade variable. In our model we use levels of PM10 due to the cointegration between PM10 and PM2.5 time series (cfr. section A.5.2).

The model in equation (A.2) also includes a vector, $\boldsymbol{T}_t$, for the time trend (Day_t) and its square (Day_t^2). The terms $\boldsymbol{\beta}$, $\boldsymbol{\delta}$ and $\boldsymbol{\zeta}$ are vectors of parameters; α and v_{it} are a constant and the error term.

A.6.2 Testing for cointegration between PM10 and PM2.5 time series

In order to test for cointegration between PM10 and PM2.5, we use the Engle–Granger two-step method (Engle and Granger, 1987). In the first step we estimate the following equation through OLS:

$$PM10_t = \lambda PM2.5_t + \varepsilon_t \tag{A.5}$$

where λ is the parameter to be estimated and ε_t are residuals.

We estimate the equation (A.5) alternatively for time series of PM10 and PM2.5 in provinces of Bergamo, Brescia and Milano. The coefficients estimated on PM2.5, reported in table A.6, are positive and significant at the 1% level.

Table A.6. Results of the Ordinary Least Square estimation of equation (A.5).

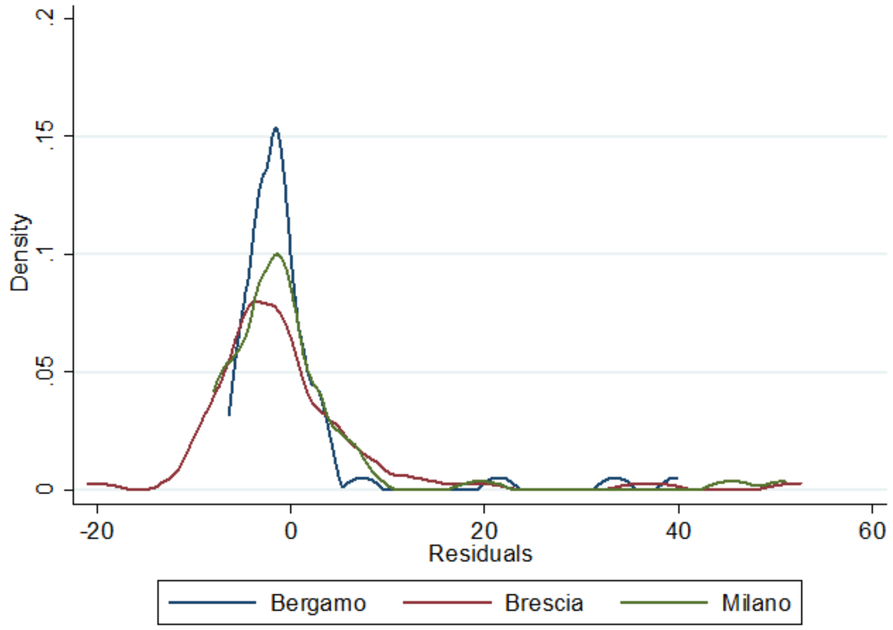
	Dependent variables		
Variables	PM10 (Bergamo)	PM10 (Brescia)	PM10 (Milano)
PM2.5 (Bergamo)	1.227***		
	(0.042)		
PM2.5 (Brescia)		1.436***	
		(0.050)	
PM2.5 (Milano)			1.498***
			(0.053)
Observations	70	70	70
R-squared	0.926	0.922	0.920

Notes: Standard errors are in parentheses.

*** Significant at the 1 percent level.

We construct residuals based on the static regression results of table A.6 and plot their kernel density estimates (figure A.8). Residuals are distributed around the zero.

Figure A.9. Kernel density estimates of residuals.



In the second step, we perform the augmented Dickey–Fuller (ADF) test on the residuals in order to test for cointegration. The null hypothesis (H_0) is to test the non-stationarity of residuals, which implies no cointegration between PM10 and PM2.5, versus the alternative hypothesis (H_1) that residuals are stationary, implying cointegration between PM10 and PM2.5.

$$H_0: \varepsilon_t = I(1) \quad \text{vs.} \quad H_1: \varepsilon_t = I(0) \tag{A.6}$$

Hamilton (1994, p. 766) suggests 5% critical values of -2.67 for making inference in such cases.

Table A.7. Results of the Augmented Dickey-Fuller test for unit root.

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Bergamo	-3.648	-2.614	-1.950	-1.610
Brescia	-4.292	-2.614	-1.950	-1.610
Milano	-3.639	-2.614	-1.950	-1.610

Comparing the ADF test statistics for each province, reported in table A.7, with the critical value of −2.76, we reject the null hypothesis of no cointegration between PM10 and PM2.5 at the 5% level.

