Journal of the Royal Statistical Society Series A: Statistics in Society, 2024, **00**, 1–41
https://doi.org/10.1093/jrsssa/qnae091

ROYAL STATISTICAL SOCIETY DATA | EVIDENCE | DECISIONS
Journal of the Statistics Society **Series A** Statistics in Society

Original Article

Administrative border effects in COVID-19 related mortality

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Abstract

Lombardy, the first region in Italy to be hit by COVID-19 and one of the first in Western countries, was in the spotlight during the first wave of the pandemic in 2020 due to its high mortality rates. Simple regional comparisons are, however, hampered by potentially unobservable variables affecting mortality, such as the virus spread. To address this 'unobserved heterogeneity' concern, we adopt a Difference in Geographic Regression Discontinuity Design (DiD-GRDD), which compares 2020 vs. 2017–2019 excess mortality in Lombardy's municipalities close to the administrative borders with neighbouring municipalities in other regions. Our study documents a one to two percentage point higher excess mortality in Lombardy limited to the oldest age group (81+). An exploratory mediation analysis points to the management of nursing homes during the pandemic as a possible critical factor explaining higher mortality in Lombardy.

Keywords: administrative borders, COVID-19 regional mortality, geographic regression discontinuity design, Italy

JEL codes: I10, H12

> *'Why Covid Caused Such Suffering in Italy's Wealthiest Region? Lombardy has been overwhelmed by the pandemic, in part because of a poorly executed medical privatization program' (Published Nov. 19, 2020; Updated Nov. 20, 2020)*
>
> –Peter S. Goodman and Gaia Pianigiani, *The New York Times*

> *'Fewer deaths in Veneto offer clues for fight against virus. Divergence of fortunes with nearby Lombardy stems from keeping more patients away from hospitals, experts say'. (Rome, April 5 2020)*
>
> –Miles Johnson, *Financial Times*

1 Introduction

Comparing mortality rates in the first year of the COVID-19 pandemic, some countries appear to have been hit more severely than others. Eurostat reports March (December) excess mortality rates for 2020 compared to 2016–2019 of 49.6% (27.1%) and 53.0% (9.4%) for Italy and Spain,

Received: March 10, 2023. **Revised:** August 21, 2024. **Accepted:** August 27, 2024

respectively, against 15.5% (15.7%) and −2.5% (30.8%), for France and Germany, respectively (Eurostat, 2024).

The Lombardy region in Italy, in particular, was the first geographic area to be heavily affected by COVID-19 outside China, the country from which the pandemic originated.

Although demographic factors (e.g. the age structure of the population) are often advocated to explain differences in COVID-19-related mortality in addition to the different spread of the virus (Mesas et al., 2020; Onder et al., 2020), an important question remains unanswered: are mortality differences partly attributable to the ways governments reacted to the pandemic?

Recent papers have tried to answer this question by reporting evidence on the effectiveness of single or bundles of policies, such as stay-at-home orders, lock-downs, or the use of protective masks, on the diffusion of the pandemic and the level of mortality (Chernozhukov et al., 2021; Hsiang et al., 2020). The adoption of these policies is unlikely to be exogenous and may depend on the spread of the virus and the capacity of the health system, e.g. the availability of Intensive Care Unit (ICU) beds. To put it in other words, to assess the relative merits (or demerits) of different governments, one should compare like with like, for instance, by taking into account the level of diffusion of the virus in the population. However, data were not available due to non-existent or low COVID-19 testing, especially in the first wave of the pandemic.

In this paper, we investigate regional differences in mortality outcomes related to COVID-19, focusing on the Italian case. Owing to the autonomy of Italian regions in several domains, including the management of their health systems (See Appendix A for an outline of the recent history of the Italian National Health Care System and a detailed explanation of regional autonomy), Italy can be considered an ideal 'laboratory' to investigate the role played by regional governments in the differential mortality rates experienced locally. Pisano et al. (2020), for instance, state: 'The fact that different policies resulted in different outcomes across otherwise similar regions should have been recognized as a powerful learning opportunity from the start'.

