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The gray zone: How not imposing a strict lockdown at the beginning of a pandemic can cost many lives[☆]

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ABSTRACT

The public debate on the effectiveness of lockdown measures is far from being settled. We estimate the impact of not having implemented a strict lockdown in the Bergamo province, during the first wave of the COVID-19 pandemic, despite observing an infection rate in this area similar to the one observed in nearby municipalities where a strict lockdown was instead promptly implemented. We estimate the causal effect of this policy decision on daily excess mortality using the synthetic control method (SCM). We find that about two-thirds of the reported deaths could have been avoided had the Italian government declared a Red Zone in the Bergamo province. We also clarify that, in this context, SCM and difference-in-differences implicitly restrict effect heterogeneity. We provide a way to empirically assess the credibility of this assumption in our setting.

1. Introduction

In March and April 2020 the northern Italian province of Bergamo was not only the site of the deadliest outbreak of the first wave of the COVID-19 pandemic in the Western world. It was also the first place where the pandemic gained its foothold in Europe and the first place where the horrors of COVID-19 were felt outside of China. According to official data from the Italian National Institute of Statistics (ISTAT), the small town of Nembro, in the industrial and densely populated Serio Valley in Bergamo province, registered a 1000% increase in deaths in the first three weeks of March 2020, compared to the same period of the previous year (11 deaths in the first three weeks of 2019 against 121 in the first three weeks of 2020).[3] Alzano Lombardo, another town with a comparable population in the same area, registered a 937.5% increase in deaths in the same period (from 8 in the first three weeks of 2019 to 83 in the first three weeks of 2020). The number of deaths in the Lombardy region in March and April 2020 compared to the previous five years average for the months of March and April was 191.2% and 117.1% higher, respectively (ISTAT, 2021).

Surprisingly, the Italian government decided against declaring a Red Zone in the province of Bergamo, despite having opted for it sixty miles to the south, where another serious outbreak of COVID-19 had occurred only a few days before. The opposite policy decisions adopted in response to similar events in two areas of Lombardy in the same time period afford an ideal setting for a quasi-experimental study.

The main goal of this paper is to assess whether a causal relationship exists between (the failure to) declaring a Red Zone in the area of Bergamo in early March 2020, and the daily excess mortality before containment measures had been adopted at national level.

☆ Comments from Matteo Galizzi, Seetha Menon, seminar participants at Birkbeck, University of London, at the Department of Economics and Statistics, University of Siena, at the Department of Economics, University of Bergamo, at DaCHe and from participants at the 2021 A.I.S.Re, DAGstat 2022, ESPE 2022, COMPIE 2022, NHESG 2022, ICEEE 2023, IAAE 2023, EEA2023, and EALE 2023 conferences are gratefully acknowledged. F. Crudu's research benefited from financial support provided by the University of Siena via the F-CUR grant 2274-2022-CF-PSR2021-FCUR 001.

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To estimate the causal impact of not implementing a Red Zone, we use the Synthetic Control Method (SCM, Abadie and Gardeazabal, 2003; Abadie et al., 2010). Specifically, we consider – one at a time – the three main municipalities of the lower Serio Valley, i.e., Nembro, Alzano Lombardo, and Albino, and we use SCM to construct their counterfactual versions in the event that a Red Zone had been promptly implemented. As a robustness check we also implement the augmented SCM of Ben-Michael et al. (2021) and the synthetic difference-in-differences of Arkhangelsky et al. (2021) finding similar results. The former improves pre-treatment fit by allowing for negative weights, the latter allows for differential pre-treatment trends between the treat and the synthetic control as soon as they are parallel.[4]

Finally, we clarify that the assumptions needed to use synthetic control or similar methods, such as difference-in-differences (DID), to estimate the impact of policy interventions in the contest of the COVID-19 pandemic impose restrictions on effect heterogeneity.

It is striking that the lower Serio Valley (in the province of Bergamo) did not opt for a Red Zone despite the contingent and structural similarities with the province of Lodi. It seems unlikely that the opposite decisions in response to the same event stem from different risk assessments or from different attitudes of the population towards the pandemic. The two provinces, in fact, belong to the same region, Lombardy, and are located less than sixty miles away from each other. They share similar socio-economic and demographic structures. In 2020 their population's political orientation was rather similar as well.[5] The homogeneity of conditions suggests that the choice against a Red Zone in the lower Serio Valley was likely to be unanticipated.

To construct the counterfactuals, we use as control units the 11 municipalities that were declared a Red Zone. The comparison between the outcome of the treated municipalities and their estimated counterfactuals provides an estimate of the effect of the policy. Since Red Zone implementation can be considered a treatment that depends on being affected by COVID-19, we also estimate the impact of COVID-19 on our three municipalities. To construct the counterfactual version in the absence of pandemic, we use similar municipalities where COVID-19 did not spread until later.

Our results suggest that declaring a Red Zone around the Serio Valley would have reduced the number of reported all-cause deaths by about two-thirds between March and April 2020.

Our analysis is connected to the recent literature on the effectiveness of non pharmaceutical interventions (NPIs). A Red Zone can be thought of as an articulated set of measures aimed at containing the spread of a disease involving limitations to movement, closure of public spaces and buildings, as well as information campaigns. Such measures do not necessarily imply the use of medical treatments. In the absence of mass screening and aggressive contact tracing, the timely set up of a Red Zone has been recognized as one of the most effective NPIs for containing the spread of COVID-19, preventing hospitals from being overwhelmed, and potentially limiting the number of deaths (Acemoglu et al., 2021; Chernozhukov et al., 2021a; Fagiuoli et al., 2020; Signorelli et al., 2020). Previous studies using counterfactual analysis have shown that strict initial lockdown measures played an important role in limiting the spread of the COVID-19 infection (Cerqueti et al., 2022; Chernozhukov et al., 2021a; Cho, 2020; Fang et al., 2020; Flaxman et al., 2020a). However, there is still considerable uncertainty about the ability of NPIs to mitigate the consequences of the pandemic. In a blog post, for example, Philippe Lemoine questions the robustness of the conclusions in Chernozhukov et al. (2021a) about the effectiveness of mask mandates, which promptly sparked a reply criticizing Lemoine's approach and results (Chernozhukov et al., 2021b).[6] The widely cited paper by Flaxman et al. (2020a) on the impact of various types of NPIs also went through critical scrutiny, see Soltesz et al. (2020) and the reply by Flaxman et al. (2020b).

While the general effectiveness of NPI measures seems to be settled, Singh et al. (2021) suggest that their actual impact may depend on the characteristics of the groups that receive the treatment and ultimately on their compliance. Acemoglu et al. (2021) study the effect of selective lockdowns, targeting different age groups, and find that this approach may significantly outperform uniform policies, particularly when the policy is stricter for the oldest (and at highest risk) age group. This strand of literature suggests that: (a) timely adoption is crucial for NPIs' effectiveness, and (b) policy changes may trigger voluntary changes in individual behavior. In the unfolding of events that led to the Bergamo tragedy both elements were missing.

There are limited studies that directly assess the causal impact of stringent lockdown measures on excess mortality. One notable example is the work by Ege et al. (2023), which evaluates the consequences of Sweden's decision not to impose a lockdown. Their findings suggest that up to 10% of deaths could have been prevented if Sweden had enacted a lockdown, though this analysis spans a significantly extended timeframe. Another pertinent study is Arias et al. (2023), which employs 2020 data from Belgium alongside structural vector autoregressions and local projections methodologies. This research indicates that a strict lockdown could have resulted in approximately 1000 fewer deaths within two months, equating to about 6% of the total 16,840 deaths recorded from mid-March to the end of November 2020. However, due to the differences in the duration covered and the methods used to establish causality, direct comparisons between these studies and our own research are challenging.

Our analysis is also related to public policy decision making under uncertainty and the Precautionary Principle (Gollier et al., 2000; Treich, 2001; Aldred, 2012). The Precautionary Principle defines a standard of risk management, involving a sequential decision process and timely prevention efforts, when the very existence of risk of irreversible or irreplaceable losses is subject to some scientific uncertainty. The risk the virus created to human health justified strong prevention measures, yet in dealing with two very similar situations the Italian Government adopted opposite measures, not conforming to case-based decision theory (Gilboa and Schmeidler, 2001; Gilboa et al., 2006), in which decisions are made by referring to past decision problems and past experiences.

When assessing the impact of lockdown measures, it is important to consider not only their economic and social costs but also the overall benefits or drawbacks to society. Our paper evaluates the foregone advantages, specifically the potential human lives that could have been saved, had a Red Zone been established in the Bergamo area. These missed benefits should be weighed against the costs associated with halting economic activities, which include effects on individuals' employment and earnings as well as on the profits of firms.

The literature on the economic effects of lockdown measures presents varying findings. One study (Auray and Eyquem, 2020) develops a calibrated model to explore the macroeconomic impacts of lockdown policies in Euro area countries, revealing that outcomes vary based on labor market adjustments. If adjustments occur through the intensive margin, characterized by a decrease in labor utilization, the effects include minimal output impacts, negligible unemployment changes, slight welfare losses, and inflationary pressures. In contrast, adjustments through the extensive margin, marked by an increase in job separation, result in significant output, unemployment, and welfare

[4] Robustness checks and additional results are collected in a supplemental appendix.