A.6.3 Description of pollution data

In order to control for the correlation between pollution and COVID-19 contagions, we collected data on historical annual average values of PM10 and PM2.5 in mg/mc registered in 2018 by city monitoring posts in each region from the ISPRA database. To control for the effect of current level of PM10, we gathered daily data on PM10 fraction at the provincial level from Regional Agencies for Environmental Protection (ARPA) websites. For each provincial capital, where available, we selected monitoring posts located in areas where the pollution levels are mainly based on emissions from nearby traffic. If monitoring stations were not available, we used the value detected from the closest monitoring station.

A.6.4 Empirical results

In order to detect the delayed effects of policy interventions on COVID-19 contagion, we estimate different specification of equation (A.2), using 0-days, 7-days, and 14-days delay. To corroborate our results, we also control for different combination of pollution levels (i.e., average year levels of PM10, average year levels of PM2.5, and the number of provinces in a region that exceed the legal limits of PM10 daily).

The results are reported in table A.8 and show that a higher number of days delay correspond to a more robust effect. For instance, the effect of the lockdown is observable only after two weeks from its implementation. As suggested in Becchetti et al. (2020), effects of lockdown are distributed over time, thus a higher number of leaded days correspond to a stronger effect. The Italian government enacted policy interventions to contain the diffusion of COVID-19 contagion with a different timing across Italian regions. However, infectious diseases do not stop at regional borders, thus the timing of lockdown across regions may affect the diffusion of COVID-19 contagion at the national level (Goodman-Bacon and Jan Marcus, 2020).

Differently, while the decision of suspending events and teaching activities to allow for social distancing seems to contribute to the growth of contagion, it has no effects in a longer timeframe.

We also find that, while the closure of industries contributes to the reduction of COVID-19 contagions both in the short- and long-run, the closure of retail business and parks shows its effect in the short-run. The immediate impacts of the closure of retail business and parks may be due to an anticipation effect determined by the announcement of new interventions ahead of time. When governments inform about a forthcoming policy, behaviour may change in response to that information (Goodman-Bacon and Jan Marcus, 2020). It also worth noting that the closure of industries, retail business and parks are social distancing measures introduced after other stringent measures, such as lockdown; thus, the beneficial effects on the diffusion of contagions observed in the short-run should be associated with the effects of previous non-pharmaceutical interventions. As suggested in Germann et al. (2006) and Hatchett et al. (2007), a combinations of social distancing measures contribute to slow down the outbreak spread.

Table A.8. Delayed effects of policy intervention in explaining variation in COVID-19 contagion.

	w/ PM10 (avg. year levels)			w/ PM2.5 (avg. year levels)			w/ PM10 over limits		
Variables	0-days delay	7-days delay	14-days delay	0-days delay	7-days delay	14-days delay	0-days delay	7-days delay	14-days delay
Lockdown	0.023	-0.005	-0.013***	0.026	-0.005	-0.013**	0.022	-0.005	-0.013***
	(0.034)	(0.004)	(0.003)	(0.035)	(0.004)	(0.003)	(0.034)	(0.004)	(0.003)
Social distancing (events, teaching activities)	0.015	-0.008	0.003	0.016*	-0.006	0.001	0.015*	-0.008	0.003
	(0.007)	(0.015)	(0.006)	(0.008)	(0.017)	(0.007)	(0.007)	(0.015)	(0.006)
Social distancing (fitness and wellness)	-0.009	-0.0001	0.003	-0.010	-0.001	0.003	-0.009	-0.0002	0.003
	(0.006)	(0.005)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)	(0.006)
Social distancing (retail business)	-0.018	-0.007*	-0.006	-0.019	-0.007*	-0.007	-0.018	-0.007*	-0.005
	(0.033)	(0.003)	(0.006)	(0.034)	(0.003)	(0.005)	(0.033)	(0.003)	(0.006)
Social distancing (parks)	-0.005*	-0.005**	-0.002	-0.006**	-0.006**	-0.002	-0.005*	-0.004*	-0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Social distancing (industries)	-0.019***	-0.013***	-0.006***	-0.019***	-0.013***	-0.006***	-0.019***	-0.014***	-0.006**
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)
Disinfection of public transports	-0.012	0.012	-0.023	-0.014	0.015	-0.023	-0.012	0.012	-0.023
	(0.016)	(0.013)	(0.020)	(0.015)	(0.014)	(0.020)	(0.016)	(0.013)	(0.020)
Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-squared	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day × PM10 (avg. year levels)	Yes	Yes	Yes	No	No	No	No	No	No
Day × PM2.5 (avg. year levels)	No	No	No	Yes	Yes	Yes	No	No	No
PM10 over limits	No	No	No	No	No	No	Yes	Yes	Yes

