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Drawing policy suggestions to fight Covid-19 from hardly reliable data. A machine-learning contribution on lockdowns analysis.

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Abstract

Feedback control-based mitigation strategies for COVID-19 are threatened by the time span occurring before an infection is detected in official data. Such a delay also depends on behavioral, technological and procedural issues other than the incubation period. We provide a machine learning procedure to identify structural breaks in detected positive cases dynamics using territorial level panel data. In our case study, Italy, three structural breaks are found and they can be related to the three different national level restrictive measures: the school closure, the main lockdown and the shutdown of non-essential economic activities. This allows assessing the detection delays and their relevant variability among the different measures adopted and the relative effectiveness of each of them. Accordingly we draw some policy suggestions to support feedback control based mitigation policies as to decrease their risk of failure, including the further role that wide swap campaigns may play in reducing the detection delay. Finally, by exploiting the huge heterogeneity among Italian provinces features, we stress some drawbacks of the restrictive measures specific features and of their sequence of adoption, among which, the side effects of the main lockdown on social and economic inequalities.

Keywords: Covid-19; coronavirus; lockdown; feedback control; mitigation strategies.

JEL Classification: C63; I14; I18;

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To know is to know that you know nothing

Socrates

1. Introduction

The academic effort in analyzing and forecasting the pandemic dynamics of the COVID-19 smacks of an unprecedented hackathon. However, the quality of many studies does not always correspond to a comparable quality of the available data. The time series of confirmed cases are the most relevant example. This is not only because of the dependency of the data from the number of swabs and thus on the different testing policies and capacities. Instead, this is an issue assessed by both established epidemic model and econometric identification strategies, taking into account the intensity of swaps, although the real extent of the contagion is still an open issue. A further different and relevant problem comes from the delay occurring from the real contagion up to the time when it appears as a confirmed case in official statistics, i.e. the contagion detecting delay. Different delays concur in determining the overall detected one. The first and more commonly assessed one is the incubation time, which finishes when first symptoms emerge. A time span that the literature suggests at being about 5.2 days and may last up to 14 days, as reported amongst others by Backer et al. (2020), WHO (2020), and Lauer et al. (2020)[2], and that may be related to the features of the infected individual. In the analyses of space data, this might involve a bias related to the corresponding features of the population in the territorial units. Besides, unless a person is tested for other reasons, once the symptom onset, a medical consultation may occur after some days, in the hope for an improvement in their conditions, in particular when the population has little knowledge and is not accustomed to the virus. Time may also be necessary for individuals to be allowed to make the test, in particular when extended test policies are not set up and swap are limited to cases with severe symptoms. Furthermore, available technologies and health system quality impact on the time needed to analyze the swaps. A last delay occurs for the confirmed case to be included in official "daily" statistics. All these delays can be very different both in space and time.

The literature usually set up the overall delay by considering only the average incubation time. The extent of this delay varies from 10 days as in Pederson and Meneghini (2020) to two weeks as in Qiu et al. (2020). Some others consider a higher though exogenously fixed delay to take into account of the other components of the detection delay. For instance, Fanelli and Piazza (2020) consider 20 days, while Remuzzi and Remuzzi (2020) 15-20 days.

The only exception is Casella (2020) that calibrates the additional components of the detection delay by using Chinese and Italy's Lazio Region data to argument against the option of this data to assess feedback control strategy. Indeed, more than a methodological challenge, this is a relevant issue on the assessment of proper policies since many countries are going to relax social distance measures using daily data as signals of inherent restarting exponential growth paths. Furthermore, in the same countries such delays might vary in time because of changing test policies and swap capacities. This might be relevant in particular outside East Asia, for countries having found themselves not prepared to manage the virus at its early stages and having learned in time by their same mistakes how to cope with. Variations in time of this delay may also be related to the level of the contagion, in case of

[2] Some empirical studies actually report a wider range for the COVID-19 incubation period, even up to 24 days after exposure to the virus, but these cases have to be however considered as outliers (Bai et al. 2020; Guan et al. 2020).

saturated health facilities and testing infrastructures. Also, the test technology has been changing during the pandemic widespread by reducing the time for performing the test on swaps (Sheridan 2020; Edwards 2020). Finally, lockdown measures may change the various delays both directly by changing the features of the infected population and indirectly through the different channels above.

The first contribution of the paper is to use a machine learning procedure to get an insight on the overall detection delay and its variations due to the different lockdowns. We consider the case of Italy, the first non-Asian country where the COVID-19 has spread. We move in the same direction of Casella (2020), though in a different framework and perspective, since our aim is to try obtaining some useful insights more than questioning the reliability of feedback control strategies. We provide an iterative procedure to detect possible structural breaks in the dynamics of COVID-19 infections at territorial unit level and to confront the relative impact of each structural break[3]. The machine learning approach allows avoiding any prior about the number and the time distribution of the structural breaks. By analyzing the effect of past lockdowns, this also allows to remove the assumption that a lockdown is effective and also to take into account that its impact on infections might begin before its implementation, as a result of an announcing effect. Through the use of a model selection machine-learning algorithm, we disentangle the dates when significant discontinuities on the epidemic dynamics occur. Since we obtain exactly a number of three structural breaks, we can relate them to the three successive and different lockdown measures adopted and then assess the different detection delays.

As a further contribution out of any forecasting purpose (for which epidemiological models would be better fitted), once computed the dates of the structural breaks, we compare the relative impact of the three consecutive and specific lockdowns (mainly school closure, confinement at home and closure of non-essential activities). Then, the third and final contribution is to exploit the huge differences between Italian provinces features as to focus on some peculiar aspects of discontinuities involved by the three different social distance measures, including controversial side effects and the relationships with economic inequalities.

The sequence of the paper is as follows. We first briefly describe the Italian case: the features and timings of the lockdowns, some descriptive evidences and some related recent literature. Then we present the methodology. The last three sections present the results. First, we show the result of the machine-learning procedure that allows determining the detection delays. Then we analyze the coefficients of the best model selected. Next, we include some interactions with space variant variables in the structural break model to assess for lockdown specific features. The last section concludes. Robustness checks are reported in the Appendix together with data description.

2. The case of Italy

Italy has been the first non-Asian country experiencing the widespread of the COVID-19. Based on data provided by the Italian Civil Protection Department (2020),[4] Figure 1 shows the dynamics of positive cases, hospitalized and deaths from the 24th of February onwards.

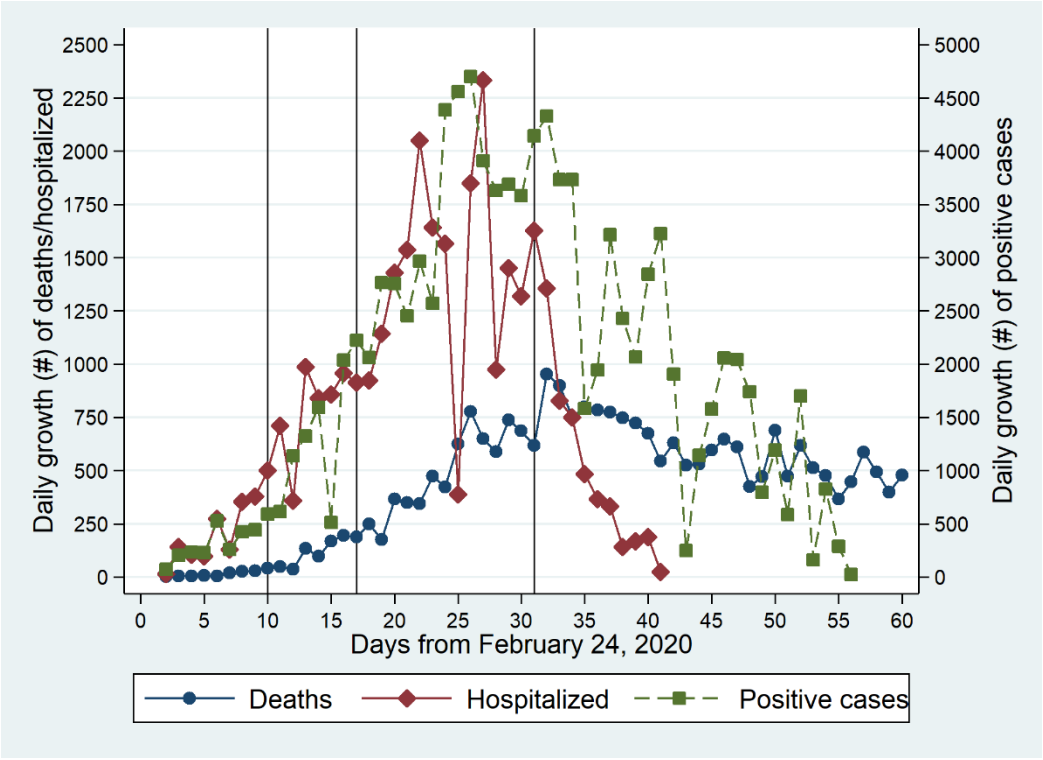
[3] The full Stata Routine detecting the structural breaks is disposable under request to the authors.
[4] Italian Civil Protection Department. Repository of COVID-19 outbreak data for Italy. https://github.com/pcm-dpc/COVID-19.