[5] In 2020 the Province of Lodi was administered by the center-right coalition. The Province of Bergamo was administered by an independent list, with a substantial presence of center-right parties' members in the provincial council. The mayor of Codogno (at the center of the Red Zone), Francesco Passerini, was a member of the Northern League like Camillo Bertocchi, the mayor of Alzano Lombardo in the Serio Valley.

[6] Lemoine's original blog post can be found here: https://www.cspicenter.com/p/lockdowns-econometrics-and-the-art-of-putting-lipstick-on-a-pig.

losses, alongside deflationary pressures. This study suggests that the extensive margin adjustment offers a more accurate depiction of lockdown policies' effects in the Euro area. Another study (Caselli et al., 2022) examines the balance between protecting lives and supporting the economy with lockdown measures. It finds that while lockdowns significantly reduce economic activity during their implementation, stricter lockdowns have diminishing negative economic impacts and enhanced benefits in terms of infection reduction. This indicates that the immediate economic drawbacks of lockdowns could be offset by increased future economic activity, potentially leading to positive economic effects.

In their study focusing on Italy and its labor market outcomes, Casarico and Lattanzio (2022) examine the immediate impacts of COVID-19 on labor market dynamics and the effectiveness of governmental policies in protecting workers from the economic fallout caused by the lockdown. They present evidence of a significant decrease in net hirings, a trend that ceased following the lifting of the nationwide lockdown. This research highlights the critical role of policy interventions in mitigating the adverse effects of the pandemic on employment and underscores the importance of timely and targeted government action in stabilizing the labor market during crises.

The existing body of research partially supports the notion that lockdown measures may lead to temporary and non-structural impacts on the labor market, particularly in developed countries (Pizzinelli and Shibata, 2023). However, our work provides a contrasting perspective by presenting evidence of the irreversible costs associated with the decision not to implement a Red Zone during the initial outbreak of COVID-19. This distinction underscores the critical importance of timely and decisive action in the face of public health emergencies, highlighting the long-term economic consequences of delayed or inadequate responses.

This article proceeds as follows. The next section provides a narrative account of the events relevant to our empirical analysis. Section 3 discusses the identification strategy adopted to assess the causal impact of the failure to declare a Red Zone. Section 4 describes the data in detail. Sections 5 and 6 report our results and inference respectively. Section 7 presents our conclusion. A supplemental appendix contains a battery of robustness checks and results based on alternative SCMs.

2. Background

In January 2020, after the COVID-19 outbreak in the city of Wuhan, family doctors in the Lombardy region had reported anomalous pneumonia cases and were prescribing more scans than usual, but these scans did not include testing for SARS-COV2, because Italy had adopted the new WHO protocols which had limited testing for COVID-19 to people with a link to China.[7]

On February 20, a doctor in the town of Codogno, in Lodi province (Lombardy), broke with WHO protocol and tested a man with serious pneumonia who was not responding to standard treatments. The man's test results came back positive and he became Italy's first known locally transmitted case of COVID-19.

On February 23, the government ordered Italy's military police to seal the borders and declared a Red Zone around 10 municipalities in the province of Lodi, including Codogno, which would last until the nationwide lockdown of March 23. An additional Red Zone was declared around Vo' Euganeo, a small town in Padua province in the Venetian region (Presidente del Consiglio dei Ministri, 2020c). On the same day, another patient tested positive to COVID-19 at the Pesenti Fenaroli hospital of Alzano Lombardo, a town in the Serio Valley, in Bergamo province, 60 miles away from Lodi. While a few days earlier the Minister of Health and the Governor of the Lombardy Region had signed an ordinance to anticipate the Red Zone in Lodi area, no request to establish a Red Zone in the Serio Valley was made by the Region or the mayors of the Serio Valley municipalities.

A unique characteristic of Italy's Red Zones is the sealing of borders by military police, strictly prohibiting the entering or exiting of the zone throughout the containment measure. Within the borders of the Red Zone residents would be quarantined, all commercial activities, schools and universities would be closed, and all non-essential economic activities and public transports would be stopped.

On February 28, when Bergamo's province reported 103 positive COVID-19 cases, Confindustria Bergamo, the province industrial association, posted a video in English titled "Bergamo is running".[8] The central government's committee of scientific advisors from the Higher Health Institute (HHI) did not advise in favor of a Red Zone at that point, nor did Lombardy health officials. The New York Times (Horowitz, 2020) reported that business leaders, and even the Alzano Lombardo mayor, resisted a lockdown, and contacted their commercial associations that had clout in Rome.

On March 2, the government's scientific committee advised in favor of a Red Zone in the Serio Valley around Nembro and Alzano Lombardo. Three days later, the Minister of Health signed the draft decree to implement the Red Zone. However, that decree was not signed by the Prime Minister and never came into force. On the same day, 400 soldiers were sent to the entrance of the Serio Valley with the purpose of sealing the borders. They remained in the area until March 8 2020, before being called back without ever establishing the Red Zone. No popular reaction or uprising has been documented during the four days stay of the military police.[9] On March 8, the whole Lombardy region including Milan was locked down (Presidente del Consiglio dei Ministri, 2020a). This was, however, only a partial lockdown as commercial activities, including shops, bars, and restaurants, and all productive activities, continued almost as usual.[10]

On March 23, the government declared a nationwide lockdown which would last for 69 days until May 18 (Presidente del Consiglio dei Ministri, 2020b). No Red Zone was ever declared in the Bergamo area. As a result, most business activities and manufacturing companies kept working as usual until March 23 despite the apparent lack of masks.

One concern in trying to assess the causal effect of the treatment on mortality is how "exogenous" is the fact that no Red Zone was declared in Bergamo. In light of this anecdotal and documentary evidence it seems unlikely that the missed Red Zone was due to different attitudes in Lodi and in Bergamo towards the pandemic. Rather, it seems that the Red Zone in Lodi was the reaction to the unexpected shock represented by the first outbreak of COVID-19 in Italy and Europe.

In Fig. 1, we present a timeline of public policy measures adopted to contain the first wave of the pandemic. Partial and full lockdowns refer to the entire national territory. Additional measures at the regional and local level were adopted in the same period in different areas of Italy, as detailed in Bosa et al. (2022). Fig. 2 shows a map of the north of Italy and displays the location of the treated municipalities of Alzano Lombardo, Nembro and Albino (dark gray area) near the city of Bergamo (green area), the Red Zone municipalities in the province of Lodi, Lombardy and Vo' Euganeo, Veneto (red area) and the not affected municipalities (blue area).

The decision not to declare a Red Zone in the Serio Valley at the end of February, 2020 is deemed responsible for the spread of infection

[7] As reported by the investigative television program Report on April 6, 2020 (https://www.raiplay.it/video/2020/03/Report---La-zona-grigia-d2723d6e-ca03-426f-9223-6945f1bebe50.html).

[8] The YouTube video can be found here https://youtu.be/Dt13NlmZa2Q.

[9] On April 12 2022 the Council of State established that "for reasons of significant and appreciable confidentiality requirements invoked by the Ministry of the Interior" the State must not disclose why it decided to send 400 soldiers to the entrance of the Serio Valley between 5 and 8 March 2020.

[10] Large shopping malls remained closed during week-ends; bars and restaurants remained open between 6 a.m. and 6 p.m.

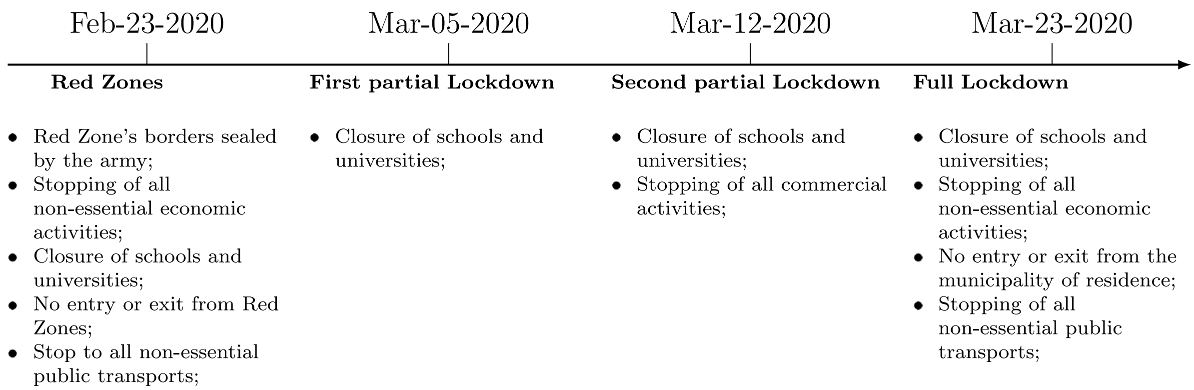


Fig. 1. Timeline of nationwide containment measures.

