The Gray Zone
How Business as Usual led to the Bergamo COVID-19 Tragedy*

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Abstract

In response to the COVID-19 pandemic, on February 23, 2020, the Italian government declared a Red Zone around 10 municipalities of the province of Lodi and in Vo' Euganeo, in Padua province. The government decided not to extend the Red Zone to municipalities of Bergamo province with similarly high infection rates. We use the Synthetic Control Method to estimate the causal effect of (not) declaring a Red Zone in the Bergamo area on daily excess mortality. We find that about two-thirds of the reported deaths could have been avoided had the Italian government declared the area a Red Zone.

Key words: COVID-19, causal impact, synthetic control method, Red Zone, Bergamo, non-pharmaceutical interventions.
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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).[1] 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.

To estimate the causal impact of not implementing a Red Zone, we use the Synthetic Control Method (SCM, Abadie & 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

[1] https://www.istat.it/it/archivio/240401

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.

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.[2] 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,

[2] 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 centre of the Red Zone), Francesco Passerini, was a member of the Northern League like Camillo Bertocchi, the major of Alzano Lombardo in the Serio Valley.

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, Kasahara & Schrimpf, 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, Kasahara & Schrimpf, 2021a; Cho, 2020; Fang et al., 2020; Flaxman, Mishra, Gandy et al., 2020). 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, Kasahara & Schrimpf (2021a) about the effectiveness of mask mandates, which promptly sparked a reply criticizing Lemoine's approach and results (Chernozhukov, Kasahara & Schrimpf, 2021b).[3] The widely cited paper by Flaxman, Mishra, Gandy et al. (2020) on the impact of various types of NPIs also went through critical scrutiny, see Soltesz et al. (2020) and the reply by Flaxman, Mishra, Scott et al. (2020).

While the general effectiveness of NPI measures seems 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.

Our analysis is also related to public policy decision making under uncertainty and the

[3]Lemoine's original blog post can be found at this link.

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 & Schmeidler, 2001; Gilboa et al., 2006), in which decisions are made by referring to past decision problems and past experiences.

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

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, 6, and 7 report our results, inference, and a battery of robustness checks, respectively. Section 8 presents our conclusion.

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.[4]

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

[4] As reported by the investigative television program Report on April 6, 2020 (link).

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".[5] 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

[5] Link to YouTube video.

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.[6] 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.[7]

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 Figure 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).

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 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

[6]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.

[7]Large shopping malls remained closed during week-ends; bars and restaurants remained open between 6am and 6pm.

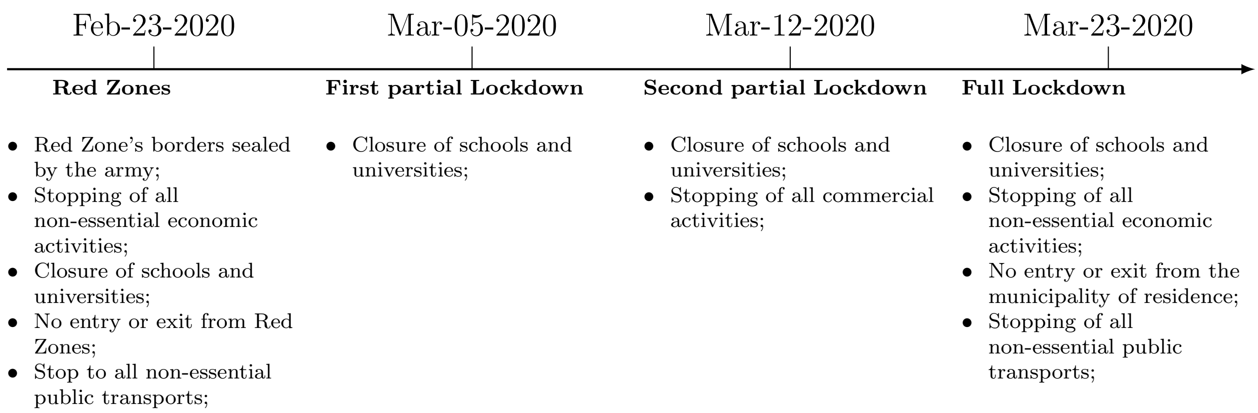

Figure 1: Timeline of nationwide containment measures.

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 & 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 it is our effect of interest. We assume that

$$Y_{jt}^{NP} = f_{jt} \text{ (no pandemic)}, \tag{1}$$

$$Y_{jt}^{RZ} = \beta_{jt} + f_{jt} = \beta_{jt} + Y_{jt}^{NP} \text{ (Red Zone)}, \tag{2}$$

$$Y_{jt}^{NRZ} = \beta_{jt} + \gamma_{jt} + f_{jt} = \gamma_{jt} + Y_{jt}^{RZ} \text{ (no Red Zone)}, \tag{3}$$

where f_{jt} are unobserved common components that determine the outcome Y. We also assume that the standard stable unit treatment value assumption (SUTVA) hold 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. There could be 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. Let us denote $\hat{w}_j$, $j = 2, \ldots, J$ 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 $\hat{\boldsymbol{w}} = (\hat{w}_2, \ldots, \hat{w}_J)'$ converges to $\boldsymbol{w}^* = (w_2^*, \ldots, w_J^*)'$ such that $f_{1t} \approx \sum_{j=2}^{J} w_j^* f_{jt}$. 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., $Y_{1t} \approx \sum_{j=2}^{J} w_j^* Y_{jt} \quad \forall t = 1, \ldots, T_0$ (see Ferman & Pinto, 2021). Notice that, since our outcome is cumulative excess mortality, our estimator is similar in spirit to the demeaned SC estimator of Ferman & Pinto (2021).

We mentioned in the beginning of this section that, differently from the standard setting described in Abadie (2021), to identify γ_{1t} it is not enough that $f_{1t} \approx \sum_{j=2}^{J+1} w_j^* f_{jt}$ but, in addition, we need to assume that

$$\beta_{1t} \approx \sum_{j=2}^{J} w_j^* \beta_{jt}. \tag{4}$$

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 be close to the convex hull of the effects of the pandemic observed in the donor pool and therefore it cannot be extreme. NEPE allows us to estimate our effect of interest by

$$\gamma_{1t} \approx \hat{\gamma}_{1t} = Y_{1t} - \sum_{j=2}^{J} \hat{w}_j Y_{jt}. \tag{5}$$

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.

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, 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. Focusing on early transmission of COVID-19 in New York City, Almagro & 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. 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. 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 equation 4 appears to be reasonable. We can, nonetheless, further investigate its plausibility.

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 2). 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

$$\gamma_{1t} + \beta_{1t} \approx \widehat{\gamma_{1t} + \beta}_{1t} = Y_{1t} - \sum_{i=J+1}^{K} \hat{w}_i Y_{it}. \tag{6}$$

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

$$\beta_{jt} \approx \hat{\beta}_{jt} = Y_{jt} - \sum_{i=J+1}^{K} \tilde{w}_i^j Y_{it}, \quad j = 2, \dots, J, \tag{7}$$

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 equation 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}. Given that we are able to estimate the effect of the pandemic on every single municipality that implemented a Red Zone, we can replace the weighted average with the largest estimated effect, i.e., we can estimate γ_{1t} as

$$\begin{aligned} \tilde{\gamma}_{1t} &= \widehat{\gamma_{1t} + \beta}_{1t} - \max_{j \in [2,\dots,J], \hat{w}_j > 0} \hat{\beta}_{jt} \\ &= \underbrace{\left(Y_{1t} - \sum_{i=J+1}^{K} \hat{w}_i Y_{it} \right)}_{\widehat{\gamma_{1t}+\beta_{1t}}} - \max_{j \in [2,\dots,J], \hat{w}_j > 0} \underbrace{\left(Y_{jt} - \sum_{i=J+1}^{K} \tilde{w}_i^j Y_{it} \right)}_{\hat{\beta}_{jt}}. \end{aligned} \tag{8}$$

If the condition in equation 4 is not met, it will induce a bias in $\hat{\gamma}_{1t}$ equal to the difference

$$\beta_{1t} - \sum_{j=2}^{J} \hat{w}_j \beta_{jt}.$$

Since, by definition,

$$\max_{j \in [2,\dots,J], \hat{w}_j > 0} \hat{\beta}_{jt} > \sum_{j=2}^{J} \hat{w}_j \beta_{jt},$$

if we replace $\sum_{j=2}^{J} \hat{w}_j \beta_{jt}$ with $\max_{j \in [2,\dots,J], \hat{w}_j > 0} \hat{\beta}_{jt}$ our new estimate of γ_{1t} will be smaller than $\hat{\gamma}_{1t}$ (see equation 5), provided that $\gamma_{1t} + \beta_{1t}$, a quantity we can estimate, is positive.