Day × Density	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day × Distance from main locus	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,454	1,323	1,176	1,390	1,260	1,120	1,454	1,323	1,176
R-squared	0.093	0.165	0.182	0.096	0.173	0.190	0.093	0.166	0.182

Notes: Fixed effects OLS estimation. The dependent variable is the day-by-day growth in active cases over the number of swabs defined in equation (A.3). Intervention variables observed with a 0-days, 7-days and 14-days delay. Robust standard errors, clustered at geographical area level, are in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

A.7 Further sensitivity analyses

A.7.1 Description of control factors

In the model of COVID-19 contagion (equation 2), we control for observed heterogeneity across regions. Becchetti et al. (2020) suggest that a plethora of geographical-specific characteristics contribute to the diffusion of contagions. To control for these region-specific characteristics, we collect data on population density from the Istat databases and for the geographical location. We also collect data from the ISPRA database on annual average values of PM10 and PM2.5 in mg/mc. Some studies suggest that the exposure to environmental pollutants is associated with an increase of diseases, such as pulmonary (Medina-Ramon et al., 2006) and heart disease (Schwartz and Morris, 1995), and that airborne particles may carry viruses and spread the contagions (e.g., Herfst et al., 2012; Zuo et al., 2013; Alonso et al., 2015; van Doremale et al., 2020; Becchetti et al., 2021).

In the model of COVID-19 fatality (equation 4), we control for structural determinants (data referred to 2019). Annual data on the percentage of hospital beds in intensive care and infectious disease wards from the official database of the Health Ministry[5]. We collect from the Istat data[6] on the number of physicians and from the Ministry of Economy and Finance data[7] on the health expenditure. The connection between healthcare expenditure and health outcomes is a complex issue. Although an increase in healthcare expenditure may significantly reduce the mortality (Crémieux et al., 1999; Nixon and Ulmann, 2006), higher intensity of care (e.g., increasing of physicians, intensive care units, beds) alone does not enough to improve health outcomes, patients' satisfaction, or access to care; rather, the social networks resulting in well-functioning public and private organisations may improve performances in health care services, also reducing the expenditures (Skinner et al., 2008). Indeed, an increase of public spending for healthcare is not necessarily related to health outcomes unless the healthcare expenditure is accompanied by policies that allow an effective allocation of funds (Bokhari et al., 2007; Moscone et al., 2019). Thus, managerial strategies (i.e., re-allocating existing

[5] Available at: http://www.dati.salute.gov.it/dati/homeDataset.jsp.

[6] Available at: http://dati.istat.it/.

[7] Available at: http://www.rgs.mef.gov.it/_Documenti/VERSIONE-I/Attivit--i/Spesa-soci/Attivit-monitoraggio-RGS/2019/IMDSS-RS2019.pdf.

resources) that include more flexible organisational models across all healthcare settings, also increasing healthcare expenditure (e.g., increasing intensive care beds), may cope the impacts of pandemic on public health. However, the measure on hospital settings generated a huge impact on hospital expenditure overcoming 1.5 billion of euros, also highlighting the unpreparedness of healthcare system to deal with pandemic mainly due to the cutbacks over the last 30 years that have reduced the public health system capacity (Mauro and Giancotti, 2021).

Regional information on lifestyle (percentage of smokers, of males, old-age rates, and monthly death rates) and environmental characteristics are referred to 2019 and collected from Istat databases[8]. The old-age rate is computed as the ratio between the old-age population (over 65 years old) and the young-age population (up to 14 years old). These controls allow us to consider social factors that may influence population health (Reibling, 2013). Lippi and Henry (2020) and Vardavas and Nikitara (2020) find that during the COVID-19 outbreak higher percentages of smokers died or needed intensive care unit support and mechanical ventilation. Furthermore, Karlberg et al. (2004) find that the probability to die among SARS patients is higher for males than for females. A positive correlation is also found between deaths and older age patients (e.g., Karlberg et al., 2004; Wu and McGoogan, 2020). We control for these factors.

A.7.2 Robustness tests on the OLS specification

We perform robustness tests on the OLS specification with respect to the dependent variable of the model of COVID-19 contagions (i.e., the model reported in column 6 of table 2).

The model may be potentially autoregressive since the dependent variable (i.e., the growth of contagions) is a timeseries variable characterised by a non-linear trend. To control for potential autocorrelation, we introduce in the model lags of the dependent variable, highlighted in a correlogram, that resulted statistically significant (specification 1).

The model may be also affected by potential endogeneity between the dependent variable and speed of recovery (i.e., recovery delta) since they are both explicative of the evolution of the epidemic. We test for potential endogeneity by removing the variable "recovery (delta)" from the model (specification 2).