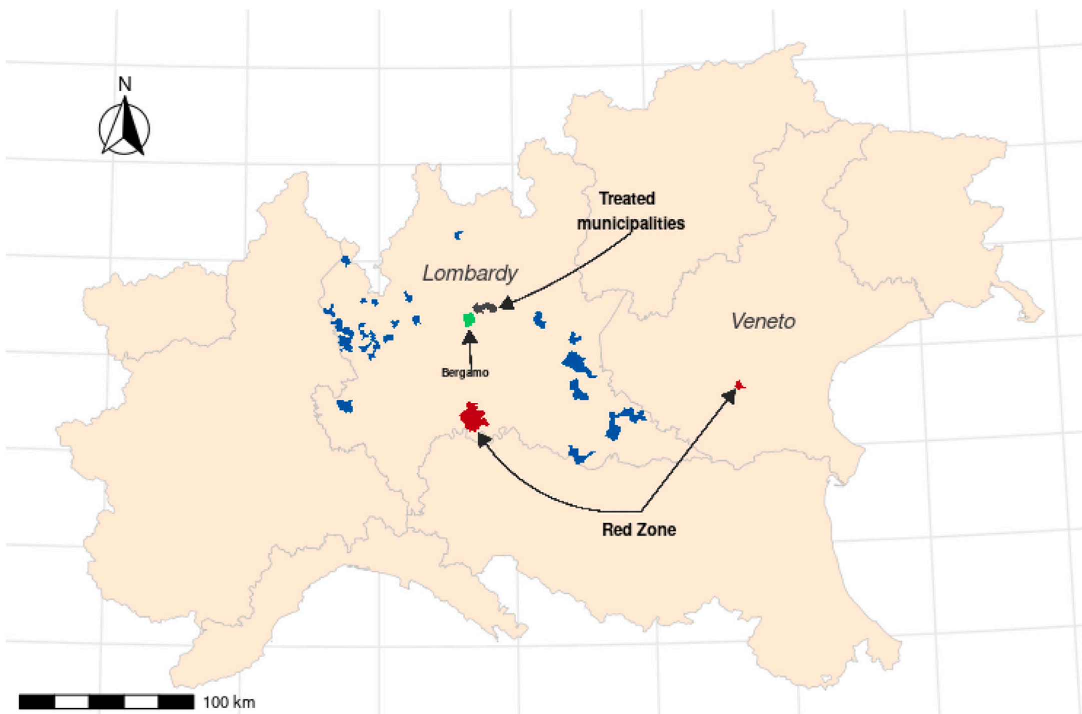


Fig. 2. Map of the North of Italy. *Note:* The dark gray area corresponds to the treated municipalities, while the red and blue areas represent the Red Zone and the not affected municipalities, respectively; the territory of the city of Bergamo is the area in green.. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

to other towns in the province of Bergamo, and then throughout Europe (Alfieri et al., 2022). Judicial investigations are still under way about the legal responsibilities for the country's response to its first coronavirus outbreak. However, as far as we know, no study has assessed whether a causal relationship exists between that political decision and the level of mortality observed in the studied area during the period under consideration.

3. Identification strategy

Our goal is to assess whether a causal relationship exists between the failure to declare a Red Zone in the area of Bergamo in early March 2020 and the rise in mortality observed in the same period. This section discusses our identification strategy in detail. Given that we have a small number of treated and control units, but a relatively long daily panel data set, the SCM introduced by Abadie and Gardeazabal (2003) appears to be the most appropriate choice. However, as the pandemic also had an impact on units in our donor pool, different from the standard setting, we need to impose an extra restriction. Specifically, we need to assume that pre-pandemic characteristics are able to approximate the effect that the pandemic would have had on the Serio Valley municipalities, had they implemented a Red Zone.

In the following, we explain this mechanism, stressing the fact that similar restrictions are implicitly imposed in other prominent studies on the effectiveness of COVID-19-related policy interventions (e.g., Cho, 2020). To better judge the plausibility of this restriction, we make use of a different donor pool that was not affected by the pandemic, at least initially.

We are interested in how the pandemic would have affected the municipalities of the Serio Valley had they imposed a Red Zone. To this end, we define three potential outcomes. We denote by Y_{jt}^{NP} the cumulative excess mortality that municipality j would have experienced at time t if there had been no pandemic. Our second potential outcome, Y_{jt}^{RZ}, is equal to Y_{jt}^{NP} plus *the effect of the pandemic in the presence of the Red Zone*, denoted as β_{jt}. Finally, the third potential outcome Y_{jt}^{NRZ} also includes *the extra effect of not having implemented a Red Zone*, γ_{jt}, which is our effect of interest. We assume that

$$Y_{jt}^{NP} = f_{jt}\ (\text{no pandemic}), \tag{3.1}$$

$$Y_{jt}^{RZ} = \beta_{jt} + f_{jt} = \beta_{jt} + Y_{jt}^{NP} \text{ (Red Zone)}, \tag{3.2}$$

$$Y_{jt}^{NRZ} = \beta_{jt} + \gamma_{jt} + f_{jt} = \gamma_{jt} + Y_{jt}^{RZ} \text{ (no Red Zone)}, \tag{3.3}$$

where f_{jt} are unobserved components that determine the outcome Y. This way of defining the potential outcome is general and does not necessarily impose a factor model as in Abadie et al. (2010). We also assume that the standard stable unit treatment value assumption (SUTVA) holds such that the observed outcome is given by

$$Y_{jt} = \begin{cases} Y_{jt}^{NP} & \text{in the absence of the pandemic} \\ Y_{jt}^{RZ} & \text{in the presence of the pandemic with a Red Zone} \\ Y_{jt}^{NRZ} & \text{in the presence of the pandemic with no Red Zone} \end{cases} .$$

Since the borders of Red Zone municipalities were sealed by the military police, we are not worried about potential spillover effects from the treated municipalities to our main donor pool. The municipalities in our second donor pool have been selected to be far enough from the treated municipalities, such that spillover effects can be ruled out for those municipalities as well. However, it is plausible to have spillover effects to neighbor municipalities not considered in our study. Therefore, not having implemented a Red Zone could potentially have affected a substantially larger area than the three municipalities we consider in this study.

Let us assume that unit 1 is one of the municipalities of the Serio Valley that was affected by the pandemic but which did not impose a Red Zone (our treated unit) and that units from 2 to J are those municipalities that imposed a Red Zone. Furthermore, let T_0 be the number of pre-intervention periods (Days from November 1, 2019 to February 22, 2020, in our case). Let us denote $\hat{w}_j,\ j = 2,\dots,J$ as the weights estimated by a SC-type estimator to recover the potential outcome Y_{1t}^{RZ} of our treated unit in the post-intervention period using the Red Zone municipalities as the donor pool. Assume that, as $T_0 \to \infty$, the set of weights $\hat{\boldsymbol{w}} = (\hat{w}_2,\dots,\hat{w}_J)'$ converges in probability to $\boldsymbol{w}^* = (w_2^*,\dots,w_J^*)'$ such that $f_{1t} = \sum_{j=2}^{J} w_j^* f_{jt} + o_p(1)$. This condition is satisfied, for example, if we assume that f_{jt} follows a factor model as in Abadie et al. (2010), under the assumption of a pre-intervention perfect fit, i.e., $Y_{1t} = \sum_{j=2}^{J} w_j^* Y_{jt} \quad \forall t = 1,\dots,T_0$, and other regularity conditions (see Ferman and Pinto, 2021). Zhang et al. (2022) show that even if the perfect fit assumption is violated the SCM is still asymptotically optimal in the sense that it achieves the lowest possible squared prediction error. Notice that, since our outcome is cumulative excess mortality, our estimator is similar in spirit to the demeaned SC estimator of Ferman and Pinto (2021). Moreover, in a robustness check we use two alternative methods which are designed to relax the perfect fit assumption, i.e., the augmented synthetic control method and the synthetic difference-in-differences. We mentioned at the beginning of this section that, differently from the standard setting described in Abadie (2021), to identify γ_{1t} it is not enough that $\sum_{j=2}^{J+1} \hat{w}_j f_{jt} = f_{1t} + o_p(1)$ but, in addition, we need to assume that the effect of the pandemic was not extreme

$$\sum_{j=2}^{J} w_j^* \beta_{jt} = \beta_{1t}. \tag{3.4}$$

Since we use the original SCM of Abadie et al. (2010), we refer to this assumption as non-extreme pandemic effect (NEPE), as it implies that β_{1t} must lie in (be close to) the convex hull of the effects of the pandemic observed in the donor pool and therefore it cannot be extreme. The problem is that in the pre-pandemic period we only observe Y_{jt}^{NP} for both treated and control units, Y_{jt}^{RZ} is never observed for the treated units and Y_{jt}^{NRZ} is never observed for the units in the donor pool. Even if the SCM assumptions are satisfied, the SCM estimator of γ_1 gives

$$\hat{\gamma}_{1t} = Y_{1t} - \sum_{j=2}^{J} \hat{w}_j Y_{jt}^{RZ} = (\gamma_{1t} + \beta_{1t} + f_{1t}) - \sum_{j=2}^{J} (w_j^* + o_p(1))(\beta_{jt} + f_{jt}).$$