Under the reasonable assumption that the pandemic cannot (at least in the short time period we consider) reduce mortality, we can provide two interpretations for the quantity in equation 8, depending on whether the true value of β_{1t} is smaller or larger than $\max_{j\in[2,\ldots,J],\hat{w}_j>0}\hat{\beta}_{jt}$.

By combining equation 6 and equation 8 we find that $\tilde{\gamma}_{1t} \approx \gamma_{1t}+(\beta_{1t}-\max_{j\in[2,\ldots,J],\hat{w}_j>0}\hat{\beta}_{jt})$. It is easy to see that if $\beta_{1t} < \max_{j\in[2,\ldots,J],\hat{w}_j>0}\hat{\beta}_{jt}$, which it is arguably the most plausible scenario, then equation 8 can readily be interpreted as a lower bound for γ_{1t}. If, on the other hand, $\beta_{1t} > \max_{j\in[2,\ldots,J],\hat{w}_j>0}\hat{\beta}_{jt}$ and we are willing to assume that the effect of non implementing a Red Zone is non-negative ($\gamma_{1t} \geq 0$), equation 8 gives us the difference between the effect of the pandemic the treated municipalities would have experienced had they implemented a Red Zone, and the most extreme effect estimated in Red Zone municipalities ($\beta_{1t}-\max_{j\in[2,\ldots,J],\hat{w}_j>0}\hat{\beta}_{jt}$), plus the effect of non implementing a Red Zone (γ_{1t}). Therefore, if $\tilde{\gamma}_{1t}$ in equation 8 is large it is unlikely for γ_{1t} to be small or even zero unless one believes that the effect of the pandemic would have been much higher than the most extreme observed effect, had the treated municipalities implemented a Red Zone. Since those municipality are very similar to each other, we believe this not to be plausible.

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 7,903 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 1,000 inhabitants at the municipality level. 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. Figure 2 shows the trends in cumulative excess mortality per 1,000 inhabitants of our treated units (Albino, Alzano Lombardo and Nembro) and the 11 control municipalities (left panel), and for the unaffected municipalities (right panel).

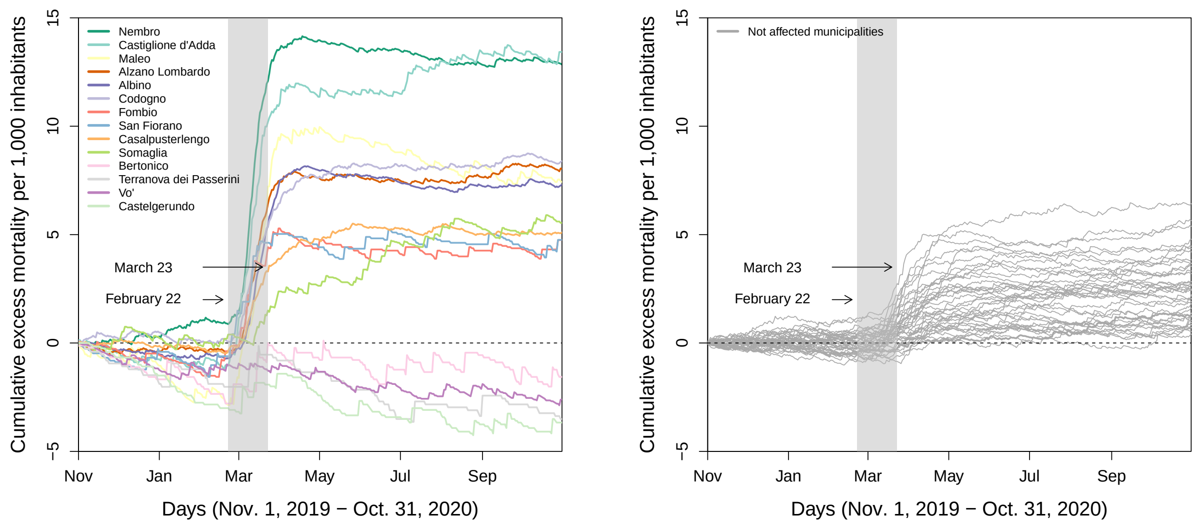

Figure 2: Cumulative excess mortality per 1,000 inhabitants (raw data).

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 Figure 2. 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).[8]

We use a set of cumulative excess mortality predictors.[9] Epidemiological studies indicate demographic factors such as population, rate of urbanization and population density as crucial for understanding the spread of COVID-19 (Cho, 2020; Rocklov & Sjogin, 2020). For this reason, we include the percentage of males in the population and population density (residents per km^2) of each municipality.[10] We also control for the number of employees in manufacturing, for PM-10 as a measure of air quality and for the percentage of the population aged 65+ and 85+.[11] 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 in

[8]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.

[9]We 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.

[10]Population data, measured as resident population in each municipality on December 21, 2019 by gender, come from ISTAT, Demographic Statistics (link).

[11]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 (link). These variables 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.

the area under investigation.[12] 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.[13]

The vector of synthetic weights is chosen to minimize the distance between the pre-intervention characteristics of the treated and the weighted characteristics of the donor pool. Typically, this distance is the square root of a weighted sum where the positive weights reflect the predictive power of each of the, say, k predictors of the donor pool, and can be chosen via an in-sample and out-of-sample validation procedure. To find the weights to be assigned to each element of the vector of predictors, say, $\boldsymbol{v} = (v_1, ..., v_k)'$, we split the pre-treatment period into a training period and a validation period, and then selected the weights by minimizing the out-of-sample error in the validation period.[14] The predictors weights for the two donor pools are shown in Table 2. Finally, considering these predictors weights, we estimate the municipalities' weights, and the synthetic control units for the three treated municipalities.

5 Results

Figure 3 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

[12]Altimetric area data come from the Main Geographic Statistics on Municipalities by ISTAT, "Statistical Classifications and Size of Municipalities" section (link). The Attraction Index information comes Sistema Informativo STorico delle Amministrazioni Territoriali (SISTAT) (link).

[13]Distances in meters from the municipality hosting the closest and the second closest hospital are taken from the Distance Matrices supplied by ISTAT (link).

[14]We use as training period days between November 1-30, 2019, and as validation period days between December 1, 2019 and January 1, 2020.

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 Figure 2). 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.