[8] Available at: http://dati.istat.it/.

A further concern may be the non-linearity of policy interventions (particularly those that vary within regions, such as the lockdown). To consider potential linearity of regressors, we introduce in the model the square of the variable "lockdown" (specification 3).

We then compare our results with each specification and perform Hausman's specification test. The null hypothesis to test is that the difference in coefficients is not systematic between specifications. The results of the test are reported below:

Our model – Specification 1 (potential autocorrelation)

chi2 = 68.03

Prob>chi2 = 0.6427

We fail to reject the null hypothesis

Our model – Specification 2 (potential autocorrelation and endogeneity, non-linearity)

chi2 = 68.49

Prob>chi2 = 0.6277

We fail to reject the null hypothesis

Our model – Specification 3 (potential autocorrelation, endogeneity)

chi2 = 37.36

Prob>chi2 = 0.9998

We fail to reject the null hypothesis

The results of Hausman's specification tests prove that there are no systematic differences between coefficients in our model and in each specification.

A.7.3 Controlling for macro-regions heterogeneity

We test the robustness of our results including macro-region fixed effects: the results are reported in tables A.9 and A.10. We follow the classification of the National Institute of Statistics (Istat) and classify regions in the following macro-regions: Northwest (Piemonte, Valle d'Aosta, Liguria, Lombardia), Northeast (Trentino-Alto Adige –divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento–, Veneto, Friuli-Venezia Giulia, Emilia-Romagna), Centre (Toscana, Umbria, Marche, Lazio), South (Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria), Islands (Sicilia, Sardegna).

Tables A.9 and A.10 provide a comparison between our findings and results of the sensitivity analysis. Table A.9 refers to the model of COVID-19 contagion (equation 2); table A.10 refers to the model of COVID-19 fatality (equation 4). Main results are confirmed.

Table A.9. COVID-19 contagion: controlling for macro-regions heterogeneity.

	Our results			Sensitivity analysis		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	-0.0120***	-0.0121***	-0.0115	-0.0122***	-0.0124***	-0.0151
	(0.0029)	(0.0029)	(0.0074)	(0.0028)	(0.0028)	(0.0102)
Social distancing (events, teaching activities)	0.0013	0.0012	0.0019	0.0024	0.0023	0.0034
	(0.0073)	(0.0073)	(0.0104)	(0.0066)	(0.0066)	(0.0098)
Social distancing (fitness and wellness)	0.0026	0.0025	0.0050	0.0022	0.0022	0.0048
	(0.0054)	(0.0054)	(0.0044)	(0.0055)	(0.0055)	(0.0044)
Social distancing (retail business)	-0.0057	-0.0055	-0.0186	-0.0055	-0.0052	-0.0208
	(0.0048)	(0.0048)	(0.0115)	(0.0048)	(0.0048ì)	(0.0135)
Social distancing (parks)	-0.0033***	-0.0025**	0.0018	-0.0032***	-0.0024**	0.0018
	(0.0010)	(0.0011)	(0.0012)	(0.0010)	(0.0011)	(0.0011)
Social distancing (industries)	-0.0046***	-0.0048***	-0.0069***	-0.0046***	-0.0048***	-0.0069***
	(0.0012)	(0.0012)	(0.0008)	(0.0012)	(0.0012)	(0.0006)
Disinfection of public transports	-0.0226	-0.0227	-0.0227	-0.0235	-0.0236	-0.0236
	(0.0199)	(0.0199)	(0.0173)	(0.0206)	(0.0206)	(0.0181)
Recovery (delta)	-0.00001**	- 0.00001***	- 0.00001***	- 0.00001***	- 0.00001***	- 0.00001***
	(0.000005)	(0.000005)	(0.000004)	(0.000004)	(0.000004)	(0.000003)
Macro-region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	Yes	No	No	Yes	No
Time dummies	No	No	Yes	No	No	Yes
Observations	1,134	1,134	1,134	1,134	1,134	1,134
Number of ID	21	21	21	21	21	21
R-squared						
within	0.1756	0.1757	0.1951	0.1757	0.1758	0.1952
between	0.8470	0.8473	0.8449	0.4536	0.4544	0.4607
overall	0.2009	0.2010	0.2196	0.1858	0.1859	0.2048

Notes: The dependent variable is the growth of contagions computed as in equation (1). Policy variables are observed with a 14-days delay. Time trend included in specifications (2) and (5); time dummies included in specifications (3) and (6). ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

Table A.10. COVID-19 fatality: controlling for macro-regions heterogeneity.