By rearranging, we find

$$\begin{aligned}\hat{\gamma}_{1t} &= \gamma_{1t} + \left(\beta_{1t} - \sum_{j=2}^{J} w_j^* \beta_{jt}\right) + \left(f_{1t} - \sum_{j=2}^{J} w_j^* f_{jt}\right) + o_p(1) \\ &= \gamma_{1t} + bias(\hat{\gamma}_{1t}) + \left(f_{1t} - \sum_{j=2}^{J} w_j^* f_{jt}\right) + o_p(1)\end{aligned}$$

where the $o_p(1)$ term relies on reasonably weak assumptions on the moments of β_{jt} and f_{jt} and $bias(\hat{\gamma}_{1t}) \equiv \left(\beta_{1t} - \sum_{j=2}^{J} w_j^* \beta_{jt}\right)$. Notice that, given the perfect fit assumption, only under NEPE we have

$$\hat{\gamma}_{1t} = \gamma_{1t} + o_p(1). \tag{3.5}$$

Clearly, studies that estimate the impact of policy measures implemented to mitigate the pandemic implicitly impose a similar assumption, as they typically compare a treated group that implemented a certain policy and a control group that did not (see, for example, Cho, 2020). Intuitively, both groups are affected by the pandemic in potentially different ways, regardless of the implemented policy. For example, consider a standard two-periods two-groups DID and let $D_i = 1$ if unit i belongs to the treatment group; let $t = 1$ in the pandemic period and $t = 0$ in the pre-pandemic period, and define the potential outcomes as before. A DID estimator is the sample analog of

$$\gamma_{i1}^{DID} = [E(Y_{i1}|D_i = 1) - E(Y_{i1}|D_i = 0)] - [E(Y_{i0}|D_i = 1) - E(Y_{i0}|D_i = 0)]$$

Assume that the standard parallel trend assumption holds, i.e.,

$$E(f_{i1}|D_i = 1) - E(f_{i0}|D_i = 1) = E(f_{i1}|D_i = 0) - E(f_{i0}|D_i = 0),$$

after some simple algebra we get

$$\gamma_{i1}^{DID} = E(\gamma_{i1}|D_i = 1) + [E(\beta_{i1}|D_i = 1) - E(\beta_{i1}|D_i = 0)].$$

Therefore, DID requires $E(\beta_{i1}|D_i = 1) - E(\beta_{i1}|D_i = 0) = 0$, which is a strong restriction on effect heterogeneity. Callaway and Li (2023) give a different but related reason why using DID is not recommendable in this settings.

Consolandi (2021) shows that the social and geographical characteristics of the territory were among the determinants of the virus outbreak in the Serio Valley. Specifically, the following elements were identified as favoring the contagion: territorial morphology (we control for a measure of altimetric area), the density of the industrial zone and its network of commercial exchanges at national and international level, the intense daily commuting to schools and workplaces, the polycentric type of settlement that characterizes the Po Valley's urban areas (these two aspect are captured by the attraction index). Focusing on early transmission of COVID-19 in New York City, Almagro and Orane-Hutchinson (2021) show that workers in jobs with a high degree of human exposure constituted one of the main determinants of the spread of the virus in New York City (we control for number of people working in the manufacture sector). Glaeser et al. (2021) find that the level of mobility within urban areas was an important factor in explaining the spread of COVID-19 in five major U.S. cities (this is captured by the attraction index). As we explain in the next section, we are able to control for many of the above elements. In light of these studies, our NEPE assumption of Eq. (3.4) appears to be reasonable. However, there are still a few important factors that we are unable to observe, which are arguably relevant for understanding the spread of the virus. Firstly, it would be beneficial to account for variables that measure the number of infected individuals prior to the implementation of the Red Zone. Unfortunately, to the best of our knowledge, this data is not available at the municipal level. Moreover, such a measure would likely be highly susceptible to measurement error. Secondly, it would be crucial to consider the number of available hospital beds at the beginning of the pandemic. However, since all treated and control municipalities are (besides Vo' Euganeo) within their respective provinces, there is no variation in this variable, preventing its use in our analysis. Finally, constructing a measure of awareness about the virus, such as coverage in local media, is not feasible for the same reason.

First, by using units that were not affected by the pandemic at the beginning of the period, we can easily estimate the overall effect of the pandemic in the Serio Valley municipalities. This is done by running a standard SCM using municipalities in Lombardy that are far away from both the Serio Valley and the province of Lodi (see Table 3). Arguably, those municipalities were either not affected or marginally affected by the pandemic, especially at the beginning of the estimation period. Let units from $J+1$ to K be the units not affected by the pandemic and let $\hat{w}_i, i = J+1, \ldots, K$ be the SCM weights. Under the standard SCM assumptions we can recover the total effect of the pandemic on our treated unit as

$$\widehat{\gamma_{1t}+\beta_{1t}} = Y_{1t} - \sum_{i=J+1}^{K} \hat{w}_i Y_{it} = \gamma_{1t} + \beta_{1t} + o_p(1). \tag{3.6}$$

Second, we can similarly estimate the effect of the pandemic on the municipalities that implemented a Red Zone (and received a positive weight):

$$\hat{\beta}_{jt} = Y_{jt} - \sum_{i=J+1}^{K} \tilde{w}_i^j Y_{it} = \beta_{jt} + o_p(1), \quad j = 2, \ldots, J, \tag{3.7}$$

where $\tilde{w}_i^j$ are the weights obtained by running a standard SCM for Red Zone municipality j using the unaffected municipalities as a donor pool.

Recall from Eq. (3.4) that to estimate the additional effect of not implementing a Red Zone we use a weighted average of the effect of the pandemic in the municipalities that implemented a Red Zone, $\sum_{j=2}^{J} \hat{w}_j \beta_{jt}$, to approximate the effect that the pandemic would have had on our treated unit β_{1t} (Assumption NEPE). If NEPE is violated, provided that all the SCM assumptions are satisfied, our estimator of γ_{1t}, $\hat{\gamma}_{1t}$, will have a bias component equal to $bias(\hat{\gamma}_{1t})$.

Given that we are able to estimate the effect of the pandemic on every single municipality that implemented a Red Zone, we can construct a "worst case" estimator of γ_{1t} by replacing $\sum_{j=2}^{J} \hat{w}_j \beta_{jt}$ with the highest effect estimated in municipalities who receive positive weights, i.e.,

$$\hat{\beta}_{1t}^{\max} = \max_{j \in [2,\ldots,J], \hat{w}_j > 0} \hat{\beta}_{jt}.$$

Thus, we can estimate γ_{1t} as

$$\begin{aligned}\tilde{\gamma}_{1t} &= \widehat{\gamma_{1t}+\beta_{1t}} - \hat{\beta}_{1t}^{\max} = \gamma_{1t} + \left(\widehat{\gamma_{1t}+\beta_{1t}} - \gamma_{1t} - \beta_{1t}\right) - \left(\hat{\beta}_{1t}^{\max} - \beta_{1t}\right)\\ &= \gamma_{1t} + bias(\tilde{\gamma}_{1t}) + o_p(1)\end{aligned}$$

where $bias(\tilde{\gamma}_{1t}) \equiv \beta_{1t} - \hat{\beta}_{1t}^{\max}$. This estimator of γ_{1t} will be smaller than $\hat{\gamma}_{1t}$, provided that $\gamma_{1t} + \beta_{1t}$, a quantity we can estimate, is positive with bias $bias(\tilde{\gamma}_{1t})$.

Under the reasonable assumption that the pandemic cannot (at least in the short time period we consider) reduce mortality (i.e., $\beta_{1t} \geq 0$), we can provide two interpretations for $\tilde{\gamma}_{1t}$, depending on whether the true value of β_{1t} is smaller or larger than $\hat{\beta}_{1t}^{\max}$.

It is easy to see that if $\beta_{1t} < \hat{\beta}_{1t}^{\max}$, which is arguably a quite plausible scenario, $\tilde{\gamma}_{1t}$ can readily be interpreted as a lower bound for γ_{1t}. If $\beta_{1t} > \hat{\beta}_{1t}^{\max}$, assuming that not implementing a Red Zone cannot reduce mortality ($\gamma_{1t} \geq 0$ at least in the short run), then $\tilde{\gamma}_{1t}$ overestimates the true effect of not having implemented a Red Zone. If $\tilde{\gamma}_{1t}$ is large, it is unlikely for γ_{1t} to be small or even zero. As $\tilde{\gamma}_{1t} = \gamma_{1t} + \underbrace{\beta_{1t} - \hat{\beta}_{1t}^{\max}}_{bias(\tilde{\gamma}_{1t})} + o_p(1)$, for this to happen the true effect of the pandemic in the treated municipality, β_{1t}, had it implemented a Red Zone, should be much higher than the most extreme estimated effect such that $bias(\tilde{\gamma}_{1t})$ is larger than the true effect γ_{1t}. Since those municipalities are in the same region and are very similar to each other, we believe this is not plausible. Estimates of $\tilde{\gamma}_{1t}$ for every treated municipality are reported in the online appendix.

4. Data

We use an historical data set released by ISTAT on March 5, 2021. The data set contains the daily number of deaths (all-causes) for the period January 1 - October 31, 2020, in all 7903 Italian municipalities (local administrative units, LAUs). In addition, we use data on the daily number of deaths for all Italian municipalities for the years 2011–2019.

The outcome variable of interest is the cumulative daily excess mortality per 1000 inhabitants at the municipality level.[11] Daily excess mortality is measured as the difference between daily mortality and the average mortality on the same day in the previous eight years. Our investigation period runs from November 1, 2019 to October 31, 2020, covering 365 days. The pre-treatment period includes 114 days from November 1, 2019 to February 22, 2020.

In the main analysis, we estimate the causal impact of not declaring a Red Zone, using 11 municipalities that experienced a Red Zone between February 23 and March 23, 2020, as a control group. These include the 10 municipalities in the provinces of Lodi and Vo' Euganeo, a municipality in the province of Padua, which was subject to the same restrictions. Fig. 3 shows the trends in cumulative excess mortality per 1000 inhabitants of our treated units (Albino, Alzano Lombardo and Nembro) and the 11 control municipalities (left panel), and for the unaffected municipalities (right panel).