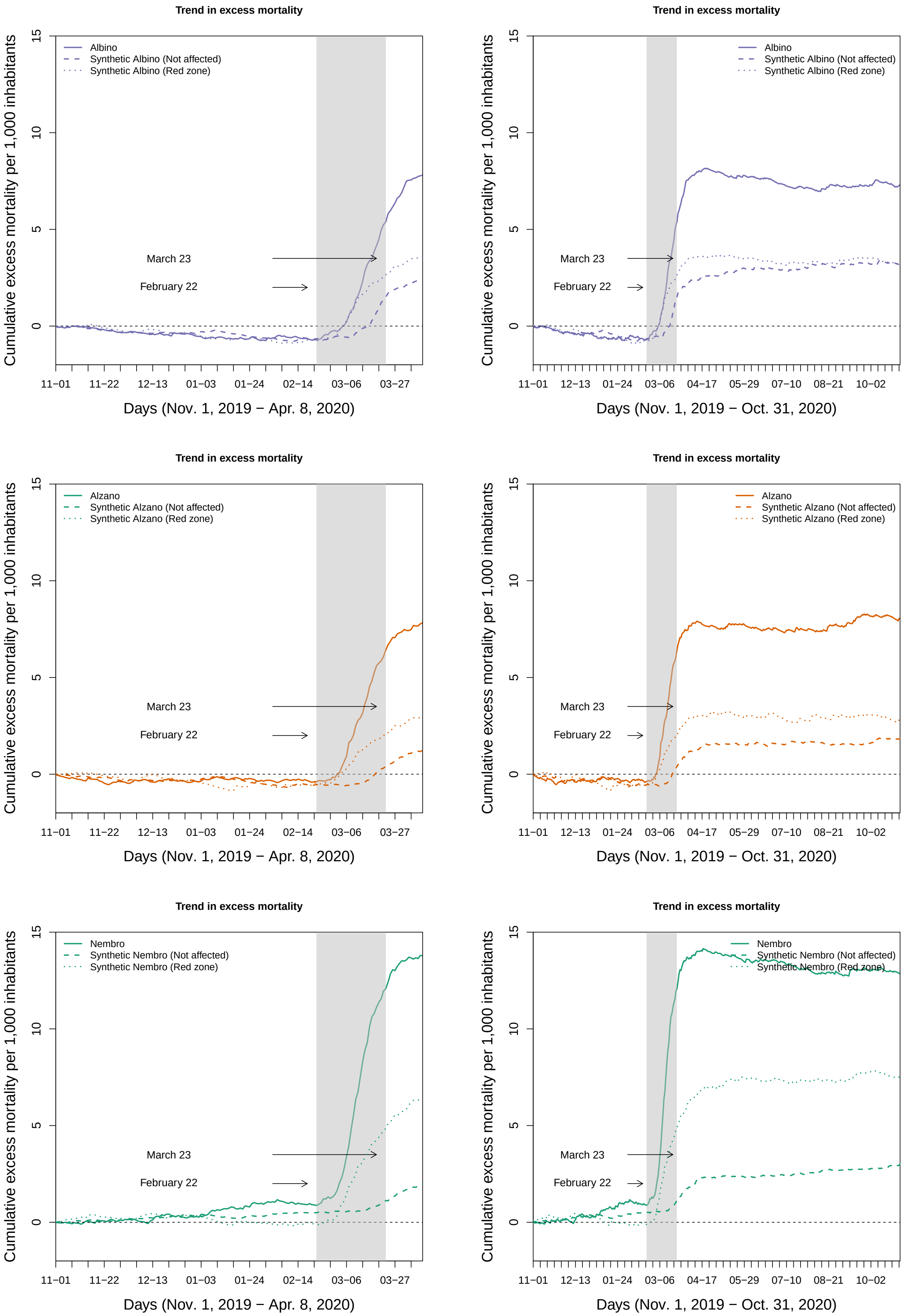

Figure 3: Trends in cumulative excess mortality per 1,000 inhabitants. The gray area represents the treatment period before the nation-wide lockdown (Feb. 22-March 23).

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 1,000 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 1,000 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 1,000 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.

The synthetic control units for Albino, Alzano Lombardo and Nembro are weighted averages of the municipalities in the donor pools. Table 2 displays the contributions of each of the municipalities in both donor pools to the synthetic control. The weights reported in Table 2 indicate that cumulative excess mortality per 1,000 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 Albino and Alzano Lombardo while four contribute to "synthetic" Nembro. As it is well known, the sparsity of the weights in Table 2 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).

Table 2: 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	0.503	0.164	1	Cardano al Campo	0.001	0	0
2	Bertonico	0	0	0	2	Caronno Pertusella	0	0	0
3	Casalpusterlengo	0.089	0	0	3	Castellanza	0	0	0
4	Castiglione d'Adda	0	0	0	4	Fagnano Olona	0.001	0.524	0.044
5	Codogno	0.865	0.494	0.484	5	Lonate Pozzolo	0.009	0	0
6	Fombio	0	0.003	0.111	6	Luino	0.143	0	0
7	Maleo	0	0	0	7	Malnate	0.001	0	0
8	San Fiorano	0	0	0	8	Olgiate Olona	0.001	0	0
9	Somaglia	0	0	0	9	Samarate	0.11	0	0
10	Terranova dei Passerini	0	0	0.175	10	Sesto Calende	0.001	0	0
11	Castelgerundo	0.046	0	0.066	11	Somma Lombardo	0	0.013	0
					12	Erba	0.001	0	0
					13	Olgiate Comasco	0.001	0	0.215
					14	Morbegno	0	0	0
					15	Arluno	0.002	0	0
					16	Busto Garolfo	0.001	0	0
					17	Canegrate	0.001	0	0
					18	Castano Primo	0	0	0
					19	Cerro Maggiore	0	0	0
					20	Cesate	0.001	0	0
					21	Nerviano	0	0	0
					22	Rescaldina	0.001	0	0
					23	Solaro	0.049	0	0
					24	Vanzaghello	0.197	0	0
					25	Bedizzole	0	0	0
					26	Calcinato	0	0.297	0.742
					27	Carpenedolo	0	0	0
					28	Gardone Val Trompia	0.23	0	0
					29	Gavardo	0.24	0	0
					30	Lonato del Garda	0	0.167	0
					31	Sarezzo	0.002	0	0
					32	Mortara	0	0	0
					33	Casalmaggiore	0	0	0
					34	Castel Goffredo	0	0	0
					35	Curtatone	0	0	0
					36	Porto Mantovano	0.001	0	0
					37	San Giorgio Bigarello	0.002	0	0
					38	Besana in Brianza	0.002	0	0
					39	Lentate sul Seveso	0.001	0	0

Our estimate of the effect of a Red Zone on excess mortality is the difference between the solid lines on the right panel in Figure 3 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 Figure 3. The Red Zone would have produced a decrease in excess mortality, net of the pandemic.

Table 3 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 1,000 inhabitants in Albino and Alzano, respectively. This amounts to around 116 and 96 inhabitants, respectively. In Nembro, the impact of the pandemic is greater, reaching about 12 deaths per 1,000 inhabitants, i.e., around 135 inhabitants. The introduction of a Red Zone would have reduced the number of deaths per 1,000 inhabitants by about 4.5 in Albino, 5 in Alzano Lombardo, and 8 in Nembro. Since excess deaths in Nembro reached around 12 persons per 1,000 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.

Table 3: Treatment effects per 1,000 inhabitants.

	April 8, 2020	Max.
Albino (Red Zone)	4.27	4.61
Albino (not affected)	5.38	5.64
Alzano Lombardo (Red Zone)	4.91	5.35
Alzano Lombardo (not affected)	6.59	6.73
Nembro (Red Zone)	7.38	7.84
Nembro (not affected)	11.80	11.95

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 no 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 ($\beta_1 \approx \sum_{j=2}^{J} w_j^* \beta_j$). 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 Figure 4. In each panel, the gray lines show the gap in excess mortality per 1,000 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. The estimated gap for all three treated municipalities is quite large relative to the distribution of the gaps and root mean squared prediction error (RMSPE) ratios for the municipalities in the donor pool. In Figure 5 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.[15] 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. The estimated p-values are 0.075 for Albino, and 0.1 for both Alzano and Nembro. One aspect worth emphasizing is that municipalities with a higher RMSPE have either a negative effect in the post-treatment period or very small effects as shown in Figure 4. Alzano and Nembro have the highest post-treatment RMSPE, and Albino has the second highest (highest positive). Using post RMSPE would give a p-value for the effect of non having implemented

[15] 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.

a red zone of 0.025 for Nembro and Alzano and of 0.05 for Albino (see Figure 6).