Given the very different levels of diffusion of COVID-19 within Italy (Bertuzzo et al., 2020), we focus on Northern Italy, and in particular on Lombardy and its neighbouring regions. As the first Western region to suffer a COVID-19 outbreak, Lombardy quickly became in the spotlight of international media.

The immediate reaction to the first case diagnosed in the municipality of Codogno (province of Lodi, Lombardy) was the set up of a 'red zone' involving 50,000 citizens, which suspended all the economic activities and its residents' movements from and to this area. This action led to a reduction in the spread of the epidemic, but it was an exception in the Italian context. Indeed, a couple of days later, a new outbreak was discovered in a small hospital located in the municipality of Alzano (province of Bergamo, Lombardy). Alzano's hospital was not closed, and no 'red zone' was declared in the area, with the consequence that in a few days the number of detected cases, hospitalizations, and deaths dramatically increased. The choices to keep the Alzano hospital open and not to establish a 'red zone' nearby are among the most debated aspects of Italy's COVID-19 crisis management. What is clear is that both the National and Lombardy governments waited several days before placing in quarantine the areas of Bergamo, Brescia, Cremona and the rest of the region.

In addition, during the worst period of the epidemic, when the hospitals were collapsing, Lombardy's government asked nursing homes meeting special requirements to admit patients discharged by hospitals. These requirements were established in the regional regulation DGR N. 3018/2020 (e.g. presence of 24-hour medical assistance, 24-hour nursing care, presence of geriatric/cardiologist/pneumologist specialists, possibility to perform laboratory investigations, possibility to undergo radiological diagnostics, ability to provide oxygen therapy, ability to implement both individual isolation and cohort isolation for positive COVID-19 patients). Nursing homes host elderly people mainly affected by several illnesses which proved to be the weakest segment of the population during the COVID-19 crisis. First evidence shows that nursing homes were not fully prepared for an epidemic, with limited numbers of protective masks and other protective equipment for the working personnel. These hazardous choices may have had an impact on the increase in mortality in nursing homes (Alacevich et al., 2021).

In synthesis, the Lombardy region tackled the COVID-19 epidemic by letting the healthcare system be subject to excessive stress.

In contrast to Lombardy's experience, the Veneto region appeared more ready to deal with the COVID-19 outbreak. Veneto addressed the COVID-19 epidemic by extensive testing of symptomatic and asymptomatic citizens, broad contact tracing around positive cases, quarantine for cases and suspected cases with daily telephone monitoring, detailed practical guidelines on home isolation, minimization of contacts with physicians and nurses, and limited hospital admissions to patients with major healthcare needs. A similar approach to the COVID-19 epidemic was adopted in Emilia Romagna, which shifted to territorial and home management of patients, reducing the pressure on the hospital system.

The different ways of tackling the health emergency by regional administrations may have contributed to the gaps observed in regional mortality rates. Indeed, the very different levels of mortality between Lombardy and some neighbouring regions (see Figure 1), such as Veneto, Piedmont, and Emilia Romagna, fed harsh criticism against the presumed incapacity of Lombardy's regional governance and the unpreparedness of its regional health system to deal with the pandemic. In particular, Lombardy was criticized for its hospital-centric management of the pandemic, irrespective of the level of severity of patients, which partly contributed to the spread of the virus and the quick saturation of hospitals (Castaldi et al., 2021). Veneto, on the other hand, was often praised for its policies based on a more diffused management of the emergency, with hospitals only representing the last resort for patients and the implementation of a tracking system based on high levels of COVID-19 testing.

However, such regional comparisons are subject to an important caveat: the diffusion of the pandemic was not even across regions, and in some cases for factors not under the regions' control, and it is therefore not possible to observe how regions would have performed under the same conditions (counterfactual). Thus, to compare like with like, we focus on municipalities located in different regions but close to the regions' administrative borders and apply a Difference in Geographical Regression Discontinuity Design (DiD-GRDD). On the one hand, leveraging the time dimension through the Difference-in-Differences (DiD) component of the estimator, one can estimate the *excess* in total mortality presumably due to COVID-19. This addresses potential measurement issues related to the fact that deaths caused by COVID-19 were difficult to identify during the first pandemic wave because of low COVID-19 testing. On the other hand, exploiting the spatial (GRDD) component of the estimator and comparing neighbouring municipalities makes it likely that municipalities' observable characteristics, but also potential unobservables such as the spread of the virus in the population, were similar.