The dynamics of positive cases and hospitalized people become significant by the end of February, with an exponential trend reaching the peak in the second half of March; afterwards, the respective variations took a declining path. Deaths followed a similar path with approximately a ten days delay, although their extents were still significant at the end of April.

A first measure to prevent the outbreak by the national government was implemented the 30th January, before the virus was officially detected in the country, by blocking all flights to and from China and declaring the state of emergency, thus allowing for higher discretional future policies. The 21st of February, when a cluster of cases was detected in the Lombardia region, the government decided to declare "red areas" and tried to isolate some little municipalities. Nevertheless, the virus spread throughout the North-East of the country and on the 23rd of February, Italy became the European country with the highest number of recorded infected people.

Since the beginning of March, the Italian government reacted to the emergency through a series of increasingly stringent rules for social distancing. It has been the first European country implementing significant restrictions to citizens' mobility and personal freedoms. The first measure at national level was announced and signed by the First Minister Giuseppe Conte on March 4 and became effective the day after. The main restriction concerned the suspension of school activities at any grade.[5]

Figure 1 – Daily growth of COVID-19 deaths, hospitalized and positive cases at national level



Source: Civil Protection Department (2020). Notes: For COVID-19 positive cases we mean the overall number of COVID-19 cases with the exclusion of those who died or recovered. The three vertical lines represent respectively the introduction days of the schools-lockdown, main lockdown and companies-lockdown.

[5] http://www.governo.it/sites/new.governo.it/files/DPCM4MARZO2020.pdf Accessed April 24th 2020.

On March 8, the Italian government signed another extraordinary restriction act for Lombardia and other 14 Northern provinces. This measure became effective the day after although the national press spread the news the day before the act was signed. On March 12, the day-after the World Health Organization declared it as "pandemic", and with the virus already spreading on other regions and provinces, the Italian government extended the same measures to the whole country territory.[6] The measures involved the shutdown of all commercial and retail businesses activities, except to those referred to basic necessities. Even food services as bars and restaurants were closed with the exception of take-away services. Furthermore, people mobility was restricted to work, shopping for food and emergency reasons.

Vertical lines in Figure 1 correspond to the starting dates of national lockdowns. The third vertical line in the graph, on March 25,[7] corresponds to the last containment measure adopted: the closure of all "non-essential" economic activities. The enforcement of this lockdown had a fuzzy evolution: a first version of the decree was announced on March 21, published on March 22 and then modified after a meeting with workers' unions and representations of the entrepreneurs.[8] After this measure, only 53% of firms were allowed to remain opened (Centra et al. 2020).

Many studies have tried to forecast the contagion dynamics in Italy (Remuzzi and Remuzzi 2020; Grasselli et al. 2020; Fanelli and Piazza 2020), or in Italy together with other countries (see amongst others, Zhang and Wang 2020). Some studies have also focused on the lockdowns effect, trying to evaluate the impact in terms of saved life and contagion reduction. Casella (2020) compares two types of restrictive measures: the tight lockdown adopted in China and the significant but less severe measures adopted in the Lazio region concerning the closure of schools and the main lockdown. He develops a control-oriented model capturing the control-relevant dynamics to homogenize territories. He concludes that suppression strategies can be effective if enacted very early, while mitigation strategies are prone to failure.

Pederson and Meneghini (2020) implement a SIQR (Susceptible, Infectious, Quarantined, Recovered) model through which they evaluate the effect of lockdown measures in the North of Italy using data until March 19. They conclude that restrictions measures have slowed down the exponential growth rate, but they did not reduce incisively the COVID-19 spread. Giordano et al. (2020) propose a SIDARTHE (Susceptible, Infected, Diagnosed, Ailing, Recognized, Threatened, Healed, Extinct) model able to predict the epidemic trend. Considering the period from February 20 to April 5, they analyse how the progressive restrictions have affected the spread of the epidemic. They found that lockdown measures had a moderate effect, probably due to their incremental nature. The main conclusion in this paper is that lockdown measures have to be combined with widespread testing and contact tracing to defeat the virus. The document redacted by *Direzione Centrale Studi e Ricerche INPS* (DCSR-INPS 2020) tries to quantify the effect of the third lockdown by exploiting the space variation on the degree of closure of economic activities. This report claims that the reduction in COVID-19 positive cases started from the day the decree was introduced, without any delay. In any case, all this studies but Casella (2020) suffer from the same set of limits in the specification of the detection delay that we already stressed in the introduction. Furthermore, except the DCSR-INPS

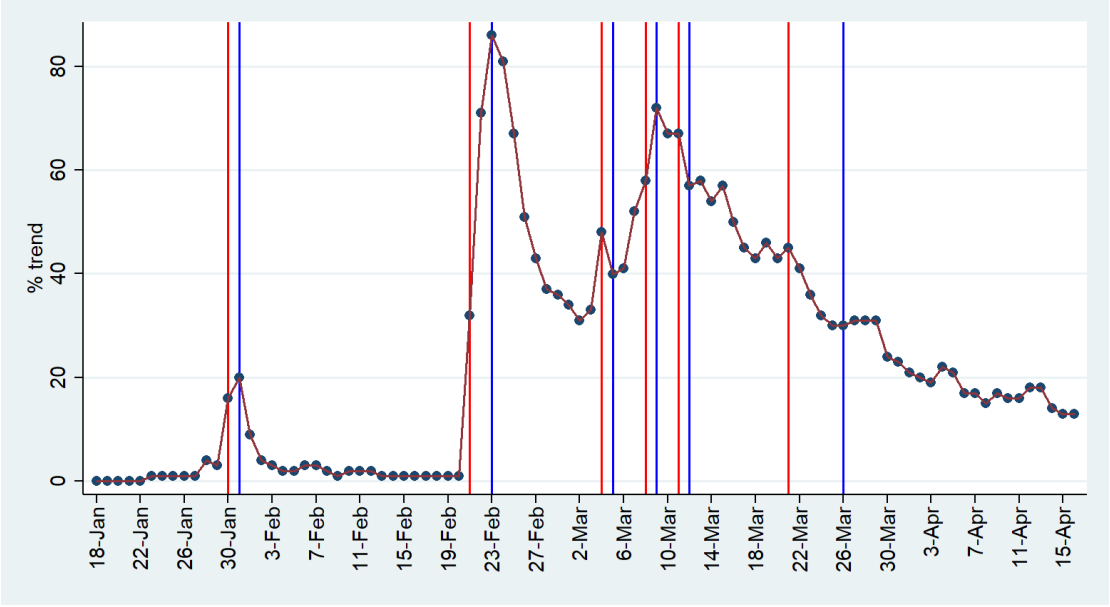
[6] http://www.governo.it/it/articolo/coronavirus-conte-firma-il-dpcm-11-marzo-2020/14299
[7] https://www.gazzettaufficiale.it/eli/id/2020/03/26/20A01877/sg
[8] http://www.governo.it/node/14363

study, they are more focused on the forecasting of possible future scenarios and none perform a retrospective analysis of the features of the different kinds of restrictive measures.