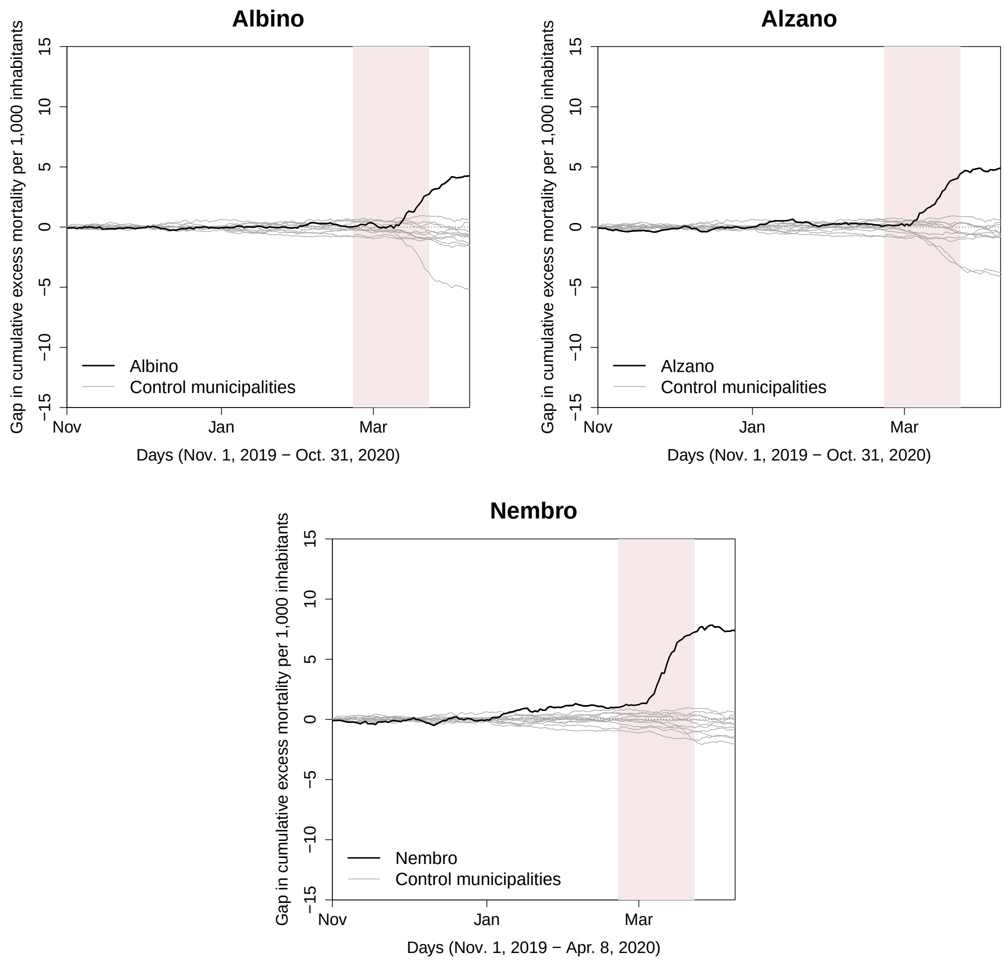

Figure 4: Placebo tests.

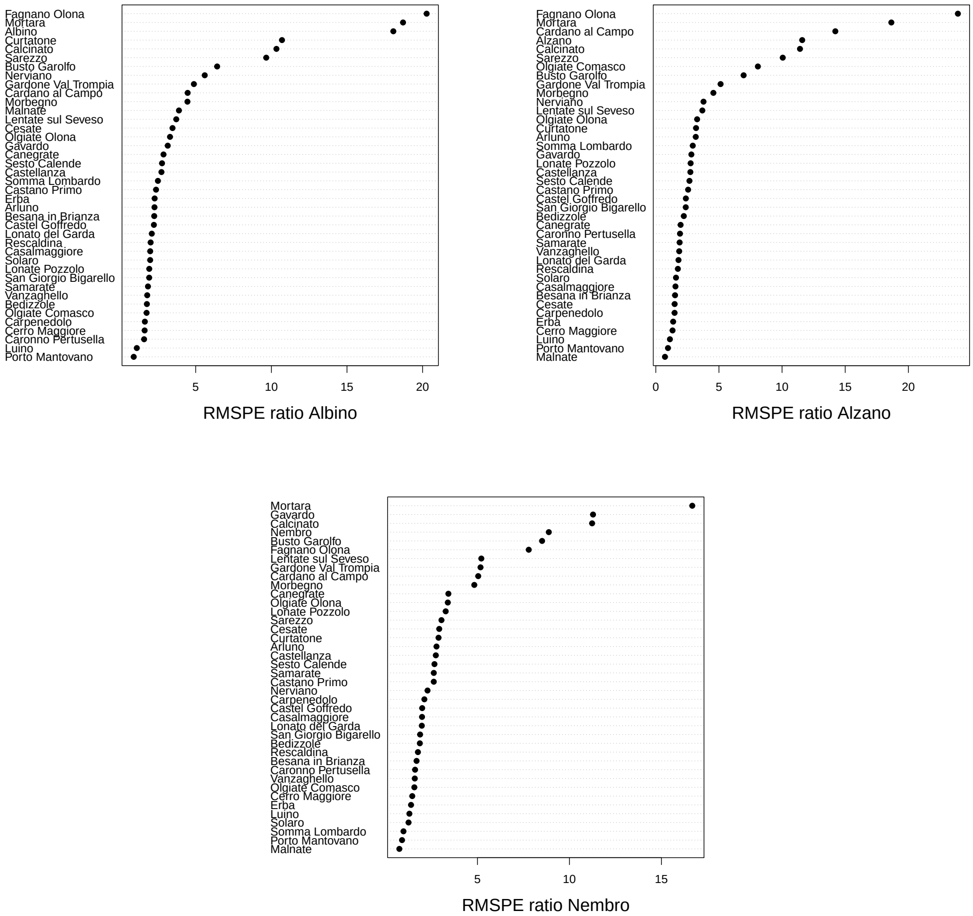

Figure 5: Ratios of post- and pre-treatment RMSPE.

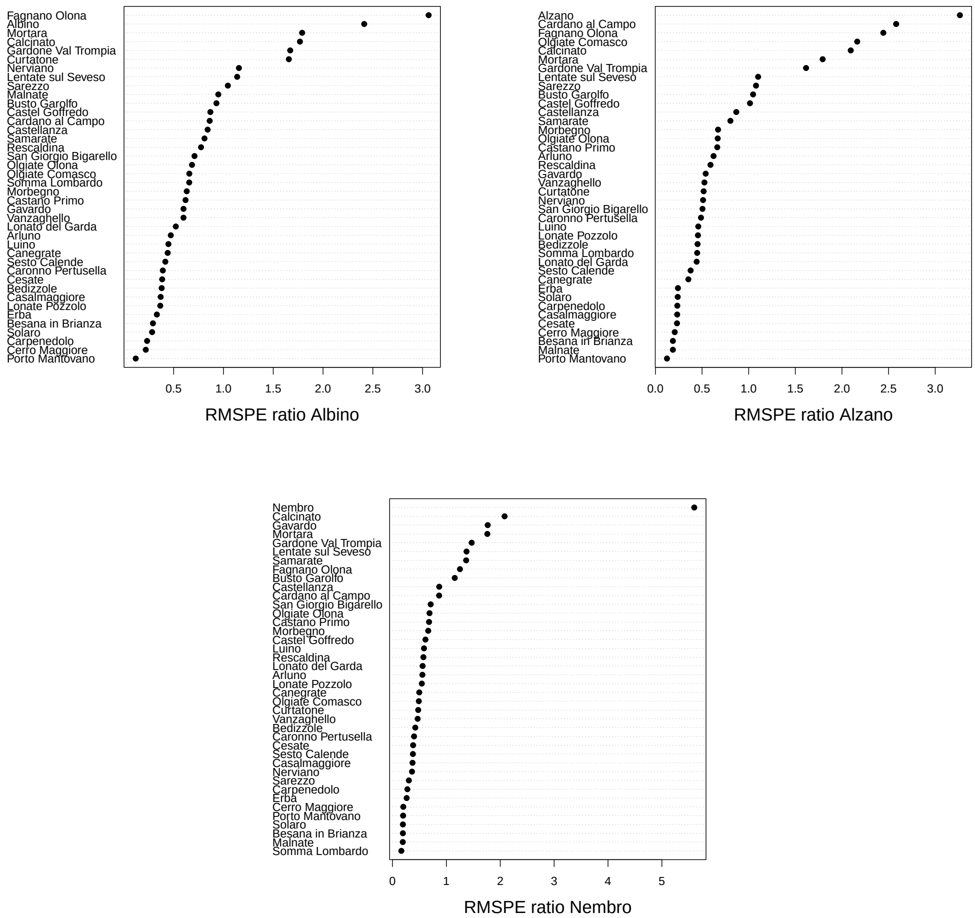

Figure 6: Post-RMSPE.