Our analysis, focused on first-semester mortality, documents between one and two percentage points (pp, hereafter) higher excess mortality in Lombardy for the 81+ population in 2020 compared to the neighbouring regions. Lombardy's higher excess mortality in the 71–80 age bracket only emerges compared to Emilia Romagna. Differential mortality is not observed in younger age groups.

Several 'stress tests' for our analysis, such as a placebo analysis setting a fake border within the Lombardy region, a test to verify the balancing of relevant covariates at the border and the classic parallel trend test (carried out with an event-study analysis), confirm our main findings.

Although the estimated administrative border's differences can be roughly interpreted as mortality gaps emerging because of both past administrative choices reflected in current regional features (e.g. Regional Health Systems) and the decisions made to tackle the pandemic (e.g. about the management of nursing homes) without the possibility to disentangle the specific contributions of each factor with the data at hand, we make an attempt at exploring the potential correlates of higher excess mortality. An exploratory mediation analysis considering two of the most frequently cited possible causes of the higher excess mortality in Lombardy, namely, the larger presence of the private sector in the health system and the poor management of nursing homes during the pandemic, highlights only the latter as a possible critical factor but only to explain differences with Emilia Romagna.

The rest of the paper unfolds as follows. Section 2 presents our empirical strategy and Section 3 describes the data used in the empirical analysis. The main results are commented on in Section 4 while several robustness checks are carried out in Section 5. Section 6 explores potential mechanisms driving Lombardy's higher excess mortality, and the last section summarizes the main findings and draws conclusions. Further material is reported in the Appendices. Appendix A provides some background information on the Italian National Health System and the main differences across the regions studied in this paper. Control variables included in the empirical models are described in Appendix B. In Appendix C, we comment on the robustness checks. Additional tables and figures are included in Appendix D.

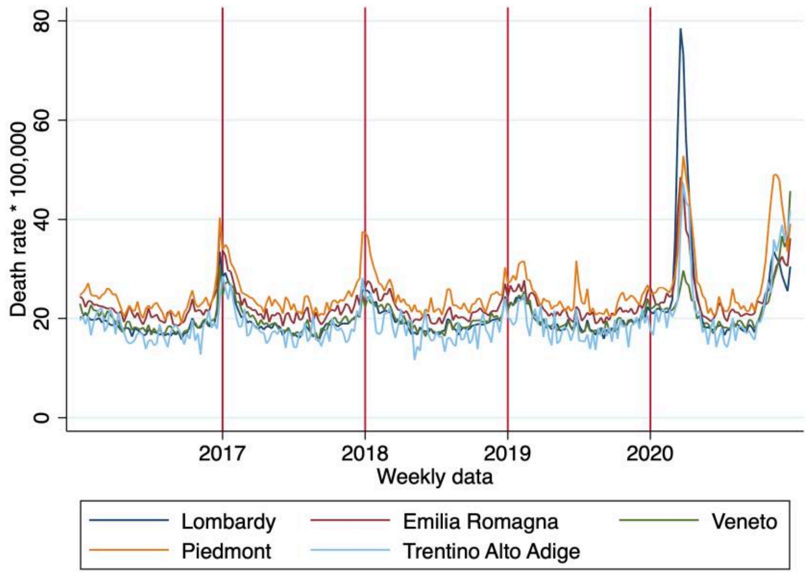

Figure 1. Weekly mortality rates. *Note.* Weekly mortality rates computed using ISTAT (Italian National Statistical Institute) data.