Finally, what such literature have understated is that measures have both direct impacts, due to the specific measures adopted and depending on the date they are enforced, and indirect effects for which things can be different and the distinction between lockdowns fuzzy. A prominent example is the announcement effect. Indeed, the COVID-19 reproductive rate also depends on individual behaviours as avoiding strict and skin contacts or hands washing, that can be modified by the perception and knowledge of the phenomena, on which both the announcement and the implementation of the restrictive measures can have a relevant impact, in particular in a country shaping these perspectives has been one of the most affected by the novel coronavirus.

Figure 2 reports the Google trends in Italy for "*Coronavirus Italia*" from half January to the half of April 2020. The red line corresponds to the announcement date of the corresponding restrictive measure whose actual introduction corresponds to the blue line. The first peak for the Google searches corresponds to the closure date of air traffic with China and the state of emergency announcement. The second peak is also recorded contemporary to the announcement and implementation of "red-zones" in some Northern municipalities. The following peak occurs the 4th of March, when the first national lockdown was announced. From this day on, the Google searches followed an increasing up to the implementation of the following lockdown in the northern regions and starting to decline on March 12, when the second lockdown has been implemented at national level. The upsurge of interest on the phenomenon related to the former restrictive measures announcement might have affected the epidemic path independently from the direct impact of the specific measures.

Figure 2 – Google Trends for "Coronavirus Italia" in Italy

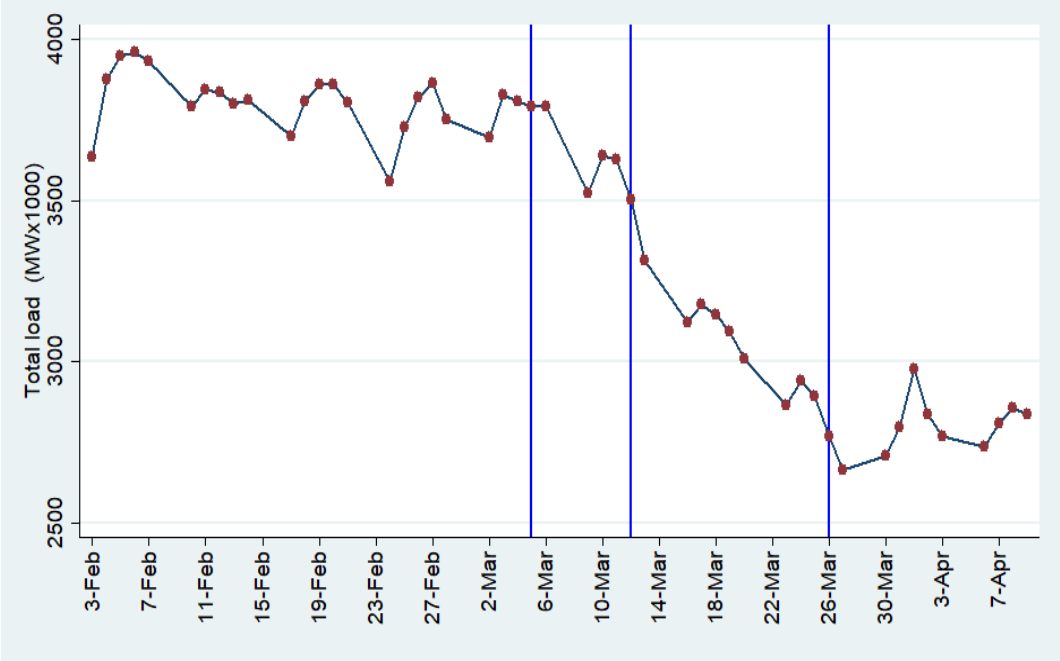


Source: Authors' elaborations from https://trends.google.it.

The same increased awareness might have other indirect effects by a massive shift of white collars towards smart working and the decision of many firms to reduce their overall activities because of the incoming fall in final demand. Figure 3 displays the trend of electric consumptions in Italy from February 3 to April 9, 2020. Blue lines correspond to the dates when the three national lockdowns

were implemented. The electricity consumption reduction begins with the first lockdown, but it decreases sharply after the second and main lockdown. Thus, standard economic activities seem to have decreased their electricity consumptions already after the first lockdowns, although the shutdown was imposed only to a minority of economic activities, mainly schools, food facilities, and part of retail, leisure and cultural activities. The last lockdown, that has imposed the closure of all the (remaining) non-essential activities, seems to have a lesser impact on energy consumption, that some few days later even showed a slightly increase.

Figure 3 – Daily energy consumption in Italy, weekends excluded



Source: Authors' elaboration from https://www.terna.it.

All these descriptive evidences reinforce the need of a non-epidemic econometric strategy to deepen the detection delay issue and to assess the effect involved by the different lockdowns by also inspecting possible indirect and side effects. This is what we try to do in the next section.

3. Methodology

Our underlying hypothesis is that the lockdown involves a structural change on the dynamics of the contagion. This structural change occurs after a time span, the detection delay This might vary from one lockdown to the other according to the specificity of the lockdown, the changing policies on test performing, the progressive technological improvement in the analysis of test results, and the change in the administrative procedures for the accounting of COVID-19 cases. Beside, we assume no priors about the features of dates when this structural breaks should occur, and nor about their number, thus avoiding to assume ex-ante that each or some of the three lockdowns is effective or that some other factors have caused additional structural breaks.

The econometric strategy is composed of two sequential parts. In the first one, we analyze the overall effect of the lockdown on the dynamics of COVID-19 cases by performing a machine learning

algorithm of model selection to select the best structural changes date. Since they actually result to be three, we can thus obtain the delay of each of the three subsequent lockdowns and obtain the best model to assess their effectiveness. However, the result is not the delay of the lockdowns but only the date when they become effective, since, as we discussed in Section 2, part of the lockdown effects could be related on their announcement in previous days. In the second stage, we use exploit the space variability of some variables by studying their interaction with the structural breaks dynamics.

For the first part, we consider the following baseline panel data model specification:

$$\Delta y_{it} = \alpha + \boldsymbol{\beta X_{it}} + \gamma y_{i(t-1)} + \gamma_1 I_{ti}^{t1} y_{i(t-1)} + \gamma_2 I_t^{t2} y_{i(t-1)} + \cdots + \gamma_k I_t^{tk} y_{i(t-1)} + \theta_t + \eta_i + \varepsilon_{it}$$

where y_{it} is the number of COVID-19 cases in province i at time t, $\boldsymbol{X_{it}}$ is a vector of two time varying province level control variables: the number of recovered and the number of deaths at regional level weighted by the share of province level COVID-19 cases over the regional level ones.[9] A more detailed description on both the dependent variable and control variables may be found in Appendix (Table 4). The variables I_t^{tj} are time variant dummies taking value 1 from $t \geq t_j$ and 0 elsewhere and k is the number of lockdowns considered. The dummy variable I_{ti}^{t2} has also the province index since for the 26 provinces that experienced the second lockdown 3 days before (i.e. on March 9 rather than March 12), we correspondently give value 1 also for $t_j - 3 \leq t < t_j$. θ_t and η_i are respectively time and province dummy variables and ε_{it}.

For given k and $t_1 \ldots t_k$ the model is a panel model with time and space fixed effects and k structural breaks for the effect of the lagged variable y on its variations at time t, where the t_j corresponds to the time at which the structural break occurs. To select the best k and t_j we perform a machine learning algorithm by estimating the model for k varying form 0 to 5 for all the possible combinations of the t_k parameters, ranging from the 5th of March to the 24th of April.

The same procedure is repeated for different specifications of the model that exclude alternatively the control variables and the time dummies. Specifically, we define as: 1) Model 1, the model specification with nor time dummies nor control variables; 2) Model 2, the specification with time dummies but no control variables; 3) Model 3, the specification with both time dummies and control variables; 4) Model 4, the specification with control variables but no time dummies.