7 Robustness Checks

As discussed in Section 3, it is possible to investigate the sensitivity of our results to a possible violation of our NEPE assumption. To this end, we can compare the effect of not having implemented the Red Zone, estimated as in the previous section, and an alternative estimate where we use the most extreme pandemic effect observed in the Red Zone municipalities (that receive non-negligible weights). This provides an alternative estimate for the effect the pandemic would have had in our treated municipalities, had they implemented the Red Zone. In all three treated municipalities, cumulative excess deaths are positive at the end of the period even with the new estimates. The new estimated effects in Albino are very small and close to zero but increasing over time until the effect of the nationwide lockdown takes over. For Nembro, the new estimated effects are almost identical to the ones we find in our main specification. As we explained in Section 3, this provides strong evidence that our results are robust to violations of our NEPE assumption.

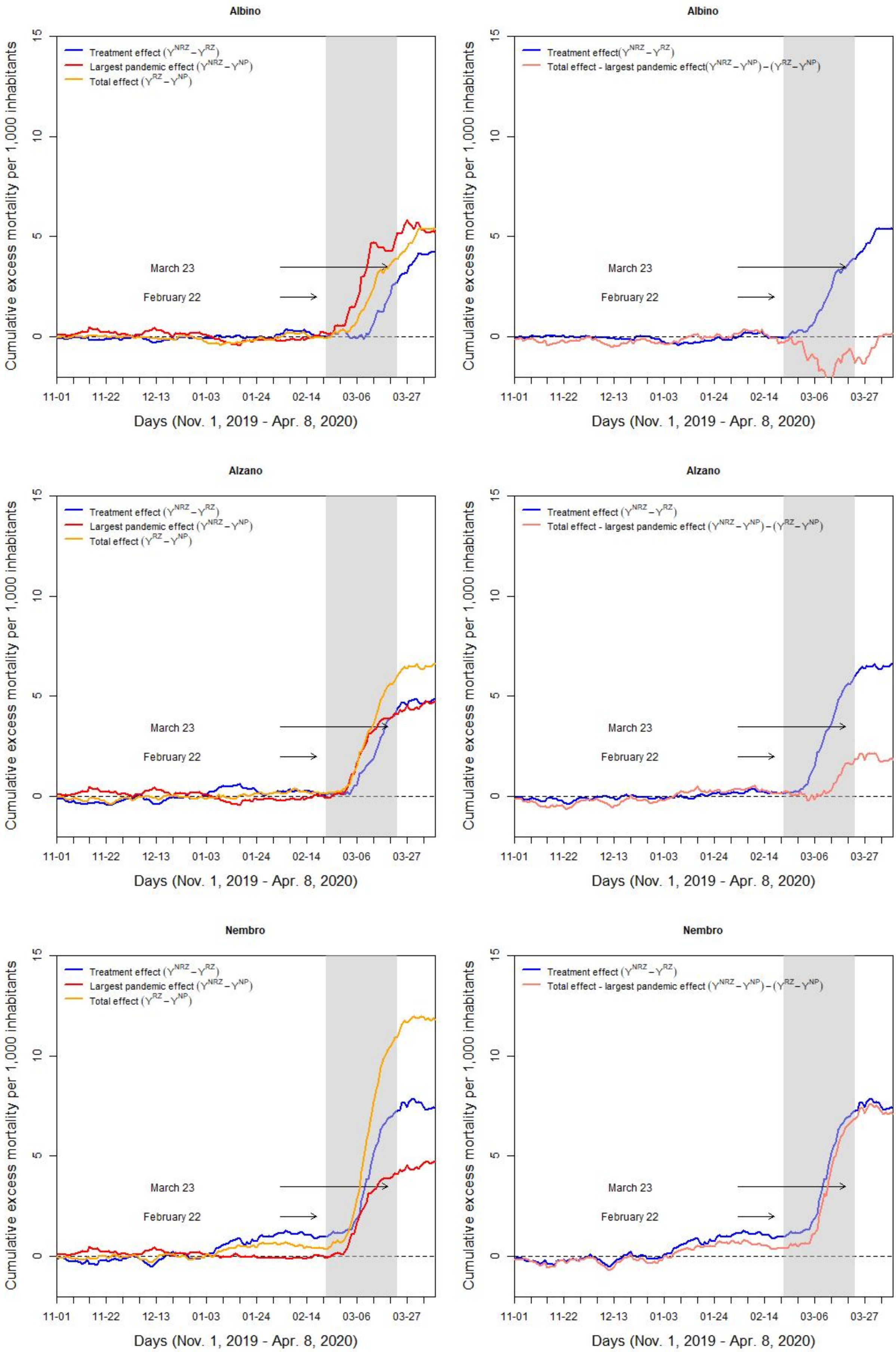

Figure 7: Trends in cumulative excess mortality per 1,000 inhabitants.

In addition, we conduct various standard checks to assess the sensitivity of our main results with respect to changes to the study design. In particular,

1. we run the usual leave-one-out analysis,

2. we exclude Vo' Euganeo from the donor pool,

3. we anticipate the treatment date to January 1, 2020.

In Figure 8 we report the results of the leave-one-out analysis excluding, one at a time, one of the municipalities that received a positive weight (see Table 2). Figure 8 shows that synthetic Albino, Alzano, and Nembro are always well below their real counterparts.