	Our results			Sensitivity analysis		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Swabs per population	-0.0303***	-0.0305***	-0.0051	-0.0266**	-0.0269**	-0.0110
	(0.0113)	(0.0116)	(0.0162)	(0.0116)	(0.0121)	(0.0120)
Hospitalised per swabs	1.9836***	1.7984***	1.1637*	2.0785***	1.9165***	1.4771***
	(0.3312)	(0.3457)	(0.6342)	(0.2858)	(0.3108)	(0.4210)
Confined with symptoms per swabs	1.6144**	1.6394**	1.3010***	1.9286***	1.9476***	1.6871***
	(0.6432)	(0.6408)	(0.3687)	(0.6061)	(0.6186)	(0.3827)
Growth of contagions (delta)	0.0187	0.0170	0.0209	0.0185	0.0170	0.0184
	(0.0281)	(0.0287)	(0.0159)	(0.0276)	(0.0281)	(0.0136)
Macro-region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	Yes	No	No	Yes	No
Time dummies	No	No	Yes	No	No	Yes
Observations	1,083	1,083	1,083	1,083	1,083	1,083
Number of ID	21	21	21	21	21	21
R-squared						
within	0.5700	0.5734	0.5844	0.5710	0.5744	0.5883
between	0.8689	0.8715	0.9167	0.4871	0.4865	0.5004
overall	0.6460	0.6493	0.6711	0.5506	0.5533	0.5667

Notes: The dependent variable is the fatality ratio computed as in equation (3). Growth of contagions (delta) is observed with a 14-days delay. Time trend included in specifications (2) and (5); time dummies included in specifications (3) and (6). ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

A.7.4 Controlling for differences in income across regions

In a sensitivity analysis, we control for differences in income across regions. Table A.11 compares our findings and the results of the sensitivity analysis for the model of contagion, whereas table A.12 shows findings for the model of fatality. Results are confirmed.

Table A.11. COVID-19 contagion: controlling for differences in income across regions.

	Our results			Sensitivity analysis		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	-0.0125***	-0.0127***	-0.0141*	-0.0125***	-0.0127***	-0.0137
	(0.0027)	(0.0027)	(0.0082)	(0.0027)	(0.0027)	(0.0086)
Social distancing (events, teaching activities)	0.0027	0.0026	0.0039	0.0027	0.0026	0.0040
	(0.0066)	(0.0065)	(0.0097)	(0.0065)	(0.0065)	(0.0097)
Social distancing (fitness and wellness)	0.0026	0.0025	0.0050	0.0026	0.0025	0.0050
	(0.0054)	(0.0054)	(0.0044)	(0.0053)	(0.0053)	(0.0043)
Social distancing (retail business)	-0.0058	-0.0055	-0.0189	-0.0058	-0.0055	-0.0190
	(0.0047)	(0.0048)	(0.0118)	(0.0046)	(0.0047)	(0.0116)
Social distancing (parks)	-0.0029***	-0.0020*	0.0031**	-0.0029***	-0.0020*	0.0029*
	(0.0011)	(0.0012)	(0.0015)	(0.0011)	(0.0012)	(0.0015)
Social distancing (industries)	-0.0049***	-0.0051***	-0.0080***	-0.0049***	-0.0051***	-0.0078***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Disinfection of public transports	-0.0235	-0.0236	-0.0233	-0.0235	-0.0236	-0.0232
	(0.0201)	(0.0201)	(0.0173)	(0.0201)	(0.0201)	(0.0174)
Recovery (delta)	-0.00001**	-0.00001**	-0.00001**	-0.00001**	-0.00001**	-0.00001**
	(0.000005)	(0.000005)	(0.000005)	(0.000005)	(0.000005)	(0.000004)
PM10 (avg. year levels)	Yes	Yes	Yes	Yes	Yes	Yes
Density	Yes	Yes	Yes	Yes	Yes	Yes
Distance from main locus (Lombardia region)	Yes	Yes	Yes	Yes	Yes	Yes
Income	No	No	No	Yes	Yes	Yes
Time trend	No	Yes	No	No	Yes	No
Time dummies	No	No	Yes	No	No	Yes
Observations	1,134	1,134	1,134	1,134	1,134	1,134
Number of ID	21	21	21	21	21	21

R-squared						
within	0.1757	0.1758	0.1952	0.1757	0.1758	0.1952
between	0.4920	0.4940	0.5018	0.4934	0.4953	0.5025
overall	0.1876	0.1877	0.2067	0.1877	0.1878	0.2068

Notes: The dependent variable is the growth of contagions computed as in equation (1). Policy variables are observed with a 14-days delay. Time trend included in specifications (2) and (5); time dummies included in specifications (3) and (6). ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table A.12. COVID-19 fatality: controlling for differences in income across regions.