2 Difference in geographic discontinuity designs (DiD-GRDD)

Assessing the impact of different regional governments in the case of unevenly spread health shocks is challenging, as several confounding factors may affect the outcome of interest (mortality in our case). In this paper, we take advantage of the regions' administrative borders. On the one hand, given the regional autonomy in the management of the healthcare system in Italy, each region implemented its healthcare governance model and was in charge of making timely decisions to respond to the health emergency. On the other hand, we posit that since the virus diffusion mainly depended on individual mobility and contacts between people (Kraemer et al., 2020), the spread of the pandemic should have been very similar in neighbouring municipalities located on each side of regional administrative borders. In other words, considering sufficiently near geographical units is assumed to control for unobservable variables related to COVID-19 mortality that may change across space. Thus, in our analysis, we leverage the spatial dimension. This is the idea behind a Geographic Regression Discontinuity (GRDD) design (Dell, 2010).

Especially in the first pandemic wave, due to low COVID-19 testing, it was not possible to exactly attribute deaths to the virus. For this reason, several papers seek to estimate COVID-19 mortality using *excess mortality* compared to the pre-COVID-19 period (Bello & Rocco, 2022; Buonanno et al., 2020). Here, we apply the same approach, and in addition to the spatial dimension, we also leverage the time dimension.

The two dimensions (space and time) can be combined using a Difference in Geographic Regression Discontinuity Design (DiD-GRDD, hereafter). Namely, we focus on the administrative borders of Lombardy and assess excess mortality in 2020, compared to previous years (2017–2019) and its four neighbouring Italian regions (Piedmont, Emilia Romagna, Veneto, and Trentino Alto Adige) using municipality-level data. In the rest of the paper, we refer to the entire Trentino Alto Adige region although the data cover only one of the two autonomous provinces of the region, namely, the Autonomous Province of Trento.

In what follows, we describe the DiD-GRDD in more detail, drawing from Grembi et al. (2016), which introduced the *difference-in-discontinuities* (diff-in-disc) design. We compare mortality in different regions. The regional borders represent the cutoff of our RDD-like design and geodesic distance (correlation coefficients between geodesic and driving travel distances, calculated in minutes or kilometres, are equal to 0.944 and 0.983) our running variable. Regional governments change sharply at regions' administrative borders, that is two municipalities lying on each side of the border can be very similar in terms of economic, socio-demographic, and environmental characteristics affecting mortality, but they are subject to different regional governments. Importantly, even before COVID-19, different regions' health systems might have been more or less effective, and therefore we could observe mortality differences at the border even before the pandemic onset. Defining the treatment variable as

$$L_i = \begin{cases} 1, & \text{if } d_i > 0, \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

where the subscript stands for municipality i, d_i is the distance from the border, the running variable, and distances are positive for Lombardy's municipalities and negative otherwise ($d_i = 0$ at the border). The Lombardy indicator variable L_i takes on value one for positive distances and zero otherwise.

Let us define the potential outcome (i.e. mortality) in Lombardy as $Y_{it}(1)$ and the potential outcome in the comparison region as $Y_{it}(0)$, respectively, where t is the year subscript. The observed outcome can be written as $Y_{it} = L_i Y_{it}(1) + (1 - L_i) Y_{it}(0)$. Under the standard RDD continuity assumption in the potential outcomes, the GRDD estimate would provide the 'effect' of Lombardy on mortality, i.e. the effect on mortality produced in a municipality by being under Lombardy's administration. This is given by

$$\hat{\tau}_{grdd,pre} = E[Y_{it}(1) - Y_{it}(0) \mid d_i = 0, t \leq 2019] \tag{2}$$

in the pre-COVID-19 period, and

$$\hat{\tau}_{grdd,post} = E[Y_{it}(1) - Y_{it}(0) \mid d_i = 0, t > 2019] \tag{3}$$

in the post-COVID-19 period.

What we want to assess through our DiD-GRDD is whether Lombardy's mortality advantage or disadvantage changed in the post-COVID-19 period. Thus, we implement a difference in the two GRDDs, before vs. after the onset of COVID-19, namely

$$\begin{aligned} \hat{\tau}_{did-grdd} = {} & E[Y_{it}(1) - Y_{it}(0) \mid d_i = 0, t \leq 2019] \\ & - E[Y_{it}(1) - Y_{it}(0) \mid d_i = 0, t > 2019]. \end{aligned} \tag{4}$$

We interpret $\hat{\tau}_{did-grdd}$ as the causal effect of the past and the current Lombardy regional administrations' choices, e.g. related to the past development of the Regional Health System and the management of the pandemic emergency (nursing homes' management, institution of 'red zones', COVID-19 testing, etc.) on COVID-19-related mortality.