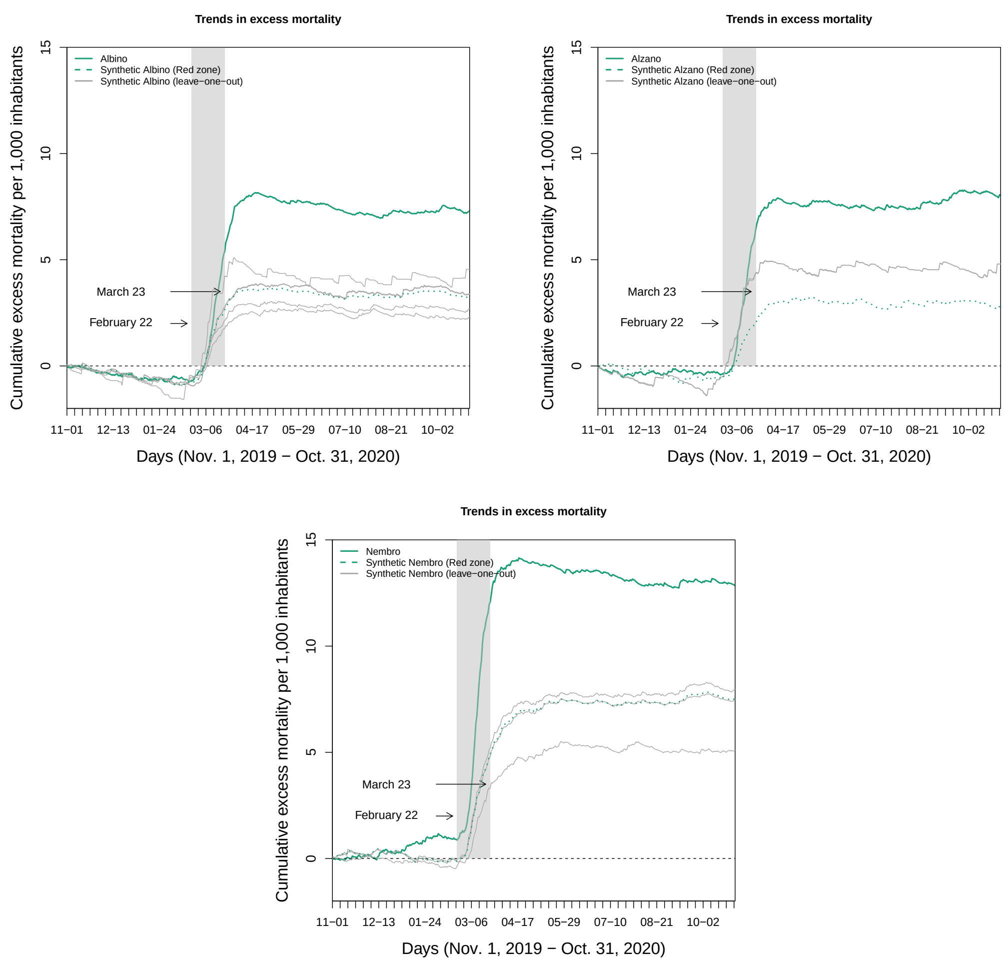

Figure 8: Leave-one-out estimates.

In a second robustness check, we restrict the donor pool to include municipalities that are located in the Lombardy region only and therefore exclude Vo' Euganeo. As explained by Abadie et al. (2010), it is important to restrict the donor pool to units with outcomes that are thought to be driven by the same structural process as the treated unit. Since the pandemic had an impact on the local health system, which in Italy is regulated at regional level, it is important to focus on the Lombardy region only. Our results do not change much when we exclude Vo' Euganeo as shown in Figure 9.

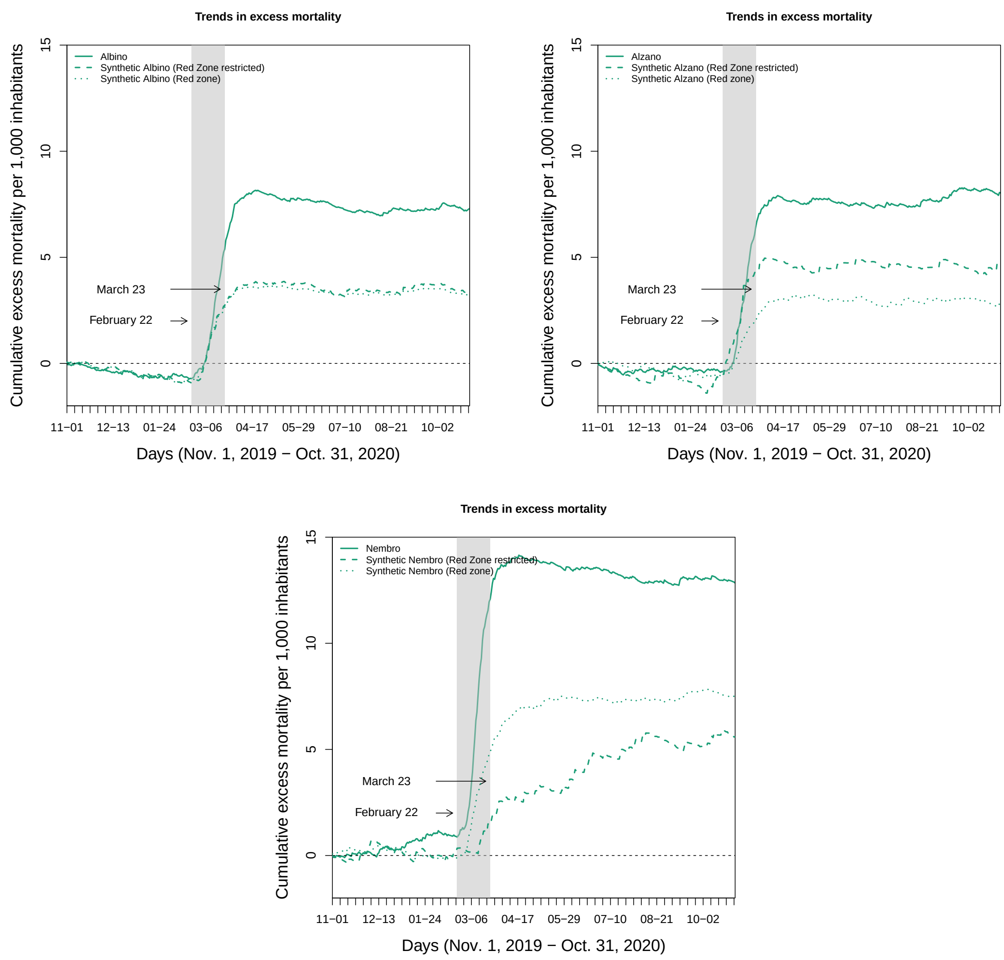

Figure 9: Restricting the donor pool to Red Zone Lombardy municipalities

Finally, we anticipate the beginning of the treatment period to January 1, 2020, and estimate anticipation effects that might have occurred before the Red Zone was introduced. The results are reported in Figure 10. Albino and Alzano do not seem to have any visible anticipation effects. For Nembro, we cannot rule out that the pandemic had already started at the beginning of the year. However, the estimated anticipation effects are relatively small and within the variation we observe among different municipalities in the entire pre-pandemic period (see Figure 2).

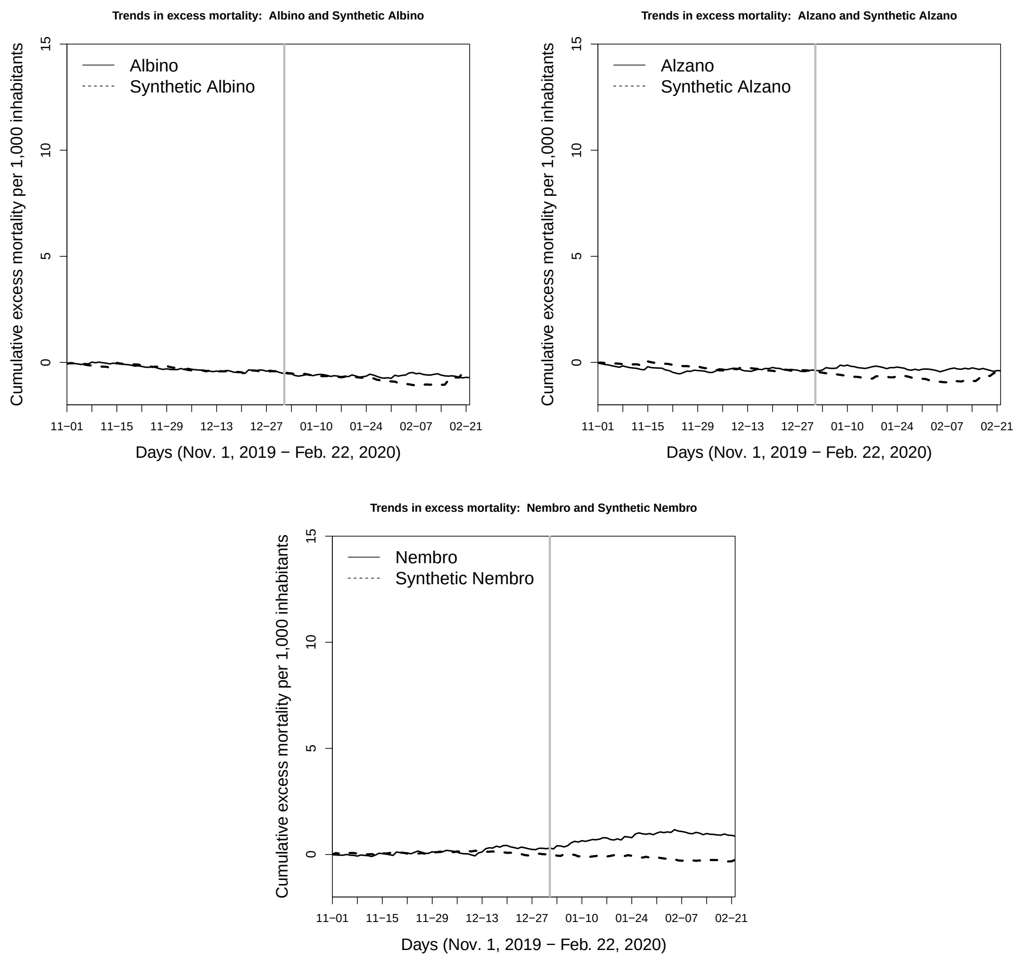

Figure 10: Backdating treatment starting date to January 1,2020.