	Our results			Sensitivity analysis		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Swabs per population	-0.0258**	-0.0260**	-0.0153	-0.0258**	-0.0260**	-0.0150
	(0.0119)	(0.0120)	(0.0147)	(0.0118)	(0.0119)	(0.0145)
Hospitalised per swabs	1.7091***	1.7070***	1.3768***	1.7123***	1.7104***	1.3880***
	(0.4354)	(0.4245)	(0.4892)	(0.4269)	(0.4174)	(0.4612)
Confined with symptoms per swabs	1.9368***	1.9399***	1.6377***	1.9388***	1.9421***	1.6477***
	(0.5944)	(0.6030)	(0.3429)	(0.5944)	(0.6031)	(0.3492)
Growth of contagions (delta)	0.0164	0.0162	0.0184	0.0164	0.0162	0.0184
	(0.0293)	(0.0290)	(0.0142)	(0.0293)	(0.0290)	(0.0141)
Hospital beds in intensive care wards	Yes	Yes	Yes	Yes	Yes	Yes
Hospital beds in infectious diseases wards	Yes	Yes	Yes	Yes	Yes	Yes
Physicians per total hospital beds	Yes	Yes	Yes	Yes	Yes	Yes
Healthcare expenditure per population	Yes	Yes	Yes	Yes	Yes	Yes
Male (%)	Yes	Yes	Yes	Yes	Yes	Yes
Old-age rate	Yes	Yes	Yes	Yes	Yes	Yes
Smoker (%)	Yes	Yes	Yes	Yes	Yes	Yes
Death rate	Yes	Yes	Yes	Yes	Yes	Yes
Income	No	No	No	Yes	Yes	Yes
Time trend	No	Yes	No	No	Yes	No
Time dummies	No	No	Yes	No	No	Yes
Observations	1,083	1,083	1,083	1,083	1,083	1,083
Number of ID	21	21	21	21	21	21
R-squared						
within	0.5774	0.5776	0.5890	0.5774	0.5776	0.5890
between	0.5155	0.5156	0.5264	0.5149	0.5149	0.5258
overall	0.5567	0.5568	0.5726	0.5566	0.5568	0.5725

Notes: The dependent variable is the fatality ratio computed as in equation (3). Growth of contagions (delta) is observed with a 14-days delay. Time trend included in specifications (2) and (4); time dummies included in specifications (3) and (5). ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

A.7.5 Controlling for neighbour-contagion effects

We perform a sensitivity analysis to control for potential neighbour-contagion effects. We introduce in the model of COVID-19 contagion (equation 2) regressors obtained from the interaction between the total number of COVID-19 cases (with a 14-days delay) and a region-specific dummy assuming value 1 for contiguous regions and 0 otherwise. For instance, in the panel, the dummy for Lombardia region is 1 for neighbour regions (i.e., Piemonte, Veneto, Trentino-Alto Adige, Emilia-Romagna regions) and 0 otherwise. The results, reported in table A.13, confirm our results.

Table A.13. COVID-19 contagion: controlling for neighbour-contagion effects.

	Our results			Sensitivity analysis		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Lockdown	-0.0120***	-0.0121***	-0.0115	-0.0121***	-0.0122***	-0.0007
	(0.0029)	(0.0029)	(0.0074)	(0.0034)	(0.0034)	(0.0019)
Social distancing (events, teaching activities)	0.0013	0.0012	0.0019	0.0009	0.0009	0.0013
	(0.0073)	(0.0073)	(0.0104)	(0.0074)	(0.0074)	(0.0105)
Social distancing (fitness and wellness)	0.0026	0.0025	0.0050	0.0020	0.0019	0.0035
	(0.0054)	(0.0054)	(0.0044)	(0.0058)	(0.0058)	(0.0034)
Social distancing (retail business)	-0.0057	-0.0055	-0.0186	-0.0049	-0.0048	-0.0020
	(0.0048)	(0.0048)	(0.0115)	(0.0053)	(0.0054)	(0.0043)
Social distancing (parks)	-0.0033***	-0.0025**	0.0018	-0.0041***	-0.0036*	0.0021
	(0.0010)	(0.0011)	(0.0012)	(0.0015)	(0.0020)	(0.0013)
Social distancing (industries)	-0.0046***	-0.0048***	-0.0069***	-0.0060***	-0.0061***	-0.0106***
	(0.0012)	(0.0012)	(0.0008)	(0.0018)	(0.0018)	(0.0023)
Disinfection of public transports	-0.0226	-0.0227	-0.0227	-0.0227	-0.0227	-0.0227
	(0.0199)	(0.0199)	(0.0173)	(0.0194)	(0.0194)	(0.0165)
Recovery (delta)	-0.00001**	- 0.00001***	- 0.00001***	- 0.00001***	- 0.00001***	- 0.00001***
	(0.000005)	(0.000005)	(0.000004)	(0.000004)	(0.000004)	(0.000003)
Total cases in neighbouring regions	No	No	No	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	Yes	No	No	Yes	No
Time dummies	No	No	Yes	No	No	Yes
Observations	1,134	1,134	1,134	1,134	1,134	1,134
Number of ID	21	21	21	21	21	21
R-squared						
within	0.1756	0.1757	0.1951	0.1855	0.1855	0.2059
between	0.8470	0.8473	0.8449	0.8702	0.8704	0.8680
overall	0.2009	0.2010	0.2196	0.2113	0.2113	0.2308