Similarly to Grembi et al. (2016), for this interpretation to be legitimate, we need two assumptions, which are adapted to our case:

Assumption 1 All potential outcomes $E[Y_{it}(l) \mid d_i = d, t \leq 2019]$ and $E[Y_{it}(l) \mid d_i = d, t > 2019]$, with $l = 0, 1$ are continuous in distance (d) at 0 (i.e. at the border).

Assumption 2 The effect of regional administrations on mortality, in the absence of COVID-19 would have remained constant over time (i.e. the same as in the pre-COVID-19 period).

The first assumption is about the continuity of potential outcomes in space, and in particular at the administrative borders. The second assumption is similar to the DiD parallel trend assumption and can be checked by looking at whether regional mortality at the border was on different trends in different regions before COVID-19. This is implemented via an event-study DiD-GRDD.

In analogy with RDDs, in the implementation of the DiD-GRDD, we assess the robustness of our estimates to varying distance bandwidths from the administrative borders. Figure 2 shows

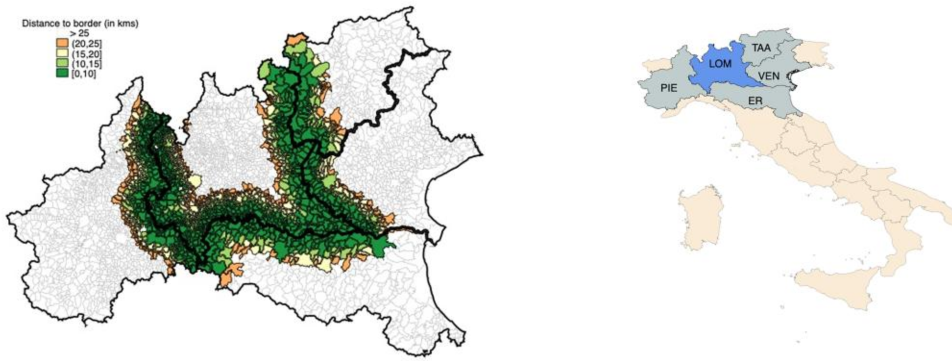

Figure 2. Municipalities included in the analysis coloured by distance to the border (in km). *Note.* This figure shows the location of Lombardy in Italy (subfigure on the right), and the municipalities of the five regions included in our analysis (subfigure on the left). These municipalities are coloured according to their distance bandwidths from the border (in kilometres). Lombardy's neighbouring regions are counterclockwise: PIE: Piedmont (West), ER: Emilia Romagna (South), VEN: Veneto (East) and TAA: Trentino Alto Adige (North-East).

the municipalities' administrative borders (thin black lines) and regions' borders (thicker black lines) in the five regions considered and highlights with different colours the set of municipalities used in the analysis depending on the distance bandwidths (10, 15, 20, and 25 km) from the border. Figure D1 in Appendix D shows how the sample size (i.e. the number of municipalities) changes when progressively increasing the bandwidths in each one of the pairwise regional comparisons.

We implement the DiD-GRDD model parametrically, as follows:

$$\begin{aligned} y_{it} = \alpha_0 + \alpha_1 post_t + \alpha_2 Lombardy_i + \underbrace{\alpha_3\ Lombardy_i \times post_t}_{\text{DiD-GRD Dterm}} + f(d_i) \\ + g(d_i) \times Lombardy_i + h(d_i) \times post_t + \\ + l(d_i) \times Lombardy_i \times post_t + \boldsymbol{\beta}\mathbf{X_{it}} + \epsilon_{it}, \end{aligned} \tag{5}$$