The best specification of the model is assessed by applying the Akaike information criterion on all the three model estimations, and all possible combinations of k $t_1 \ldots t_k$ and. As further robustness, we perform the same test also including a quadratic specification of the $y_{i(t-1)}$ variable, substituting absolute values with values relative to province level population. Finally, also the alternative BIC information criterion on the model selection has also been applied alternatively to the AIC one and results are confirmed. On the final model selected, we provide the standard Chow test for each structural break.

The machine learning methodology selects $k = 3$ and the optimal t_1, t_2, t_3, for each model specification. Thus, we can analyze the coefficients of the best model selected to assess the relative impact of each of the three lockdowns. Also for this model we perform some further robustness checks reported in the Appendix.

[9] Our imputation corresponds to the hypothesis of fix recovery and mortality rate over the same region. It is worth to notice that in Italy the health system is public (although with a large share of private provision), with management and government totally in charge of regional authorities.

For the last part, we add to the best model selected the interaction with some variables of interests:

$$\Delta y_{it} = \alpha + \boldsymbol{\beta X_{it}} + \gamma y_{i(t-1)} + \delta_0 z_i y_{i(t-1)} + \gamma_1 I_{ti}^{t1} y_{i(t-1)} + \delta_1 z_i I_{ti}^{t1} y_{i(t-1)} + \gamma_2 I_t^{t2} y_{i(t-1)} + \delta_2 z_i I_t^{t2} y_{i(t-1)} + \gamma_3 I_t^{t3} y_{i(t-1)} \gamma y_{i(t-1)} + \delta_3 z_i I_t^{t3} y_{i(t-1)} + \theta_t + \eta_i + \varepsilon_{it}$$

where z_i is a province varying time fixed variable that will be different for specifications we perform among a set of variables of interest. We consider each variable separately as it allows us to test, together with the changing impact of the variable over the four time span set up by the three lockdown thresholds t_1, t_2 and t_3, also the impact of adding the variable on the coefficients of the baseline model. The variable z_i without interaction is omitted since we already consider province fixed effects.

4. Identification of structural breaks

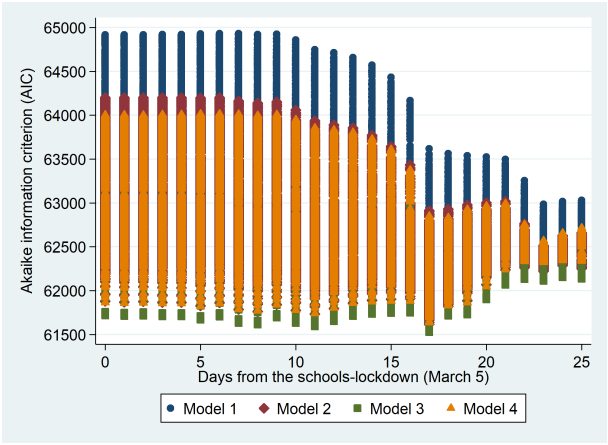
The methodology presented in Section 3 allows identifying the dates of the structural breaks in the path of COVID-19 cases. The procedure selects automatically the numbers and dates of structural breaks and the best model specification using the Akaike information criterion (AIC). The three structural breaks model is always selected as the best one, indicating that the three lockdowns have all had significant impacts. We thus define the corresponding date of the structural break as its effectiveness day.

For the sake of simplicity, to comment results of the machine learning algorithm, we present here the best model selection through a clearer step-by-step procedure. In this case, to find the best model, we thus first select the effectiveness day for the first lockdown (LD1) making varying the dates for the two other lockdowns, then the one for the second lockdown (LD2) fixing LD1 according to the first step, and finally the one for the last lockdown (LD3) setting LD1 and LD2 according to step two and three. This nested iterative procedure gives the same results of the non-nested (unrestricted) one presented in Section 3. Figure 4-A shows the AIC of all the corresponding regressions, for each combination of parameters and model specification presented in Section 3, using the days from the introduction of the lockdown as reference. We recall that the best model, and thus the combination of days/parameters representing the detection delay of the lockdowns, corresponds to the model with the lowest AIC value.

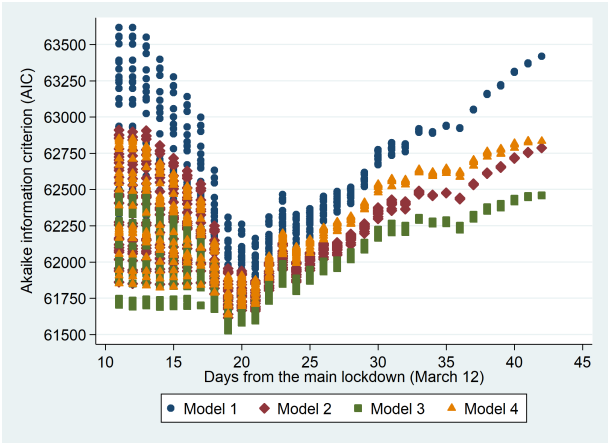
Results in Figure 4 highlight that models performing better in explaining the COVID-19 cases trend are those where the algorithm sets the LD1 effectiveness day 17 days after its introduction (i.e. March 22). Interestingly, the schools-lockdown therefore appears to become effective after a number of days which is greater than the standard incubation period of the novel coronavirus (2-14 days after exposure to the virus, as reported amongst others by Backer et al. 2020, WHO 2020, and Lauer et al. 2020) confirming the relevance of the further components of the detection delay. The same effectiveness day for LD1 is further confirmed by the other model specifications we developed. From estimations illustrated in Figure 4, we can also argue that Model 3 (i.e. the model specification including time dummies and the number of deaths and recovered at provincial level) is the best one to explain the COVID-19 cases trend as its AIC values are always smaller than those reported by the other models.

Figure 4 – Akaike information criterion values by model specification and values of the t_j parameters

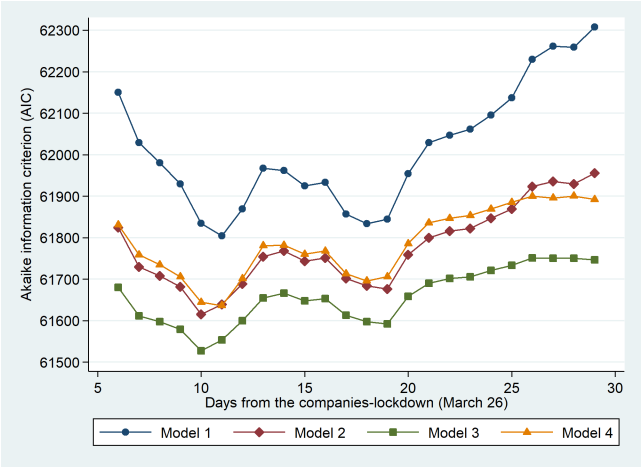
Panel A. Schools-lockdown (LD1)



Panel B. Main lockdown (LD2)



Panel C. Companies-lockdown (LD3)



Notes: The LD1 effectiveness day in models illustrated in Panel B is set up to 17 days after the LD1 introduction. The LD1 and LD2 effectiveness days in models illustrated in Panel C are set up to respectively 17 and 19 days after their introductions.

Once the effectiveness day for LD1 is identified, we select the day from which LD2 became effective looking at models with the lowest AIC values among those presenting this constraint. As a simplification of the algorithm results, Panel B of Figure 4 therefore shows AIC values of models where effectiveness days for LD2 and LD3 vary and the one for LD1 is fixed and equals to 17. Estimates in Figure 4-B highlight that the combinations of parameters which better perform in explaining the COVID-19 cases trend are those where the algorithm sets the LD2 effectiveness 19 days after its introduction. This means that the main lockdown starts to be effective on March 28 for Lombardia and the other 14 provinces listed in the Prime Minister Decree 8 March 2020, and on March 31 for the rest of Italy. Also in this case, the detection delay of LD2 seems to be greater than the presumed incubation period for COVID-19, but the same evidence is confirmed by the other model specifications we developed. The long detection delay of LD2, which is even greater than the LD1 one, may be explained by the fact that the highest daily growth values of people hospitalized because of the novel coronavirus at national level were registered just few days later the main lockdown introduction (see Figure 1 for details). The massive burden of patients suffered by the local health systems in that period, as well as the critical growth of COVID-19 cases, probably slowed down the

application and outcomes of swab tests, thus further delaying the day from which daily count of COVID-19 cases at provincial level reports the LD2 effectiveness start.