We notice that Nembro appears to have the highest cumulative excess mortality value among all the municipalities in the left panel in the days prior to the introduction of the red zones. This means that it is not possible to exactly reconstruct Nembro's outcome as a weighted average of the red zone municipalities' outcomes. However, this discrepancy is quite modest and amounts to less than one death per 1000 inhabitants.

To estimate the causal impact of the failure to declare a Red Zone, we need to assume that the impact of COVID-19 we observe in the control units can be used to recover the effect that the treated municipalities would have experienced had they implemented a Red Zone. To further investigate the plausibility of this assumption, we follow the procedure introduced in Section 3 and estimate the impact of the COVID-19 pandemic on the municipalities in our donor pool that received non-negligible weights and the total effect of the pandemic on the treated municipalities. To estimate these effects we use a donor pool consisting of a set of 39 municipalities in the Lombardy region where COVID-19 did not spread until later stages, as we can observe in Fig. 3. The population of these municipalities ranges from 11,000 to 18,000 (similar to our treated) and they are more than 60 km and 50-minute drive from Codogno (the center of the Red Zone) and Albino (the center of the Serio Valley).[12]

The vector of synthetic weights, $\boldsymbol{w} = (w_1, \ldots, w_J)'$, is selected to minimize the discrepancy between the pre-intervention characteristics[13] of the treated unit and those of the donor pool. Let X represents

[11] Measures of cumulative excess mortality evaluate the total extent of mortality from one-time point to another relative to the average for an equivalent period in the past. Daily excess mortality is calculated by taking the observed number of deaths registered on a given day and subtracting the average registered deaths for that day in the previous years. During the pandemic, it is possible for death registration to be affected by delays and changes in practice or by disruption of the related demographic services due to the emergency. This may result in delayed registrations affecting daily excess estimates, although it should not affect cumulative excess mortality where the impact of this on the cumulative figures should diminish over time.

[12] Distances in meters and in minutes of driving time are taken from the distance matrices supplied by ISTAT and can be downloaded at https://www.istat.it/it/archivio/157423. Each regional matrix provides the distance in meters and minutes of driving time between pairs of municipalities within the region. Distances are computed using commercial road graphs.

[13] Following the SCM literature, we use terms characteristics, covariates, control variables, and predictors as synonyms.

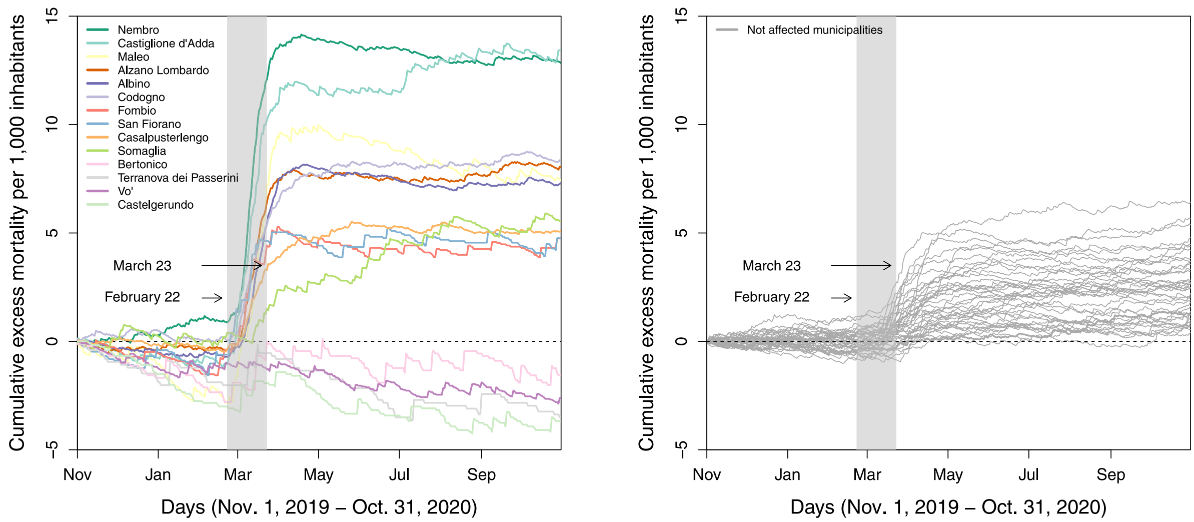


Fig. 3. Cumulative excess mortality per 1000 inhabitants (raw data). *Note:* The left panel shows the trends in cumulative excess mortality per 1000 inhabitants of the treated units (Albino, Alzano Lombardo and Nembro) and the 11 control municipalities. The right panel shows the trends in cumulative excess mortality per 1000 inhabitants of the unaffected municipalities. The gray area represents the treatment period before the nationwide lockdown (Feb. 22–March 23).

the vector of covariates, which also includes the pre-treatment values of the outcome. Additionally, let $\boldsymbol{v} = (v_1, \ldots, v_k)'$ denote a set of weights reflecting the relative importance of each control variable. The SCM chooses the vector of weights $\boldsymbol{w}$ that minimizes the following expression:

$$\left[\sum_{h=1}^{k} v_h (X_1 - w_1 X_2 - \cdots - w_J X_{J+1})^2\right]^{1/2}, \tag{4.8}$$

subject to the constraint that the weights $\boldsymbol{w}$ and $\boldsymbol{v}$ are non negative and sum up to one. Ferman et al. (2020) highlight that employing a data-driven approach to estimate the weights $\boldsymbol{v}$ assigned to each predictor, is essential to avoid the possibility of "cherry-picking" specifications that may produce arbitrarily favorable results. Therefore, following Abadie et al. (2015), we divide the pre-treatment period into a training period and a validation period. We then use the vector of weight $\boldsymbol{v}$ that minimizes the out-of-sample error during the validation period.[14] Klößner et al. (2018) show that, using this cross-validation, different choices of $\boldsymbol{v}$, even when scaled differently, can produce identical outcomes. Therefore, the minimization problem in (4.8) might not have a unique solution. To address this issue, as suggested by Abadie (2021), we show in the online appendix that our results are not particularly sensitive to the choice of $\boldsymbol{v}$.[15] Abadie 2021 emphasize the importance of incorporating strong predictors of the outcome variable since, under the factor model proposed by Abadie et al. (2010), the bias of the SCM is influenced by the variance of unobserved idiosyncratic shocks. Moreover, in our study, it is crucial to adjust for variables correlated with the virus's spread, which could act as potential confounders. Kaul et al. (2015) demonstrate that including all pre-treatment outcome values separately can lead to the assigned weights for other covariates being minimized to the extent that they become negligible. Therefore, we only use the pre-treatment average of the outcome together with the other predictors. The weights assigned to each predictor, for the two donor pools, are presented in Table 2. Notice that the weights of the other predictors are not pushed towards zero by including the pre-treatment average of the outcome, and thus do not seem to be affected by the issue described in Kaul et al. (2015). In particular, following the results of epidemiological studies, which indicate demographic factors such as population, rate of urbanization, and population density as crucial for understanding the spread of COVID-19 (Cho, 2020; Rocklov and Sjogin, 2020), we include the shares of males, the share of individuals aged over 65 and over 85, and the population density (residents per km^2) of each municipality.[16]

We also control for the number of employees in manufacturing and for PM-10 as a measure of air quality.[17] These variables account for the most vulnerable individuals and for those affected by respiratory diseases, which are more widespread in highly industrialized areas and are associated with a high mortality of patients affected by COVID-19. Recent geographical studies (Consolandi, 2021) hypothesize a causal link between the residential and mobility characteristics of the Serio Valley and the COVID-19 outbreak in the same area. To account for these characteristics we include a categorical variable measuring the altimetric area of each municipality ($1 = mountain$, $2 = coastal\ mountain$, $3 = inner\ hill$, $4 = coastal\ hill$, $5 = flat\ land$) and an Attraction Index. The latter varies between 0 and 100 and is computed as the ratio of the inflow of people into the municipality being studied for work or study reasons over the sum of inflows, outflows and resident inhabitants. The index, computed annually, provides a snapshot of the level of mobility

[14] The training period covers November 1–30, 2019, and the validation period spans December 1, 2019, to January 1, 2020. In the online appendix, Figure A.9, we report the results of a robustness check where we add the average of the outcome on the last seven days before the treatment as a further control variable.

[15] We have also experimented with a wide set of additional predictors. The results are similar to the one reported here and are available from the authors upon request.

[16] Population data, measured as resident population in each municipality on December 21, 2019 by gender, come from ISTAT, Demographic Statistics (http://demo.istat.it/bil/download.php?anno=2019&lingua=ita).