where y_{it} are age-specific total mortality rates (i.e. the number of deaths divided by the size of the corresponding age group multiplied by 100), $post_t$ is a dichotomous variable taking value 1 in 2020 (i.e. the period affected by COVID-19) and 0 before (namely, the years 2017, 2018 and 2019), $Lombardy_i$ is another dichotomous variable taking value 1 for Lombard municipalities and value 0 for all other municipalities; $f(d_i)$, $g(d_i)$, $h(d_i)$, and $l(d_i)$ are first-degree polynomials in distance in kilometres from the administrative border (i.e. the running variable). The choice of local linear regression (i.e. a first-degree polynomial in the running variable) is motivated by the small bandwidths that are used in our analysis (10, 15, 20, and 25 km). Indeed, as shown by Gelman and Imbens (2019), the use of high-degree polynomials can cause several issues in RDDs; 'noisy estimates, sensitivity to the degree of the polynomial, and poor coverage of confidence intervals' (p. 447). $\mathbf{X_{it}}$ is a vector of control variables and ϵ_{it} is an idiosyncratic error term. Models are estimated separately for each age bracket. We implement a DiD-GRDD with a single running variable (distance) instead of multiple running variables (latitude and longitude). This is common practice when using administrative regions as statistical units (see, for instance, De Blasio & Poy, 2017). Indeed, the units of observation in our analysis are municipalities and there are too few units around the regional borders to implement the multiple-running variable version of the GRDD (cf. Dell, 2010).

Given the potential for significant measurement errors in COVID-19-related death data—stemming from the lack of a standardized classification method and the non-compulsory testing of deceased individuals—we follow the approach of earlier research (Bartoszek et al., 2020; Buonanno et al., 2020). Our emphasis is on age-specific total mortality rates for all causes, a metric accurately captured through administrative data (details in the following section). This allows us to minimize measurement error in the outcome variable and estimate the COVID-19-related deaths from the excess mortality rates at the municipality level after the onset of the pandemic crisis (see Alacevich et al., 2021 for a similar approach). Mortality rates are preferred to the absolute number of deaths for ease of comparison between municipalities of different sizes.

In model (5), the main coefficient of interest is α_3, which captures the DiD-GRDD effect, i.e. the excess mortality of Lombardy's municipalities compared to those of close municipalities in a neighbouring region in 2020 compared to previous years (2017–2019). We estimate equation (5) using four different samples, each one including Lombardy's municipalities and the municipalities of Piedmont, Emilia Romagna, Veneto, and Trentino Alto Adige, respectively. Moreover, we estimate several models applying various distance bandwidths from the regional border and for different age groups. Since we have panel data at the municipality level, standard errors are clustered at the same level.

In order to check the plausibility of the DiD-GRDD assumptions, we estimate some placebo versions of the model in equation (5). In one *spatial placebo*, we only focus on mortality in Lombardy and we set a fictitious border at different bandwidths from the real one. In the absence of a different regional government's 'treatment', outcomes should be continuous at the fake border (Assumption 1). If the estimated effect in the specification of equation (5) was a genuine administrative border effect, in this placebo specification we should not find any statistical difference in mortality rates between municipalities on each side of the fake border. We also implement a *time placebo* in which we apply an event-study-like specification where the $post_t$ and the $Lombardy_i \times post_t$ indicators are replaced with year dummies D_t and $Lombardy_i \times D_t$ indicators, respectively. This specification enables us to estimate a coefficient for each $Lombardy_i \times D_t$ interaction and to check whether the *parallel trend assumption* holds before COVID-19 (a check of the credibility of Assumption 2).

The event-study DiD-GRDD specification reads as follows:

$$
\begin{aligned}
y_{it} = \alpha_0 &+ \sum_{\substack{t=2017 \\ t\neq 2019}}^{2020} \alpha_{1j} D_t + \alpha_2 \times Lombardy_i + \underbrace{\sum_{\substack{t=2017 \\ t\neq 2019}}^{2020} \alpha_{3j} Lombardy_i \times D_t}_{\text{DiD}-\text{GRD Dterms}} + f(d_i) \\
&+ g(d_i) \times Lombardy_i + h(d_i) \times post_t \\
&+ l(d_i) \times Lombardy_i \times post_t + \boldsymbol{\beta}\mathbf{X}_{\mathbf{it}} + \epsilon_{it},
\end{aligned}
\tag{6}
$$

where the polynomials in distance are allowed to vary between the pre- and the post-2019 period, but not to be year-specific. We set 2019, i.e. the year before COVID-19 onset, as the reference (omitted) year. Thus, the non-interacted Lombardy indicator captures the differential mortality of Lombardy compared to the other regions in 2019. If the parallel trend assumption holds, the $Lombardy_i \times D_t$ interaction coefficients should be zero for $t = 2017, 2018$, and be different from zero only in 2020.