Given the potential anticipation effect that we observe in Nembro, we report the results of a different specification where we consider January 1 as the treatment date and estimate the effects throughout the period. As shown in Figure 11 and Table 4 the results remain quite similar to our main specification.

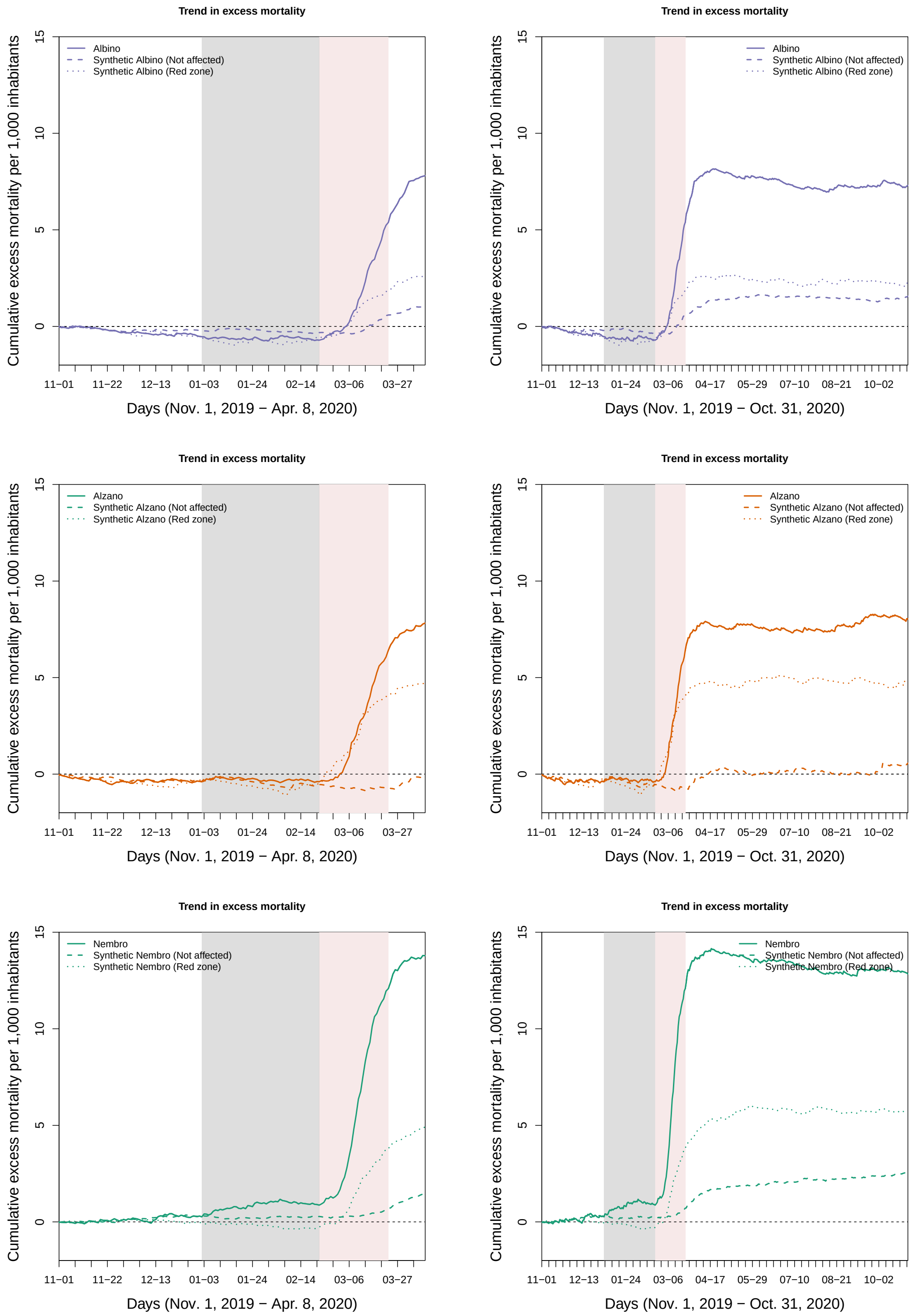

Figure 11: Trends in cumulative excess mortality per 1,000 inhabitants. The gray area (Jan. 1-Feb. 21) represent the additional treatment period, while the pink area represents the actual treatment period before the nation-wide lockdown (Feb. 22-March 23).

Table 4: Treatment effects per 1,000 inhabitants.

	April 8, 2020	Max
Albino (Red Zone)	5.22	5.71
Albino (not affected)	6.78	6.81
Alzano Lombardo (Red Zone)	3.11	3.83
Alzano Lombardo (not affected)	7.98	8.28
Nembro (Red Zone)	8.84	9.18
Nembro (not affected)	12.31	12.48

8 Alternative synthetic control methods

In this section we use different methods to estimate the effect of the pandemic and for inference. In order to make inference on the effect of not having implemented a Red Zone we follow the same procedure we used to run the placebo tests and used municipalities not affected by the pandemic as a donor pool and subtract from the outcome of the treated units the estimated effect of the pandemic in the presence of a Red Zone.

We implement the augmented SCM (ASCM) of Ben-Michael et al. (2021) with pointwise confidence intervals computed using the method of Chernozhukov, Wüthrich & Zhu (2021) and the synthetic difference-in-differences (SDID) of Arkhangelsky et al. (2021). The results are reported in Figure 12 and Figure 13, respectively, and they are similar to what we find in our main specification.