Finally, keeping constant the effectiveness day for LD1 (i.e. 17 days after its introduction) and for LD2 (i.e. 19 days after its introduction), this simplification of the machine learning algorithm results displays the day from which LD3 became effective (Panel C of Figure 4). Differently from what seen in Panels A-B of Figure 4, estimates presented here do not show a perfect concurrence between the model specifications analyzed in terms of the LD3 effectiveness day. In particular, the companies-lockdown became effective 10 days after its introduction (i.e. April 5) according to Models 2 and 3, while the LD3 effectiveness day occurred one day later (i.e. April 6) in Models 1 and 4. This slight difference in results is likely related to the exclusion of time dummies in the last two model specifications, which does not allow to control for possible time-variant (but space-invariant) factors. LD3 has so been the lockdown with the shortest detection delay (i.e. 10/11 days versus 17 days for LD1 and 19 days for LD2). There are different potential reasons for this evidence. First, the better knowledge of the novel coronavirus by the Italian population probably led to a reduction in symptoms signaling. Second, the improvement of pandemic management abilities by local authorities, together with the mitigation of the health crisis in most affected areas, has probably determined a decrease in the average time to make swabs to potential infected and to communicate test results. Third, the technology regarding COVID-19 tests has meanwhile improved, leading to swabs which provide test results in a shorter period of time (Sheridan 2020; Edwards 2020). Finally, the marked increase in the number of swabs daily performed (see Figure 6) might have had also an effective role in reducing the detection delay.

The AIC value of the best specification is 61,527.2. The Chow test accepts the structural breaks hypothesis for each of the structural breaks in each model specifications. The same best specification is chosen using the alternative Bayesian Information Criteria (BIC). In the Appendix (Table 5), we report some further robustness checks on the model specification we use to identify detection delays of the three lockdowns. In particular, we tested results of our machine learning algorithm: i) including, without and with time dummies, a quadratic (instead of linear) term for the lagged COVID-19 cases and its interactions with lockdowns variables (i.e. Models 5-6); ii) replacing control variables at provincial level with those at regional one (i.e. Model 7); iii) adding as control variable the number of swab tests made at provincial level (i.e. Model 8).[10] Robustness checks results in Table 5 overall confirm, for each lockdown, the same effectiveness days we detect in our best model specification (i.e. Model 3). The only specification reporting different delays (especially for LD3) is Model 5. This discrepancy however may be explained by the fact that, not including time dummies, Model 5 is not able to catch time-variant province-invariant factors, such as the improvements in swab tests technology occurred at the end of March. Moreover, we added Figure 6 in Appendix which shows how the model fits on actual data provided by the Civil Protection Department for the 2 regions most affected by the novel coronavirus (i.e. Lombardia and Emilia-Romagna) and the most populated region for each of the two others macro-regions of Italy (i.e. Lazio for the Centre and Campania for the South).

[10] The information regarding the number of swab tests suffers the same issue reported by the number of COVID-19 deaths and recovered: it is not available at provincial level but at regional level only. For this reason, also in this case, the variable is calculated for each province weighting regional COVID-19 swab tests by the share of regional COVID-19 cases reported by the same province.

5. Lockdowns effects on the trend of COVID-19 cases

The optimal identification of structural breaks allows us to estimate the relative effects on the dynamics of COVID-19 cases limiting as much as possible any arbitrary assumption.

As explained in Section 3, we estimate lockdowns effects on COVID-19 spread in Italy through a Fixed-Effects panel model, based on four different specifications, and using as dependent variable the daily growth of COVID-19 cases at provincial level. Lockdowns are included in all model specifications as interactions between their specific time dummy and the variable reporting of the overall number of COVID-19 cases at provincial level at time *t-1*. In particular: the dummy *LD1* is equal to 1 from March 22 March onwards (i.e. the 27th day after February 24); the dummy *LD2* is equal to 1 from March 28 onwards for both Lombard provinces and the other 14 provinces listed in the Prime Minister Decree 8 March 2020, while it is equal to 1 from March 31 onwards (i.e. the 36th day after February 24) for the remaining Italian provinces; the dummy *LD3* is equal to 1 from April 5 onwards (i.e. the 41^{h} day after February 24) in Models 2 and 3, while it is equal to 1 from April 6 onwards in Models 1 and 4 (see Section 4 for details).

Estimation results of Model 1 point out that all the three lockdowns have determined a significant alleviation in the COVID-19 spread once they became effective (Table 1). Looking at magnitudes, the schools-lockdown appears to be the most important one in reducing the growth of cases in Italy (the difference in interaction coefficients between LD1 and LD2 is statistically significant at 1 percent level). The predominant effect produced by the schools-lockdown is likely to be related to its ability in reducing mobility and keeping at home a large part of population, composed by children, upper secondary school and university students, teachers and professors, and parents with child-care tasks.

Table 1 - Effects of the three lockdowns on the daily growth of COVID-19 cases (Fixed-Effects Panel Model)

Variables	Model 1	Model 2	Model 3	Model 4
COVID-19 cases $_{t-1}$	0.120***	0.117***	0.125***	0.129***
LD1 * COVID-19 cases $_{t-1}$	-0.059***	-0.060***	-0.058***	-0.057***
LD2 * COVID-19 cases $_{t-1}$	-0.031***	-0.028***	-0.027***	-0.029***
LD3 * COVID-19 cases $_{t-1}$	-0.015***	-0.015***	-0.012***	-0.012***
Number of deaths			0.011	0.021
Number of recovered			-0.052**	-0.067***
Constant	8.165**	0.200	0.178	6.511**
Time dummies	No	Yes	Yes	No
Observations	6,313	6,313	6,313	6,313
R-squared	0.428	0.455	0.463	0.444
Number of provinces	107	107	107	107

*Notes: Standard errors are clustered by Italian province. *** p<0.01, ** p<0.05, * p<0.1.*

At the opposite, Table 1 highlights that the companies-lockdown has been the one with the lowest alleviation effect on the growth of cases in Italian provinces (the difference in interaction coefficients between LD3 and LD2 is statistically significant at 1 percent level). Similarly to LD1, the reason of the smaller effect of LD3 is probably linked to the lower number of people involved by the companies-lockdown (i.e. workers in 'non-essential' economic sectors of activity). The smaller magnitude of LD3 interaction variable may be also related to other two important aspects. First, the

economic activity was seriously indirectly affected already before as a result of the main lockdowns (see the discussion to Figure 2 in section 2). Second, the sectors of activity defined as 'essential' by the Italian government were not necessarily the less exposed to the COVID-19 infection. Third, many companies belonging to 'non-essential' economic sectors asked and realized to be exempted from the lockdown by local authorities.[11]

Table 1 shows that estimated effects of the three lockdowns on the growth of COVID-19 cases, as well as the main conclusions of our analysis, remain overall the same when including time dummies in the model specification (Model 2) and/or the controls for the number of deaths and recovered at provincial level (Models 3 and 4).

As a sensitivity analysis, in the Appendix (Table 6), we replicated the analysis presented in Table 1 for our best model specification (Model 3) in some subsamples. First, given that daily count of new COVID-19 cases may be affected by different (unobservable) local authorities' strategies (e.g. the number of swabs processed or made), we ran Model 3 estimates in a subsample considering even (or odd) days only. Second, as Lombardia has been the most COVID-19 affected region and its provinces may represent outliers, we replicated Model 3 estimates in a subsample excluding 12 Lombard provinces. Finally, we replicated our analysis referring to COVID-19 cases variables defined in relative terms with respect to the provincial population. Specifically, both the dependent variable and the lagged COVID-19 cases variable were divided by the number of inhabitants at provincial level and then multiplied by 10,000. Results of this sensitivity analyses in Table 6 overall confirm the robustness of our evidences on lockdowns effects on the daily growth of the novel coronavirus cases at provincial level.