[17] Data on employees in manufacturing come from the ISTAT Statistical Register of Active Enterprises (ASIA) archive, which covers the universe of firms and employees of industry and services at the municipal level. PM-10 information comes from Cerqua et al. (2021). They took data from the European Environment Agency (https://bit.ly/3ADQqcu). These variables, together with the share of elderly individuals, allow us to take account of vulnerability in terms of respiratory diseases and conditions associated with a high mortality in COVID-19 infection. PM-10 data in $\mu g/m^3$ is from 573 monitoring stations distributed across the Italian territory. Cerqua et al. (2021) used kriging spatial interpolation to impute the PM-10 average yearly value for each municipality.

in the area under investigation.[18] As for healthcare characteristics, we consider the distance, in meters, of each municipality from the municipality where the first and second closest hospitals are located.[19]

5. Results

Fig. 4 displays the cumulative excess mortality trends for the treated municipalities in the Serio Valley and their synthetic counterparts. The left panel focuses on days between November 1, 2019 and April 8, 2020 (two weeks after the national lockdown began), while the right panel's horizontal axis extends across the entire investigation period, i.e., November 1, 2019, to October 31, 2020 (365 days). Each plot shows the real cumulative excess mortality (solid line), the synthetic counterpart in the presence of the Red Zone (dotted line), the synthetic counterpart in the absence of pandemic, using the Not Affected donor pool (dashed line). The cumulative daily excess mortality remains close to zero throughout the pre-treatment period in Alzano Lombardo, and slightly below zero in Albino. In contrast, this is slightly positive for Nembro starting around January 1, 2020, which could suggest that Nembro might have experienced an anticipation effect of the pandemic compared to the other two treated units. However, the number of excess deaths is rather small and within the variation we observe in the pre-treatment period (see Fig. 3). The synthetic counterparts almost perfectly overlap the observed trends of both Albino and Alzano Lombardo up to the beginning of our treatment period. There is a small difference between Nembro and its synthetic counterparts starting at the beginning of the year, but here, too, the difference is rather small. This suggests that the synthetic units provide a reasonable approximation. These results are confirmed by the covariate balancing. As shown in Table 1, in most cases, the synthetic control units do a good job at reproducing the cumulative excess mortality and predictors values, in contrast with the simple averages of all municipalities in our donor pools.

The synthetic control units for Albino, Alzano Lombardo and Nembro are weighted averages of the municipalities in the donor pools. Table 3 displays the contributions of each of the municipalities in both donor pools to the synthetic control. The weights reported in Table 3 indicate that cumulative excess mortality per 1000 inhabitants prior to the introduction of a Red Zone is best reproduced in the first donor pool (Red Zone) by Codogno, which carries the largest weight for both the synthetic Nembro and Albino and the second largest for Alzano Lombardo for which Vo' Euganeo carries the largest weight. Only three municipalities contribute to the synthetic control of Nembro and Alzano Lombardo while four contribute to synthetic Albino. As it is well known, the sparsity of the weights in Table 3 is typical of synthetic control estimators and is a consequence of the geometric characteristics of the solution to the optimization problem that generates the synthetic controls (Abadie, 2021).

Our estimate of the effect of a Red Zone on excess mortality is the difference between the solid lines on the right panel in Fig. 4 and their dotted counterparts. Immediately after the introduction of a nationwide lockdown the three solid lines begin to bend noticeably, suggesting that the nationwide lockdown has been an effective policy measure. The discrepancy between the solid and dotted green lines suggests a large negative effect on excess mortality in Nembro had the government declared a Red Zone. The effect is less pronounced but still important for Albino and Alzano Lombardo. The difference between each solid line and its dashed counterpart is the total impact of the pandemic on excess mortality in our treated units. The impact on cumulative excess mortality of the introduction of a Red Zone in the Serio Valley, net of the effect of the pandemic, can be assessed considering the difference between the dotted line and the dashed line in each panel in Fig. 4. The Red Zone would have produced a decrease in excess mortality, net of the pandemic.

Table 4 shows the treatment effects on each treated unit on April 8, 2020, i.e., two weeks after the national lockdown, and on the date of the peak excess mortality. The pandemic has increased excess deaths by around 6 and 7 persons per 1000 inhabitants in Albino and Alzano, respectively, on the day at which mortality peaked. This amounts to around 116 and 96 inhabitants, respectively. Having a Red Zone would have saved about 4.5 persons per 1000 inhabitants in Albino and about 5 in Alzano Lombardo (4.61 and 5.35, respectively, see Table 4 column 3), i.e. 82% and 71%, respectively, of the deaths due to the pandemic registered in these two municipalities at peak mortality date. In Nembro, the impact of the pandemic is greater, reaching about 12 deaths per 1000 inhabitants (11.95, see Table 4 column 5) i.e., around 135 inhabitants. The introduction of a Red Zone would have reduced the number of deaths per 1000 inhabitants by about 8 in Nembro at peak mortality date (see Table 4 column 3). Since excess deaths in Nembro reached around 12 persons per 1000 inhabitants two weeks after the end of the Red Zone restrictions, this means that, had the government declared a Red Zone in Nembro, the number of excess deaths would have been about 67% lower. Overall, our results suggest that a strict and timely lockdown would have reduced the number of deaths due to the pandemic at peak mortality date by about three-quarters in Albino and Alzano Lombardo, and by about two-thirds in Nembro.

6. Inference

To run the standard inference procedures of Abadie et al. (2010) we use municipalities that (at least at the beginning) were not affected by the pandemic. In a first step we subtract from the treated municipality outcome a weighted average of the effects of the pandemic in the Red Zone municipalities using the synthetic control weights. This allows us to do inference on the effect of not having implemented a Red Zone (γ_1) using the assumption that the effect of the pandemic in treated municipalities can be approximated by a weighted average of the effects of the pandemic in the Red Zone municipalities ($\beta_1 = \sum_{j=2}^{J} \hat{w}_j \beta_j$). We run in-space placebo tests by applying SCM sequentially to each municipality in our donor pool. At each iteration, we reassign the treatment to one of the municipalities in the donor pool and estimate the impact associated with each placebo run. The cross-sectional distribution of placebo tests for Albino, Alzano Lombardo, and Nembro is shown in Fig. 5(a). In each panel, the gray lines show the gap in excess mortality per 1000 inhabitants between each municipality in the donor pool and its respective synthetic version. The superimposed black line represents the results we obtained for the respective treated unit. We highlight with different colors the trajectories of municipalities with a root mean squared prediction error (RMSPE) ratio larger than the respective treated municipality. In Fig. 5(b) we report the ratios of post- and pre-treatment RMSPE, which provide a measure of the post-treatment gap in excess mortality relative to the estimated pre-treatment gap.[20] First, we observe that the gap for all three treated municipalities is the largest among all positive gaps. For Albino, we find that both Mortara and Fagnano Olona exhibit a higher RMSPE ratio. It is important to note that neither of these municipalities receives

[18] Altimetric area data come from the Main Geographic Statistics on Municipalities by ISTAT, "Statistical Classifications and Size of Municipalities" section (https://www.istat.it/it/archivio/156224). The Attraction Index information comes Sistema Informativo STorico delle Amministrazioni Territoriali (SISTAT) (https://www.istat.it/it/archivio/189907).

[19] Distances in meters from the municipality hosting the closest and the second closest hospital are taken from the Distance Matrices supplied by ISTAT (https://www.istat.it/it/archivio/157423).

[20] We only consider the period between February 22 and April 8 to calculate the post-treatment RMSPE as, most likely due to the National look down of March 23, we observe a general flattening in cumulative excess of all municipalities deaths shortly after this date.