Notes: The dependent variable is the growth of contagions computed as in equation (1). Policy variables are observed with a 14-days delay. Time trend included in specifications (2) and (5); time dummies included in specifications (3) and (6). Specifications (4), (5), (6) control for total cases, observed with a 14-days delay, in regions neighbouring of Valle d'Aosta, Provincia Autonoma di Trento, Veneto, Toscana, Lazio, Abruzzo, Molise, Puglia, Calabria. ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Total cases in regions neighbouring of Piemonte, Lombardia, Provincia Autonoma di Bolzano, Friuli-Venezia Giulia, Emilia-Romagna, Umbria, Marche, Campania, Basilicata regions omitted because of collinearity. Sicilia and Sardegna omitted because islands. Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

A.7.6 Controlling for the effect of PM10 levels on COVID-19 fatality

The model of COVID-19 fatality (equation 4) examines factors affecting virulence (i.e., the deadliness associated with SARS-CoV-2), focusing the attention on how the healthcare system managed healthcare inputs and evolution of the epidemic. To test the robustness of our results we include in the fatality model the average year levels of PM10. Results of the sensitivity analysis, reported in table A.14, confirm our results.

Table A.14. COVID-19 fatality: controlling for levels of PM10.

	Our results			Sensitivity analysis		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Swabs per population	-0.0258**	-0.0260**	-0.0153	-0.0254**	-0.0257**	-0.0137
	(0.0119)	(0.0120)	(0.0147)	(0.0118)	(0.0119)	(0.0145)
Hospitalised per swabs	1.7091***	1.7070***	1.3768***	1.7423***	1.7401***	1.4687***
	(0.4354)	(0.4245)	(0.4892)	(0.4327)	(0.4215)	(0.4767)
Confined with symptoms per swabs	1.9368***	1.9399***	1.6377***	1.9411***	1.9404***	1.6679***
	(0.5944)	(0.6030)	(0.3429)	(0.5950)	(0.6005)	(0.3362)
Growth of contagions (delta)	0.0164	0.0162	0.0184	0.0163	0.0161	0.0181
	(0.0293)	(0.0290)	(0.0142)	(0.0293)	(0.0290)	(0.0141)
Hospital beds in intensive care wards	Yes	Yes	Yes	Yes	Yes	Yes
Hospital beds in infectious diseases wards	Yes	Yes	Yes	Yes	Yes	Yes
Physicians per total hospital beds	Yes	Yes	Yes	Yes	Yes	Yes
Healthcare expenditure per population	Yes	Yes	Yes	Yes	Yes	Yes
Male (%)	Yes	Yes	Yes	Yes	Yes	Yes
Old-age rate	Yes	Yes	Yes	Yes	Yes	Yes
Smoker (%)	Yes	Yes	Yes	Yes	Yes	Yes
Death rate	Yes	Yes	Yes	Yes	Yes	Yes
PM10 (avg. year levels)	No	No	No	Yes	Yes	Yes
Observations	1,083	1,083	1,083	1,083	1,083	1,083
Number of ID	21	21	21	21	21	21
R-squared						
within	0.5774	0.5776	0.5890	0.5774	0.5776	0.5890
between	0.5155	0.5156	0.5264	0.6350	0.6381	0.6498
overall	0.5567	0.5568	0.5726	0.5927	0.5937	0.6057

Notes: The dependent variable is the fatality ratio computed as in equation (3). Growth of contagions (delta) is observed with a 14-days delay. Specifications (1), (2), (3) control for observed heterogeneity across regions (i.e., hospital beds in intensive care wards, hospital beds in infectious diseases wards, physicians per total hospital beds, healthcare expenditure per population, percentage of males, old-age rate, percentage of smokers, death rate); specifications (4), (5), (6) control for unobserved heterogeneity across regions (i.e., region dummies). Time trend included in specifications (2) and (5); time dummies included in specifications (3) and (6). ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

A.7.7 Controlling for the effect of additional intensive care units

Healthcare systems should be flexible enough to respond to uneven shocks, such as the COVID-19 pandemic. On May 19, 2020 during the first wave of the pandemic, the Legislation Decree no. 34/2020 “Decreto Rilancio” has increased intensive care units (ICUs) to reduce the pressure on the healthcare system (table A.15).