6. Interactions with province level characteristics

Because of the strong heterogeneity across Italian provinces in terms of demographic and economic characteristics (Bratti et al. 2007; Gallo and Pagliacci 2020 among others), we explore in this Section to what extent some of them interacted with the three lockdowns on the COVID-19. To do that, as explained in Section 3, we add in Model 3 (i.e. our best model specification, see Section 4) interaction terms between the variable of interest.

We focus here on four categories of demographic and economic characteristics: i) provincial territory and infrastructures (i.e. population density, proximity to a hospital, proximity to a railway station); ii) local health system and diseases vulnerability (i.e. share of hospital dismissals regarding people aged 65 or more, past mortality rate for infectious diseases); iii) students and nursing homes (i.e. share of high-school and university students on total population aged 64 or less, number of nursing homes); iv) local labor market and income levels (i.e. unemployment rate among people aged 15-74, share of poor households on total population based on administrative data). More details on these variables are presented in Appendix (Table 4).

[11] An investigation reported by the *IlFattoQuotidiano* on April 25, 2020, shows that almost 200 thousand companies asked an exemption from the lockdown to the local authorities and the majority of them is located in Lombardia, Veneto or Emilia-Romagna, thus the three Italian regions most affected by the novel coronavirus. Link: https://www.ilfattoquotidiano.it/2020/04/25/coronavirus-quasi-200mila-aziende-riaperte-in-deroga-durante-il-lockdown-il-558-nelle-regioni-piu-colpite-prima-la-lombardia/5782265/. Other evidences in the same direction are reported here: https://www.adnkronos.com/soldi/economia/2020/04/07/allarme-sindacati-mila-aziende-chiedono-deroga-stop-governo-vigili_fib07RmwjTQwb0bEvLF51L.html; https://www.quibrescia.it/economia-4/2020/04/27/ritorno-al-lavoro-piu-di-15-mila-richieste-in-deroga-in-prefettura/560734/.

Estimates in Table 2 show that the spread of COVID-19 has been more severe in Italian provinces with higher population density or where a greater number of provincial inhabitants live in municipalities with at least one hospital or a railway station (i.e. our proxies of proximity to a hospital/railway station). This evidence is largely expected because hospitals and crowded places like railways stations or metropolitan areas have probably been important sources of contagion (Koganti et al. 2016; Lau et al. 2004). Nonetheless, as reported by the structural breaks coefficients of population density, more densely populated provinces are those in which the three lockdowns have been more effective, thus the ones where the daily growth of COVID-19 cases decreased the most in the last part of our reference period. These results are consistent with those of Qiu et al. (2020). Instead, the proximity to a hospital or a railway station by the provincial population increased the LD3 alleviation effect only.

Table *2 – Interactions of province level characteristics (infrastructures, local health system and diseases vulnerability) with lockdowns (Fixed-Effects Panel Model)*

Variables	Variable of Interest (VoI)				
	Population density	Proximity to a hospital	Proximity to a railway station	Hospital dismissals by the elderly	Mortality for infectious diseases
COVID-19 cases $_{t-1}$	0.097***	0.078***	0.071***	0.411***	0.129***
LD1 * COVID-19 cases $_{t-1}$	-0.039***	-0.036***	-0.035**	-0.196***	-0.060***
LD2 * COVID-19 cases $_{t-1}$	-0.023***	-0.027***	-0.030***	-0.088***	-0.038***
LD3 * COVID-19 cases $_{t-1}$	-0.006***	-0.007***	-0.005**	-0.072***	-0.014***
VoI * COVID-19 cases $_{t-1}$	0.014***	0.045**	0.054*	-0.305***	-0.006
VoI * LD1 * COVID-19 cases $_{t-1}$	-0.008***	-0.024	-0.029	0.146**	0.002
VoI * LD2 * COVID-19 cases $_{t-1}$	-0.001***	-0.001	0.003	0.065***	0.012***
VoI * LD3 * COVID-19 cases $_{t-1}$	-0.002***	-0.007***	-0.010***	0.066***	0.001
Number of deaths	-0.016	0.028	0.051*	0.015	0.025
Number of recovered	-0.063***	-0.044**	-0.046**	-0.063***	-0.055***
Constant	0.211	0.201	0.189	0.248	0.185
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	6,313	6,313	6,313	6,313	6,313
R-squared	0.493	0.492	0.493	0.482	0.469
Number of provinces	107	107	107	107	107

*Notes: Standard errors are clustered by province. All variables of interest are normalized at mean 1, before being interacted with lockdown variables. *** p<0.01, ** p<0.05, * p<0.1.*

Looking at characteristics of the local health system and diseases vulnerability, last two columns of Table 2 point out that the spread of COVID-19 was lower in provinces with more elderly's hospital dismissals in previous year and where the mortality rate for infectious diseases were higher in the past.[12] In the latter case, the interaction term with the number of COVID-19 cases at time *t-1* is insignificant though. After the introduction of lockdowns, however, the coronavirus infection is relatively greater in these areas. This evidence suggests that lockdown measures may be less effective

[12] Similar evidences occur when looking at the past mortality rate at provincial level for malignant tumors, mental illness, heart diseases and respiratory diseases. Results available upon request to authors.

in less healthy provinces. The same evidence is also confirmed by the third column of Table 3, i.e. the one about nursing homes.

Table 3 – Interactions of province level characteristics (incidence of students, nursing homes, local labour market and income levels) with lockdowns effects (Fixed-Effects Panel Model)

Variables	Variable of Interest (VoI)				
	High-school students	University students	Nursing homes	Unemployment rate	Poverty rate
COVID-19 cases $_{t-1}$	0.482***	0.083***	0.175***	0.110***	0.095***
LD1 * COVID-19 cases $_{t-1}$	-0.254**	-0.039***	-0.090***	-0.058***	-0.045**
LD2 * COVID-19 cases $_{t-1}$	-0.075***	-0.025***	-0.037***	-0.038***	-0.037***
LD3 * COVID-19 cases $_{t-1}$	-0.056**	-0.007***	-0.018***	-0.003	0.001
VoI * COVID-19 cases $_{t-1}$	-0.390**	0.032***	-0.067***	0.016	0.042
VoI * LD1 * COVID-19 cases $_{t-1}$	0.215**	-0.018***	0.043***	0.002	-0.020
VoI * LD2 * COVID-19 cases $_{t-1}$	0.053*	-0.002	0.013***	0.022***	0.016***
VoI * LD3 * COVID-19 cases $_{t-1}$	0.049*	-0.005***	0.009*	-0.021***	-0.022***
Number of deaths	-0.005	0.022	0.019	0.028	0.016
Number of recovered	-0.062***	-0.047***	-0.061***	-0.039**	-0.042**
Constant	0.193	0.225	0.239	0.191	0.188
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	6,313	6,313	6,313	6,313	6,313
R-squared	0.479	0.497	0.476	0.477	0.471
Number of provinces	107	107	107	107	107

*Notes: Standard errors are clustered by province. All variables of interest are normalized at mean 1 before being interacted with lockdown variables. *** p<0.01, ** p<0.05, * p<0.1.*

The incidence of high-school and university students on provincial population aged 64 or less, as well as the more frequent presence of nursing homes, also had a significant role in explaining the trend of COVID-19 cases (Table 3). The daily growth of COVID-19 cases appears higher in the first stage of pandemic in provinces with a greater share of university students and schools-lockdown alleviates this effect as also the companies-lockdown, probably because of the working students.[13] Instead, our estimation results suggest that the opposite occurred in provinces with larger relative numbers of high-school students. The public debate on LD1 had indeed pointed on the possible controversial effects of closing schools without further social distancing measures, because the alternative use of time by teenagers could expose them further more to infections.

[13] The variables reporting the number of university students imputes them to the Italian province in which the university is located, but the national institute of statistics (ISTAT) also provides the same information referred to native/residence provinces. When we look at the incremental effect of university students on the lockdowns impact using this other variable, we observe that it has no significant effect on LD1 and it even worsens the LD2 alleviation effect on the daily growth of COVID-19 cases. This interesting difference may be explained by the fact that university students came back home, on average, pushed up the infection of the novel coronavirus in their native provinces. Several evidences of this phenomenon were reported by different national newspapers, here the links to some of them: https://www.corriere.it/cronache/20_marzo_08/coronavirus-l-esodo-nord-sud-controlli-treni-autobus-arrivo-1100582c-612c-11ea-8f33-90c941af0f23.shtml; https://rep.repubblica.it/pwa/locali/2020/03/20/news/coronavirus_tra_i_contagiati_in_puglia_tanti_genitori_dei_ragazzi_rientrati_da_nord_il_15_aveva_la_febbre-251761879/.