3 Data

The estimation of the models described in the previous section relies on the extensive use of administrative municipality-level data. Unlike survey data, administrative data offers the advantages of immediate public accessibility, comprehensive population coverage, and minimal susceptibility to measurement errors.

Our main outcome variable is the mortality rate computed using the number of deaths (for any cause) in each municipality, and it is produced by the Italian National Statistical Institute (ISTAT) by integrating various administrative data sets produced by ISTAT, namely, the National Population Register (*Anagrafe Nazionale della Popolazione Residente*, ANPS), municipalities' population registers and the Tax Register (*Anagrafe tributaria*).

Currently, ISTAT provides the total number of deaths for any cause, based on an individual's residence, for 7,901 Italian municipalities and each single day of the year, by age and gender, for the period 2011–2023 (October 31st). Unfortunately, data by specific cause of death are not released by ISTAT at the municipality level. Data from population registers were integrated with those coming from the Tax Register to recover death events that were not registered in the former because they came after the closure of the time window for data acquisition from the municipalities by ISTAT.

In Appendix B, we discuss the choice of control variables and the data sources. Here, it is worth noting that (1) some control variables are measured in 2019 and are time-invariant; (2) the DiD part of the DiD-GRDD would remove time-invariant covariates (and municipality fixed effects); and (3) if the GRDD's assumptions are valid, control variables should be redundant and not significantly affect the estimates. Thus, under the validity of our DiD-GRDD, the conditional- and unconditional-on-covariate models should provide very close estimates. In Appendix C, we show that this is indeed the case, and the inclusion of control variables only improves estimates' precision.

In this paper, we limit our analysis to first-semester regional comparisons, corresponding to the first wave of COVID-19, because starting from November 2020, a four-colour system introducing differential mobility restrictions according to the evolution of the pandemic was introduced in Italy, making the inter-regional comparisons harder to interpret (see Appendix A).

Table 1 reports the percentage mortality rates in the 81+ age group, the one that was most heavily hit by COVID-19 mortality, for the four control regions with which we compare Lombardy. Statistics are reported for the two periods 2017–2019 and 2020, i.e. pre- and post-COVID-19, respectively. Two things stand out from first-semester mortality. First, from the top part of the table, considering all municipalities in each region, mortality rates for any cause in the 81+ age group were higher in 2020 compared to the previous years in all regions. For instance, the mortality rate in 2020 in the 81+ age bracket was 45.4%, 3.8%, 5.5%, 15.6%, and 15.2% higher compared to the average of the previous three years in Lombardy, Veneto, Piedmont, Emilia Romagna, and Trentino Alto Adige, respectively. Moreover, the DiD contrasts show that the excess mortality was higher in Lombardy compared to any of the four control regions, with a difference between 1.7 and 2.5 percentage points. Second, the bottom part of the table reports the same statistics computed in the sample of municipalities within 25 km from Lombardy's border, which are used in the DiD-GRDD estimation. Interestingly, although Lombardy still exhibits higher excess mortality, the differences shrink and vary between 0.6 and 1.6 percentage points. This shows that comparing like-with-like, i.e. municipalities with more similar characteristics, affects the estimated regional differences in COVID-19-related mortality. In the following section, we report DiD-GRDD parametric estimates of these contrasts obtained as described in Section 2. The DiD estimates reported in Table 1 are simple differences in unconditional means and, unlike the DiD-GRDD estimates, do not control for distance from the border.