Table A.15. Intensive care beds before COVID-19 and activated by DL no. 34/2020. Detail by regions.

	Intensive care beds per one million of inhabitants		
Regions	Before COVID-19 pandemic	Activated by LD no. 34/2020*	Total
Abruzzo	94	70 (+ 74%)	164
Basilicata	88	70 (+ 80%)	158
Calabria	55	24 (+ 44%)	79
Campania	58	49 (+ 84%)	107
Emilia-Romagna	101	70 (+ 69%)	171
Friuli-Venezia Giulia	99	45 (+ 45%)	144
Lazio	96	65 (+68%)	161
Liguria	97	47 (+48%)	144
Lombardia	85	55 (+ 65%)	140
Marche	76	78 (+ 103%)	154
Molise	99	30 (+ 30%)	129
Piemonte	75	69 (+ 92%)	144
Puglia	76	66 (+ 87%)	142
Sardegna	80	47 (+ 59%)	127
Sicilia	84	84 (+ 100%)	168
Toscana	92	68 (+ 74%)	160
Trentino-Alto Adige	129	225 (+ 74%)	354
Umbria	78	80 (+ 103%)	158
Valle d'Aosta	80	80 (+ 100%)	160
Veneto	101	103 (+ 102%)	204

Italy	**84**	**66 (+ 79%)**	**150**

Source: National Agency for Regional Health Services, 2021.

*On May 19, 2020, Legislation Decree no. 34/2020 "Decreto Rilancio" provided for an increase in intensive care beds in all regions. Data updated in March 2021.

In a sensitivity analysis, we control for the (potential) effect of additional ICUs (table A.16): our results are confirmed.

Table A.16. COVID-19 fatality: controlling for additional intensive care units (ICUs).

	Our results			Sensitivity analysis		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Swabs per population	-0.0258**	-0.0260**	-0.0153	-0.0259**	-0.0261**	-0.0158
	(0.0119)	(0.0120)	(0.0147)	(0.0119)	(0.0121)	(0.0153)
Hospitalised per swabs	1.7091***	1.7070***	1.3768***	1.7090***	1.7067***	1.3834***
	(0.4354)	(0.4245)	(0.4892)	(0.4314)	(0.4211)	(0.4653)
Confined with symptoms per swabs	1.9368***	1.9399***	1.6377***	1.9344***	1.9378***	1.6297***
	(0.5944)	(0.6030)	(0.3429)	(0.5955)	(0.6040)	(0.3573)
Growth of contagions (delta)	0.0164	0.0162	0.0184	0.0163	0.0162	0.0184
	(0.0293)	(0.0290)	(0.0142)	(0.0293)	(0.0290)	(0.0142)
Hospital beds in intensive care wards	Yes	Yes	Yes	Yes	Yes	Yes
Hospital beds in infectious diseases wards	Yes	Yes	Yes	Yes	Yes	Yes
Physicians per total hospital beds	Yes	Yes	Yes	Yes	Yes	Yes
Healthcare expenditure per population	Yes	Yes	Yes	Yes	Yes	Yes
Male (%)	Yes	Yes	Yes	Yes	Yes	Yes
Old-age rate	Yes	Yes	Yes	Yes	Yes	Yes
Smoker (%)	Yes	Yes	Yes	Yes	Yes	Yes
Death rate	Yes	Yes	Yes	Yes	Yes	Yes
Additional ICUs	No	No	No	Yes	Yes	Yes
Observations	1,083	1,083	1,083	1,083	1,083	1,083
Number of ID	21	21	21	21	21	21
R-squared						

within	0.5774	0.5776	0.5890	0.5774	0.5776	0.5890
between	0.5155	0.5156	0.5264	0.5206	0.5207	0.5295
overall	0.5567	0.5568	0.5726	0.5581	0.5582	0.5737

Notes: The dependent variable is the fatality ratio computed as in equation (3). Growth of contagions (delta) is observed with a 14-days delay. Specifications (1), (2), (3) control for observed heterogeneity across regions (i.e., hospital beds in intensive care wards, hospital beds in infectious diseases wards, physicians per total hospital beds, healthcare expenditure per population, percentage of males, old-age rate, percentage of smokers, death rate); specifications (4), (5), (6) control for unobserved heterogeneity across regions (i.e., region dummies). Time trend included in specifications (2) and (5); time dummies included in specifications (3) and (6). ID are regions/autonomous provinces (Trentino-Alto Adige region divided in Provincia Autonoma di Bolzano and Provincia Autonoma di Trento). Robust standard errors, in parentheses, are clustered at geographical area level.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

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