Finally, last two columns of Table 3 highlight that lockdowns effects differ when accounting for the spread of unemployment and poverty at provincial level. As for poverty definition, we used administrative data on declarations of ISEE (i.e. an indicator combining equivalised household income and wealth which is generally declared when applying for social benefits in Italy). For each province, we consider as poor households those declaring an ISEE value lower than 6,000 euros.[14] These two economic dimensions seem not to have influenced LD1 effect on the COVID-19 cases growth, but they significantly reduced the LD2 one. This evidence may be related to the fact that a larger part of population was probably already at home (or at least it moved less frequently) before the main lockdown in Italian provinces with high unemployment and poverty rates. Moreover, the lower effect of the main lockdown in provinces with more poor households may be also explained by the fact that the poor often live in larger households or in worse health conditions (Lanjouw and Ravallion 1995; Sarti et al. 2017). Keeping the poor at home persistently, LD2 might have exposed them to a greater risk of infection.

Since the spread of the novel coronavirus increases the future economic and non-economic damages, this territorial analysis raises great concerns about the effects of the main lockdown on income inequalities. At same time, the opposite signs on inequalities are related to the third and less effective lockdown. This is not an expected outcome as the target of companies-lockdown was to reduce the number of people moving from home for work related reasons, by producing a greater effect in provinces with more active labor markets. This peculiar outcome raises further doubts on the selection process of 'essential activities' since it seems to be biased towards more developed and richer regions[15], the ones most affected by the virus.

7. Conclusions

The motivation of this paper originates from the observation that the huge literature on COVID-19 that have attempted to forecast possible turning points of the contagion dynamics, has been seriously affected by the quality of available data. In particular, we have focused on the time span elapsing from the infection up to its detection in official statistics. Such a detection delay is not only related to the virus incubation period, it relies also on many further components with different sources ranging from behavioral up to procedural and technological ones. This delay may seriously harm feedback control-based mitigation policies. We thus set up a machine learning procedure to detect the structural breaks in the COVID-19 dynamics without any prior about their number and their occurring dates. This simple procedure can be also used to detect other changes that might be induced by relaxing restrictive measures.

By considering the case of Italy, three structural breaks are selected and they can be associated to each of the three main restrictive measures enforced at national level. This allows computing the detection delays and thus to show that the components additional to the incubation period can have remarkable impacts. While sharing some of Casella (2020) awareness about possible ineffectiveness of feedback control strategy, we also show that such delay is not constant. Indeed, considering the date

[14] We adopted this poverty threshold because it represented the income eligibility criterion to have access to the national minimum income scheme in 2018 (i.e. the Inclusion Income measure), which had as main objective to fight absolute poverty. Therefore, we reasonably believe that this threshold identifies households with concrete and severe economic conditions.

[15] https://www.internazionale.it/opinione/roberta-carlini/2020/03/24/lista-chiusura-fabbriche-lavoratori

when the restrictive measures became binding, the detection delay has been 17 days for the first measure, mainly the closure of schools, 19 days for the main lockdown restricting mobility freedom and imposing the shutdown of leisure and retail activities, 10 days for the last lockdown. The increase from the first to the second detection delay can be accounted to the saturation of health facilities since the same days following the second lockdown correspond to the peak of the contagion and of hospitalized people, but also to the mistakes in communication procedures that have increased geographic mobility in the time span between the measure announcement and its enforcement. The remarkable decrease in the third detection delay, while being partially rooted in the improvementlower severity of hospitalized and infection conditions, can also be related to a change in testing procedures and technology, as well as to a better ability of individuals to recognize the symptoms. The delay variability, the saturation and communication effects and also the role of technological advances, can be useful evidences trying to increase the effectiveness of feedback control strategies. They also suggest that wide swap campaigns could also decrease the overall detection delay avoiding such strategies to fail by reducing some of the delay components.

Analyzing the best model coefficients, we show that the first lockdown has been the more effective. Descriptive evidences suggest that, together with the direct effect of school closing, this lockdown has had also a strong indirect announcement effect, making people more aware of the phenomenon at place. The impact of the last measure, the shutdown of "non-essential" activities, results as having been hardly relevant. This is due to the fact that shutdowns of activities and transition to smart working have acquired massively well before the closure was imposed, as electricity data seems to suggest, but also to a definition of essentiality that has been based on criteria not always in line with mitigation strategies.

By exploiting huge space variation of social, health and economic feature of Italian provinces, the final part of the paper has confirmed the interpretation of the results above and obtained some other insights. One of these concerns the sequence of the different measures. This is the case for the controversial effect of the high-schools shutdown in the absence of other social distancing measures. Another relevant one is that the main lockdown has exacerbated social inequalities, an evidence that should be considered when assessing compensation measures in the next phases of this emergency.

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Appendix

Table 4 – Data and variables description

Variable	Source	Definition	Mean	Std. Dev.
Daily growth of COVID-19 cases	Civil Protection Department (2020)	Dependent variable Difference between the overall COVID-19 cases at time t and the overall COVID-19 cases at time t-1 at provincial level	30.07	61.97
Number of deaths	Civil Protection Department (2020)	Number of people dead with COVID-19 infection at provincial level. As this information is available at regional level only, the variable is calculated for each province weighting regional COVID-19 deaths by its share of regional COVID-19 cases	93.63	271.78
Number of recovered	Civil Protection Department (2020)	Number of people recovered from COVID-19 infection at provincial level. As this information is available at regional level only, the variable is calculated for each province weighting regional COVID-19 recoveries by its share of regional COVID-19 cases	156.44	452.55
Population density	ISTAT (2019)	Ratio between total provincial population and total surface area (Km2)	270.13	380.48
Proximity to a hospital	Ministry of Economic Development (2014)	Share of provincial population living in a municipality with at least one 1st level DEA hospital (i.e. a hospital providing first aid, resuscitation, and general surgery services)	0.333	0.171
Proximity to a railway station	Ministry of Economic Development (2014)	Share of provincial population living in a municipality with at least one silver railway station (i.e. a station with more than 2,500 daily visitors on average)	0.456	0.180
Hospital dismissals by the elderly	ISTAT (2018)	Share of hospital dismissals regarding people aged 65 or more (average 2016-2018) at provincial level	0.460	0.049
Mortality for infectious diseases	ISTAT (2017)	Mortality rate for infectious diseases at provincial level (x 10,000 inhabitants)	2.488	0.957
High-school students	ISTAT (2018)	Share of students attending upper secondary schools at provincial level on total population aged 64 or less	0.058	0.007
University students	ISTAT (2017)	Number of students attending universities at provincial level on total population aged 64 or less	0.025	0.026
Nursing homes	ISTAT (2011)	Number of nursing homes at provincial level (x 10,000 inhabitants)	1.129	0.638
Unemployment rate	ISTAT (2019)	Unemployment rate among people aged 15-74 at provincial level	0.104	0.057
Poverty rate	INPS (2018)	Share of households declaring an ISEE[a] lower than 6,000 euros on total provincial population of households	0.072	0.039