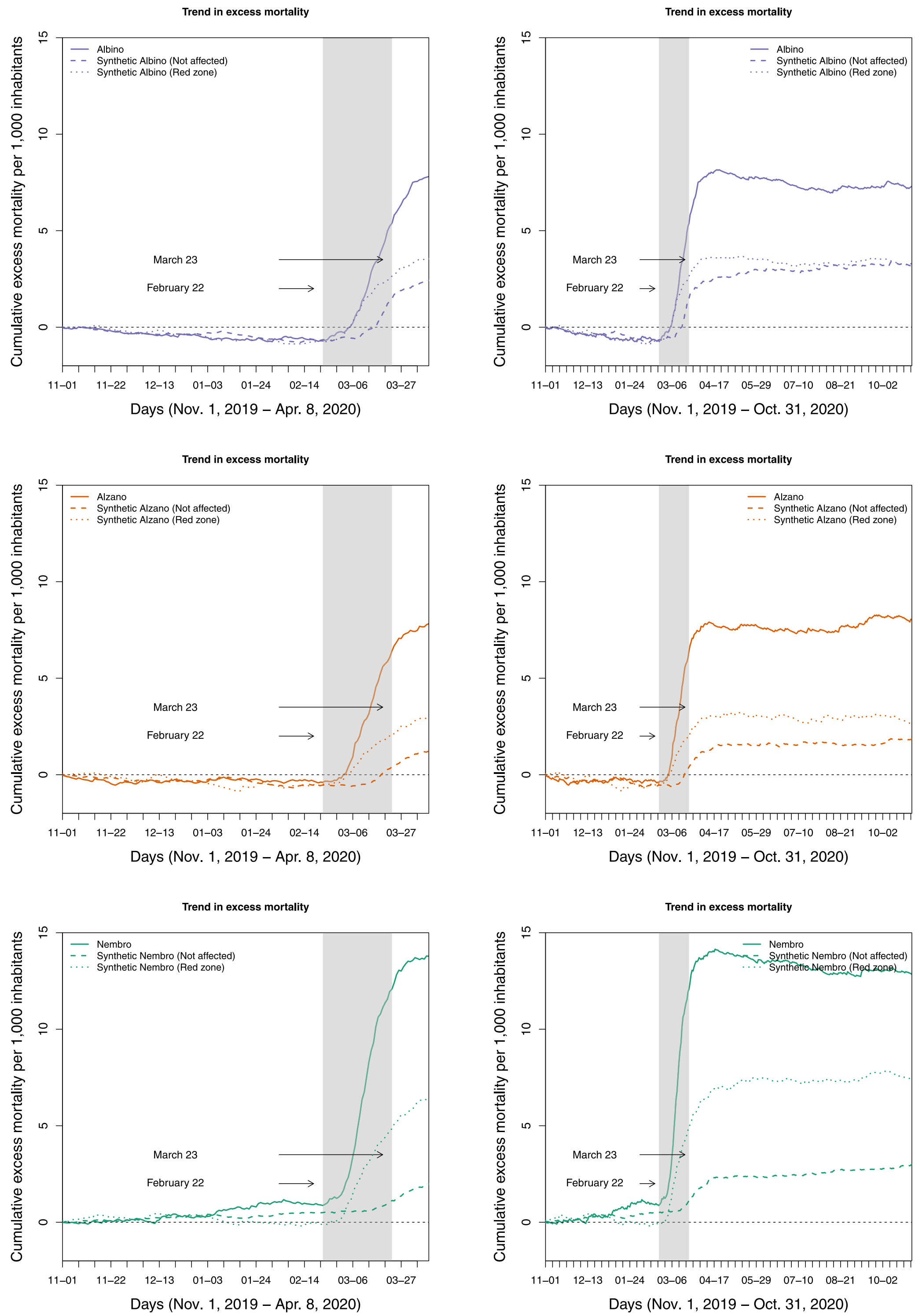


Fig. 4. Trends in cumulative excess mortality per 1000 inhabitants. *Note:* Trends in cumulative excess mortality per 1000 inhabitants for the treated municipalities (solid lines) in the Serio Valley, their synthetic counterpart in the presence of the Red Zone (dotted line), and the synthetic counterpart in the absence of the pandemic, using the not affected donor pool (dashed line). The gray area represents the treatment period before the nationwide lockdown (Feb. 22–March 23). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a high weight; Fagnano Olona, for example, receives about 4.4%. We report in the online appendix a leave-out-out exercise to ensure that our results are not driven by assigning weights to municipalities that have a negative gap. Additionally, when estimating the effect of not having implemented a Red Zone, we use the Red Zone municipalities. Among those, Albino assigns weight to Vo' Euganeo, which has a small, negative observed excess mortality. However, since this is the only municipality in a different region (Veneto), we conduct specific robustness checks, by excluding it, as detailed in the online appendix. We also perform a leave-one-out exercise for the main effect. Looking at post-treatment RMSPE, only Fagnano Olona, which has a negative gap, is above Albino. It is noteworthy that Albino's post-treatment RMSPE is substantially higher than that of Mortara. We find that Mortara, Cardano al Campo, and Fagnano Olona have a higher RMSPE ratio than

Table 1
Excess mortality, demographic, and geographical predictors means.

Red Zone							
Mortality, Demographic and Geographic variables	Albino		Alzano Lombardo		Nembro		Average of all donors ($n = 11$)
	Real	Synthetic	Real	Synthetic	Real	Synthetic	
-Cumulative excess mortality per 1000 inhab.	−0.43	−0.37	−0.39	−0.34	0.23	0.25	−0.58
-PM-10 (2019)	27.99	32.61	28.12	32.69	28.12	32.65	32.51
-Share of male population (2019)	0.49	0.49	0.49	0.49	0.49	0.48	0.50
-Share of population over 65 (2019)	0.21	0.22	0.21	0.24	0.22	0.23	0.22
-Share of population over 85 (2019)	0.03	0.03	0.03	0.03	0.03	0.03	0.03
-Employees in manufacturing (2017)	2029.75	880.48	582.13	885.83	946.02	1447.79	347.06
-Attraction index (2015)	32.63	33.20	30.13	29.99	36.23	37.52	24.44
-Population density (2019)	559.58	451.34	999.90	460.65	755.77	719.39	268.45
-Altimetric area	1.00	4.67	3.00	3.99	3.00	5.00	4.82
-Distance from the closest hospital	8100.20	6996.11	0.00	5107.57	3708.14	2882.10	10264.65
-Distance from the second closest hospital	14647.63	13474.50	7087.21	12188.25	9955.18	10439.82	17305.17
Not Affected							
Mortality, Demographic and Geographical variables	Albino		Alzano Lombardo		Nembro		Average of all donors ($n = 39$)
	Real	Synthetic	Real	Synthetic	Real	Synthetic	
-Cumulative excess mortality per 1000 inhab.	−0.43	−0.40	−0.39	−0.37	0.23	0.23	0.04
-PM-10 (2019)	27.99	30.34	28.12	28.84	28.12	28.15	28.51
-Share of male population (2019)	0.49	0.50	0.49	0.50	0.49	0.49	0.49
-Share of population over 65 (2019)	0.21	0.18	0.21	0.19	0.22	0.22	0.21
-Share of population over 85 (2019)	0.03	0.02	0.03	0.02	0.03	0.03	0.03
-Employees in manufacturing (2017)	2029.75	2051.27	582.13	1521.27	946.02	1368.77	1543.44
-Attraction index (2015)	32.63	32.21	30.13	27.85	36.23	35.58	32.58
-Population density (2019)	559.58	586.70	999.90	918.37	755.77	723.96	1000.32
-Altimetric area	1.00	4.57	3.00	4.67	3.00	3.00	4.23
-Distance from the closest hospital	8100.20	7669.61	0.00	6090.03	3708.14	3394.06	6919.05
-Distance from the second closest hospital	14647.63	14655.71	7087.21	10173.52	9955.18	15029.75	19787.23

Notes: Cumulative excess mortality per 1000 inhab. and PM-10 are averaged in the period December 1, 2019 - January 1, 2020. All other predictors are time-invariant. The Attraction index is missing for Casalpusterlengo. PM-10 is measured in micrograms per cubic meter; distance is measured in meters; the Attraction index is computed as the ratio of the inflows of people into the municipality under investigation for work or for study reasons, over the sum of inflows, outflows and resident inhabitants; Altimetric area is a categorical variable: 1 = mountain, 2 = coastal mountain, 3 = inner hill, 4 = coastal hill, 5 = flat land.
Day 1 is November 1, 2019. The Red Zone was implemented on February 23, 2020. The pre-treatment period is 114 days.

Table 2
Synthetic control weights predictors.

Red Zone			
Mortality, Demographic and Geographic variables	Albino	Alzano Lombardo	Nembro
Cumulative excess mortality per 1000 inhab.	0.30	0.06	0.07
PM-10 (2019)	0.00	0.00	0.00
Share of male population (2019)	0.02	0.15	0.00
Share of population over 65 (2019)	0.21	0.11	0.01
Share of population over 85 (2019)	0.08	0.00	0.01
Employees in manufacturing (2017)	0.01	0.00	0.00
Attraction index (2015)	0.00	0.11	0.20
Population density (2019)	0.07	0.16	0.36
Altimetric area	0.01	0.19	0.00
Distance from the closest hospital	0.18	0.06	0.27
Distance from the second closest hospital	0.10	0.15	0.06

Notes: Predictors weights for the two donor pools. To determine the weights assigned to each predictor, we divided the pre-treatment period into a training period and a validation period. The training period encompassed days from November 1 to 30, 2019, while the validation period spanned from December 1, 2019, to January 1, 2020. We then identified the optimal weights by minimizing the out-of-sample error observed during the validation period.

Alzano. However, the latter two exhibit negative gaps. Fagnano Olona receives the highest weight, which could lead to an overestimation of the pandemic's effect. As mentioned above, we address this issue through a leave-one-out robustness check. As for Albino, this would not affect our estimate of the effect of not implementing a Red Zone. Alzano also gives substantial weight to Vo' Euganeo. As shown in the online appendix, our results are robust to leaving one of the Red Zone municipalities out as well as excluding Vo' Euganeo from the donor pool. When looking at post-treatment RMSPE, Alzano is the municipality with the highest value. Mortara, Calcinato, and Gavardo have a higher RMSPE ratio than Nembro, the latter exhibiting a negative gap. Only Gavardo receives a substantial weight, while neither Calcinato nor Mortara receive any weight. This could imply an overestimation of the pandemic's effect but does not impact the estimated effect of not implementing a Red Zone. Moreover, Nembro does not assign any weight to Vo' Euganeo. Nevertheless, we also run the same robustness checks for Nembro. Nembro's post-treatment RMSPE is by far the largest, almost three times larger than the second largest.

The p-values for the effect of not having implemented a Red Zone can be calculated as $\frac{\sum_{j=1}^{40} I(RMSPE_1 \geq RMSPE_j)}{40}$, where $I(\cdot)$ is the indicator function. Using the RMSPE ratio in Fig. 5(b), the estimated p-values are 0.075 for Albino, and 0.1 for both Alzano and Nembro, respectively. Using the post-treatment RMSPE instead, would give a p-value of 0.025 for Nembro and Alzano and of 0.05 for Albino (see Fig. 5(c)).

Table 3
Municipalities' weights in the synthetic units.