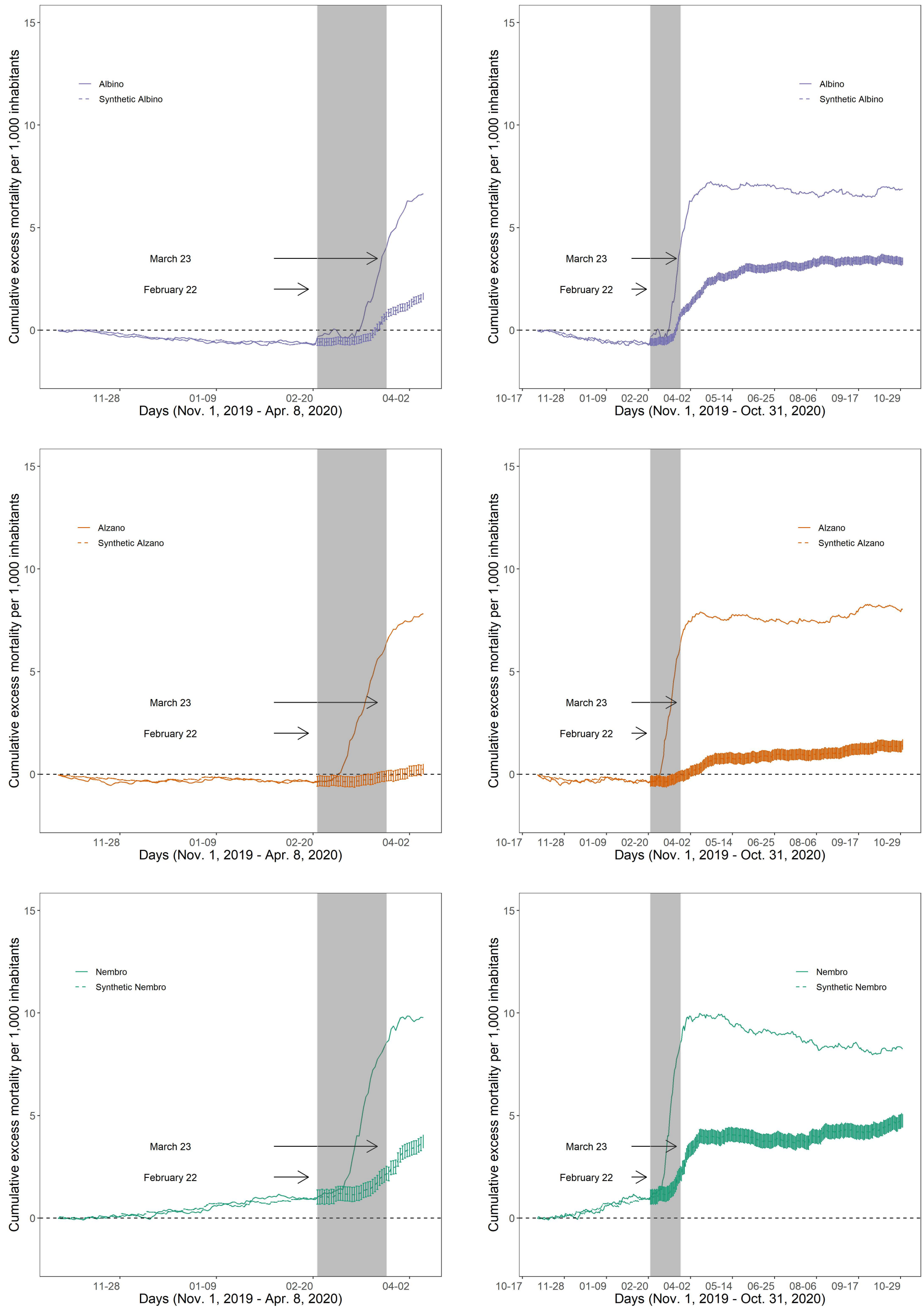

Figure 12: Trends in cumulative excess mortality per 1,000 inhabitants and respective point-wise confidence intervals computed using the method of Chernozhukov, Wüthrich & Zhu (2021). The gray area represents the treatment period before the nation-wide lockdown (Feb. 22-March 23).

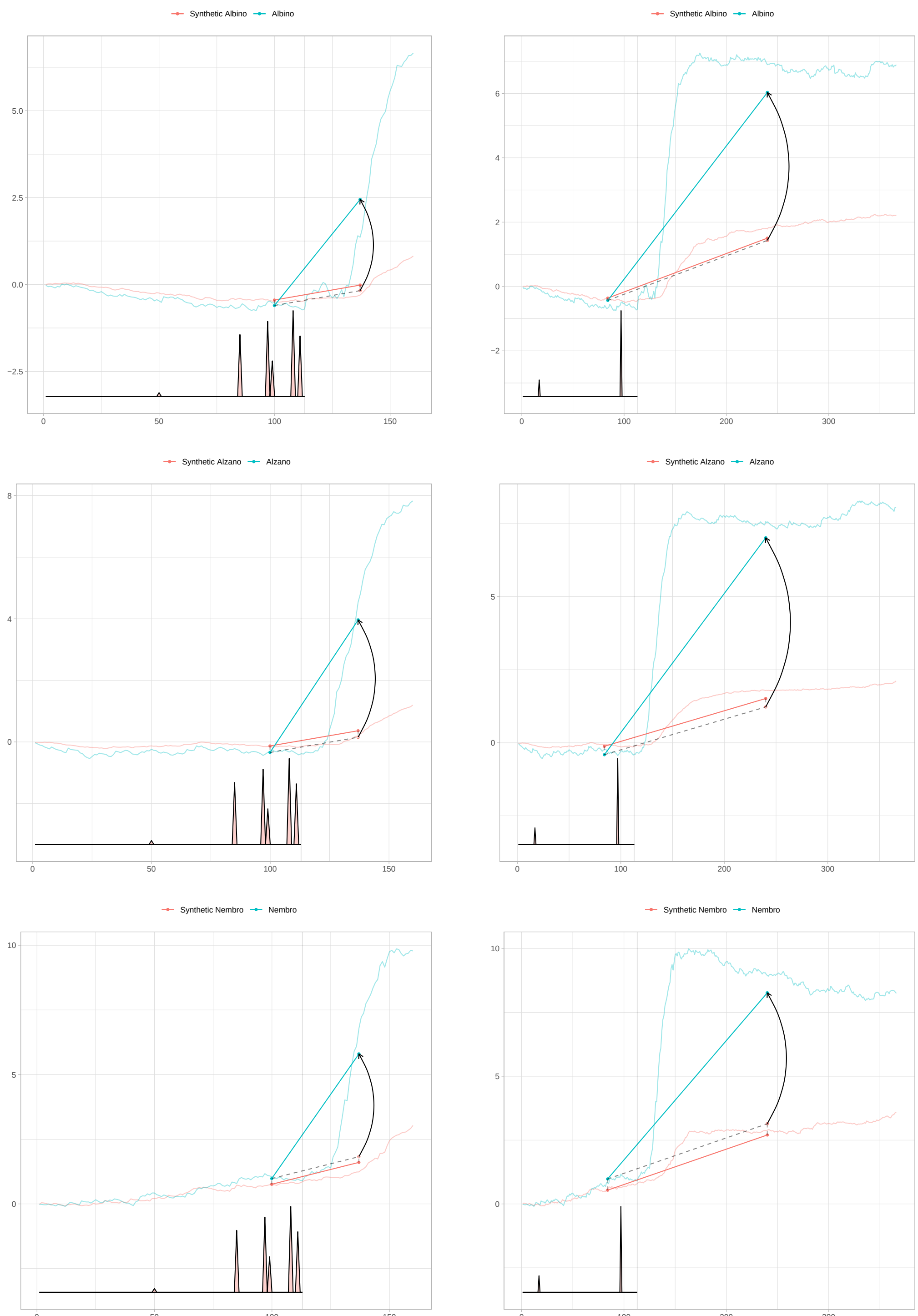

Figure 13: Trends in cumulative excess mortality per 1,000 inhabitants. The relative weights given to each pre-treatment period are reported below the corresponding period. The arrows represent the estimated treatment effects.

In the second and third columns of Table 5 we report the highest effects in each treated municipality estimated by SCM and ASCM, respectively. The last column of Table 5 shows the average (over the entire period) effects estimated by SDID in each treated municipality. The estimated effects are positive and large and the results are comparable in terms of magnitude regardless the estimation method used.

Table 5: Treatment effects per 1,000 inhabitants.

	SCM	ASCM	SDID
Albino	5.38	5.14	4.60
Alzano Lombardo	6.59	7.59	5.79
Nembro	8.84	6.91	5.13

9 Conclusion

Using the synthetic control method we estimate the causal effect of not imposing strong social distancing restrictions at the beginning of the COVID-19 pandemic in three municipalities of the province of Bergamo. We show that imposing a Red Zone, as other municipalities in the Lombardy region did, could have saved up to 67% of the deaths inflicted by the pandemic on those municipalities. Our descriptive analysis also indicates that the nationwide lockdown has potentially had a strong impact in reducing the effect of the pandemic. These effects are robust to all the standard robustness tests and to the use of different estimation methods and inference procedures. As a methodological contribution, we show that studies that rely on the synthetic control and/or similar methods, such as difference-in-differences, to estimate the impact of policy interventions in this setting implicitly impose an additional assumption on how the pandemic would have affected the treated units in the absence of the policy. To provide evidence on the validity of this assumption in our study, we use municipalities that were not affected in the early stages of the pandemic.

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