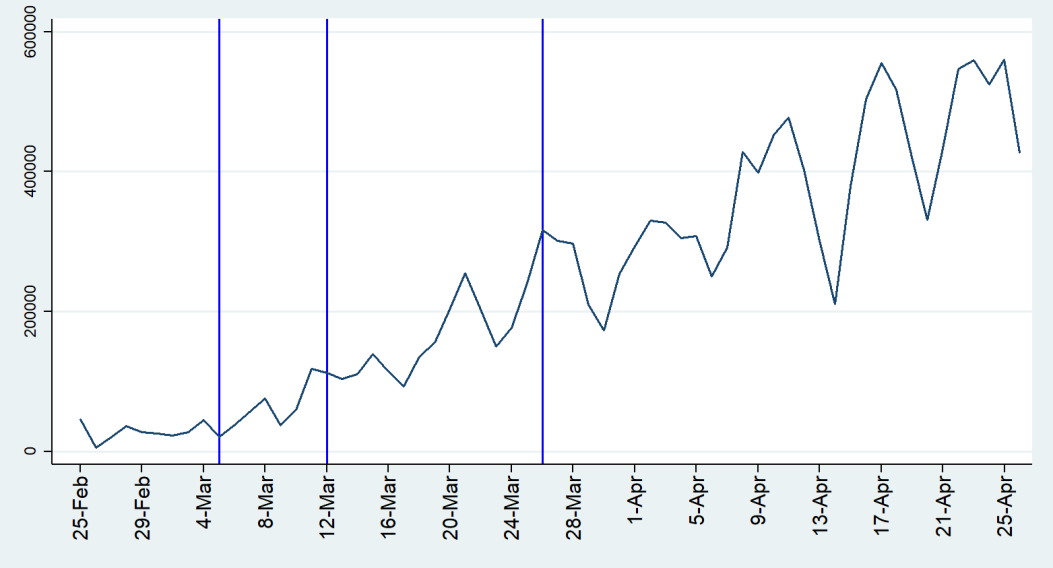
Notes: [a] The ISEE is an indicator combining household income and wealth and it is generally declared when applying for social benefits. It consists of the sum of the household income and 20% of the household wealth (in terms of both financial assets and property) divided by an ad hoc equivalence scale. The ISEE equivalence scale is equal to the number of household members raised to the power 0.65.

Table 5 – Detection delay by lockdown and model specification

Lockdown	Effectiveness delay (number of days from introduction)				
	Model 3	Model 5	Model 6	Model 7	Model 8
Schools-lockdown (LD1)	17	17	17	17	17
Main lockdown (LD2)	19	21	19	19	19
Companies-lockdown (LD3)	10	18	10	10	10

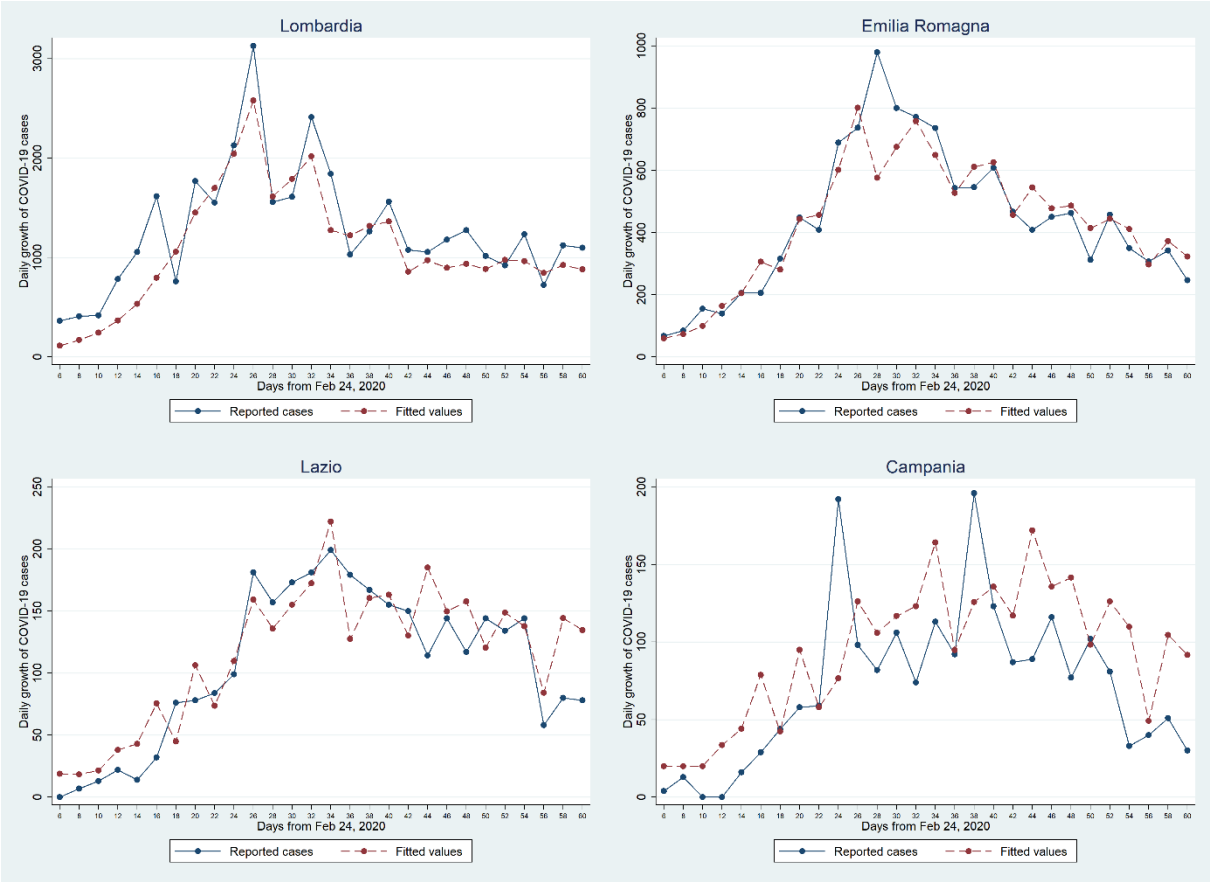
Notes: Differently from Model 3, Model 5 includes a quadratic polynomial of COVID-19 cases at time t-1 and its interactions with lockdowns variables, but there are no time dummies. Model 6 adds time dummies to Model 5. Differently from Model 3, Model 7 includes number of COVID-19 deaths and recovered at regional level instead of provincial one. Model 8 adds to Model 3 the number of swab tests made at provincial level. As this information is available at regional level only, the variable is calculated for each province weighting regional COVID-19 swab tests by its share of regional COVID-19 cases.

Figure 5 – Daily swaps performed at national level



Source: Civil Protection Department (2020).

Figure 6 – Fitted values of the daily growth of COVID-19 cases at regional level



Notes: Fitted values are based on our best model specification (Model 3).

Table 6 – Lockdowns effects on the daily growth of COVID-19 cases by subsample and definition of dependent variable (Fixed-Effects Panel Model)

Variables	Model 3	Only even days	Only odd days	No Lombard provinces	COVID-19 cases every 10,000 inhabitants	No Lombard provinces and COVID-19 cases every 10,000 inhabitants
	(1)	(2)	(3)	(4)	(5)	(6)
COVID-19 cases $_{t-1}$	0.125***	0.129***	0.121***	0.115***	0.069***	0.081***
LD1 * COVID-19 cases $_{t-1}$	-0.058***	-0.060***	-0.056***	-0.055***	-0.038***	-0.052***
LD2 * COVID-19 cases $_{t-1}$	-0.027***	-0.024***	-0.029***	-0.024***	-0.019***	-0.022***
LD3 * COVID-19 cases $_{t-1}$	-0.012***	-0.012***	-0.013***	-0.018***	-0.007**	-0.015***
Number of deaths	0.011	-0.029	0.054	0.149**	0.050	0.206**
Number of recovered	-0.052**	-0.047*	-0.059***	-0.056***	-0.019	-0.018
Constant	0.178	0.172	1.979	0.367	0.008	0.010
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,313	3,210	3,103	5,605	6,313	5,605
R-squared	0.463	0.461	0.475	0.391	0.25	0.241
Number of provinces	107	107	107	95	107	95

*Notes: Standard errors are clustered by Italian province. *** p<0.01, ** p<0.05, * p<0.1. Column 5 replicates estimates in Model 3 but all COVID-19 cases are considered in relative terms with respect to the provincial population. Specifically, both the dependent variable and variable "COVID-19 cases at time t-1" are divided by the number of inhabitants at provincial level and then multiplied by 10,000. Column 6 keeps the same feature of Column 5, but it replicates the analysis in a subsample excluding 12 Lombard provinces.*