Red Zone					Not Affected				
	Donor pool ($n = 11$)	Albino	Alzano Lombardo	Nembro		Donor pool ($n = 39$)	Albino	Alzano Lombardo	Nembro
1	Vo'	0.164	0.503	0	1	Cardano al Campo	0	0	0.001
2	Bertonico	0	0	0	2	Caronno Pertusella	0	0	0
3	Casalpusterlengo	0	0	0.089	3	Castellanza	0	0	0
4	Castiglione d'Adda	0	0	0	4	Fagnano Olona	0.044	0.524	0.001
5	Codogno	0.484	0.494	0.865	5	Lonate Pozzolo	0	0	0.009
6	Fombio	0.111	0.003	0	6	Luino	0	0	0.143
7	Maleo	0	0	0	7	Malnate	0	0	0.001
8	San Fiorano	0	0	0	8	Olgiate Olona	0	0	0.001
9	Somaglia	0	0	0	9	Samarate	0	0	0.11
10	Terranova dei Passerini	0.175	0	0	10	Sesto Calende	0	0	0.001
11	Castelgerundo	0.066	0	0.046	11	Somma Lombardo	0	0.013	0
					12	Erba	0	0	0.001
					13	Olgiate Comasco	0.215	0	0.001
					14	Morbegno	0	0	0
					15	Arluno	0	0	0.002
					16	Busto Garolfo	0	0	0.001
					17	Canegrate	0	0	0.001
					18	Castano Primo	0	0	0
					19	Cerro Maggiore	0	0	0
					20	Cesate	0	0	0.001
					21	Nerviano	0	0	0
					22	Rescaldina	0	0	0.001
					23	Solaro	0	0	0.049
					24	Vanzaghello	0	0	0.197
					25	Bedizzole	0	0	0
					26	Calcinato	0.742	0.297	0
					27	Carpenedolo	0	0	0
					28	Gardone Val Trompia	0	0	0.23
					29	Gavardo	0	0	0.24
					30	Lonato del Garda	0	0.167	0
					31	Sarezzo	0	0	0.002
					32	Mortara	0	0	0
					33	Casalmaggiore	0	0	0
					34	Castel Goffredo	0	0	0
					35	Curtatone	0	0	0
					36	Porto Mantovano	0	0	0.001
					37	San Giorgio Bigarello	0	0	0.002
					38	Besana in Brianza	0	0	0.002
					39	Lentate sul Seveso	0	0	0.001

Notes: Contributions of each of the municipalities in both donor pools to the synthetic control. The weights indicate that cumulative excess mortality per 1000 inhabitants prior to the introduction of a Red Zone is best reproduced in the first donor pool (Red Zone) by Codogno, which carries the largest weight for both the synthetic Albino and Nembro and the second largest for Alzano Lombardo for which Vo' Euganeo carries the largest weight.

Table 4
Treatment effects on each treated unit per 1000 inhabitants.

	Red Zone		Not Affected	
	April 8, 2020	Peak mortality date	April 8, 2020	Peak mortality date
Albino	4.27	4.61	5.38	5.64
Alzano Lombardo	4.91	5.35	6.59	6.73
Nembro	7.38	7.84	11.80	11.95

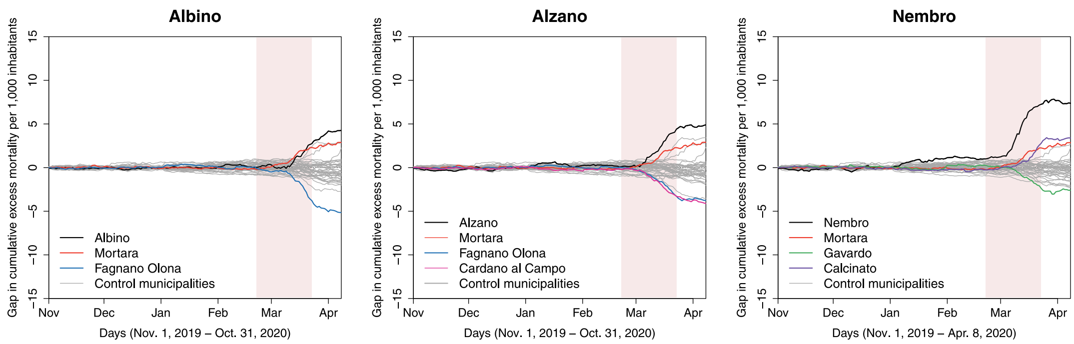
Notes: The second and third columns show the reduction in the number of deaths per 1000 inhab. had a Red Zone been introduced on April 8, 2020 and on the date of the peak of excess mortality, respectively, for each of the treated units on the rows. The fourth and fifth columns show the reduction in the number of deaths per 1000 inhab. absent the pandemic on April 8 2020 and on the date of the peak of excess mortality, respectively, for each of the treated units on the rows.

7. Conclusion

Using the synthetic control method, we estimate the causal effect of not imposing strong social distancing restrictions on cumulative excess mortality at the beginning of the COVID-19 pandemic in three municipalities of the Bergamo province. We demonstrate that implementing a Red Zone, as other municipalities in the Lombardy region did, could have prevented up to 67% of the deaths caused by the pandemic in those areas. Additionally, our descriptive analysis suggests that the nationwide lockdown potentially played a significant role in mitigating the pandemic's impact. These effects are robust across all standard robustness checks and the use of different estimation methods and inference procedures.

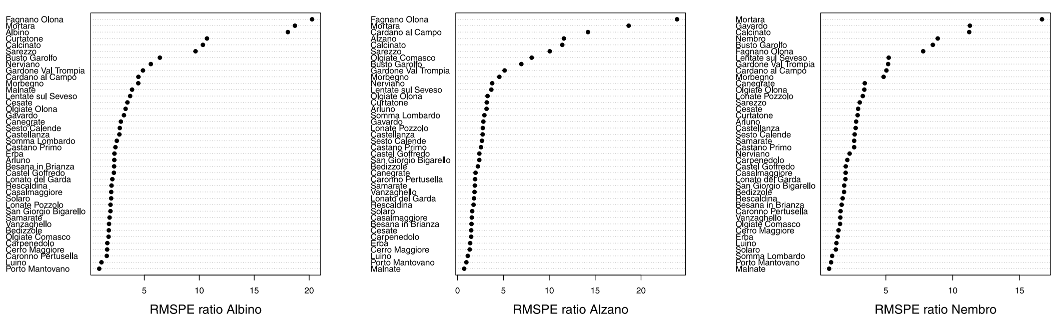
Our study contributes to the literature on the trade-offs between protecting lives and sustaining the economy and labor market through strict lockdowns, by highlighting their potential benefits in saving lives. Methodologically, we demonstrate that studies using synthetic control or similar methods (e.g., difference-in-differences) to estimate the impact of policy interventions implicitly assume a baseline scenario of how the pandemic would have influenced the treated units without the policy. To validate this assumption in our study, we analyze municipalities that were unaffected in the pandemic's early stages.

(a) Placebo tests.



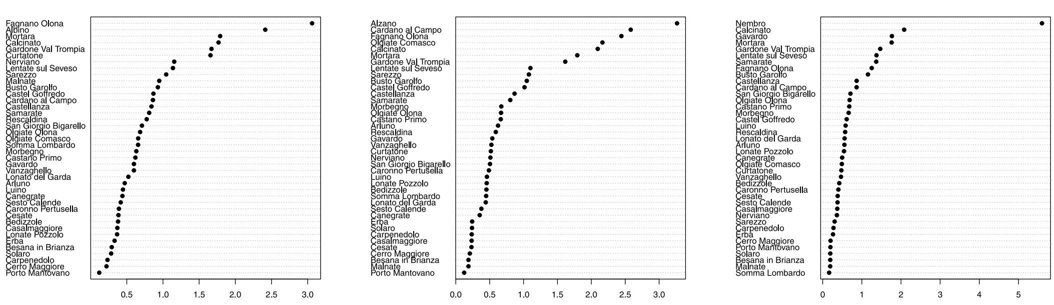
Note: Gaps in excess mortality per 1,000 inhabitants between each municipality in the donor pool and its respective synthetic version (gray lines); the treated municipality and its synthetic version (superimposed black line); municipalities with RMSPE ratio larger than the respective treated municipality and their synthetic counterpart (colored lines). The red area represents the treatment period before the nationwide lockdown (Feb. 22-March 23).

(b) Ratios of post- and pre-treatment RMSPE.



Note: Ratios of post- and pre-treatment RMSPE of each municipality in the donor pool and of each treated municipality.

(c) Post-RMSPE.



Note: Post-treatment RMSPE of each municipality in the donor pool and of each treated municipality.

Fig. 5. Placebo inference.
Note: Gaps in excess mortality per 1000 inhabitants between each municipality in the donor pool and its respective synthetic version (gray lines); the treated municipality and its synthetic version (superimposed black line); municipalities with RMSPE ratio larger than the respective treated municipality and their synthetic counterpart (colored lines). The red area represents the treatment period before the nationwide lockdown (Feb. 22–March 23).
Ratios of post- and pre-treatment RMSPE of each municipality in the donor pool and of each treated municipality.
Post-treatment RMSPE of each municipality in the donor pool and of each treated municipality.

CRediT authorship contribution statement

Federico Crudu: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Roberta Di Stefano:** Writing – review & editing,Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giovanni Mellace:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Silvia Tiezzi:**

Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used chat GPT in order to improve readability and language of the work. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.labeco.2024.102580.

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