Figure 3 gives a flavour of the type of comparisons that we make by using the DiD-GRDD. Each subgraph in the figure reports on the horizontal axis the distance from the border, which is represented by the red vertical line at zero, and on the vertical axis the percentage mortality rate. Municipalities to the right of the red vertical line belong to Lombardy, while those to the left belong to the 'control' regions used in the pairwise comparisons. Each graph plots a scatter of points for the mean 2017–2019 mortality (red points) and one for the 2020 mortality (black points). Each point in the scatter plot represents the average mortality rate of the municipalities included in a 1 km interval, and the points are interpolated by linear fits with 95% confidence intervals. The graphs show that the red linear fits (pre-COVID-19) are almost aligned at the border, while significant vertical 'jumps' are observed for Piedmont and Emilia Romagna when considering the black linear fits (post-COVID-19). The size of the discontinuities illustrated in the graphs is only indicative of the estimated effect since our parametric estimation based on equation (5) does not use the mean of 2017–2019 mortality rates for the pre-COVID-19 period but observations for each year (2017, 2018, and 2019).

4 DiD-GRDD main results

As it is well known, COVID-19-related mortality is larger among older individuals (Jordan et al., 2020; Zheng et al., 2020). Thus, we examine age-specific mortality rates by age groups 0–50, 51–70, 71–80, and over 80 (81+), by estimating separate models for each age bracket.

Results are presented through graphs displaying the point estimate of the DiD-GRDD coefficient α_3 in equation (5) and the 95% confidence interval for different bandwidth choices, i.e.

Table 1. First-semester age-specific mortality rates for the 81+ age group (%)

Statistics	Veneto	Piedmont	Emilia Romagna	Trentino AA
Full sample				
Avg mortality pre-Covid	5.77	6.41	6.08	5.60
Avg mortality post-Covid	5.99	6.76	7.03	6.45
Avg mortality pre-Covid - Lombardy sample	5.92	5.92	5.92	5.92
Avg mortality post-Covid - Lombardy sample	8.61	8.61	8.61	8.61
DiD	2.47	2.34	1.74	1.84
DiD-GRDD sample				
Avg mortality pre-Covid	5.93	6.57	6.07	5.47
Avg mortality post-Covid	6.35	7.40	7.61	6.91
Avg mortality pre-Covid - Lombardy sample	5.89	6.05	6.10	5.87
Avg mortality post-Covid - Lombardy sample	7.92	7.46	9.16	8.14
DiD	1.62	0.58	1.52	0.83

Note. Average first-semester mortality rates by sub-period (pre- and post-COVID-19, i.e. 2017–2019 and 2020, respectively) for the municipalities of the four comparison regions included in our analysis computed from the raw data. DiD rows report the unconditional DiD contrasts (mean post Lombardy-mean pre Lombardy)—(mean X post-mean X pre), where X stands for each comparison region. The table reports the age-specific mortality rates (%) for the 81+ age group computed using all municipalities in each region—in the top part of the table—and in the subsample of municipalities within 25 km from the Lombardy's administrative border—in the bottom part of the table. (Our computations are based on ISTAT mortality data, https://www.istat.it/it/archivio/240401.).

municipalities within 10, 15, 20, and 25 km from the Lombard administrative border. In all graphs, we also report the standard DiD estimates obtained by including in the estimation sample all municipalities in each region-pair comparison. In this case, the estimated equations include the same terms as in equation (5) but omit distance and all distance interactions. The DiD approach provides evidence of the average increase in mortality (compared to 2017–2019) in (all) Lombard municipalities—including those that are far away from the border—compared to those located in the control region. The DiD estimate may be considered a useful benchmark to grasp what we actually gain from using the more rigorous (in terms of internal validity) DiD-GRDD approach.

Figure 4 shows the results for the oldest age group (81+). Lombardy has a higher excess mortality compared to all neighbouring regions than Trentino Alto Adige, for which mortality is not statistically different. The DiD-GRDD point estimates are quite precise and rather stable varying the bandwidths around the border as reported in Table D1. Estimates of Lombardy's mortality premia range between 1.13–1.48 pp, 1.46–1.86 pp, and 1.07–1.74 pp for Piedmont, Veneto, and Emilia Romagna, respectively. In contrast, estimated mortality contrasts are nil compared to Trentino Alto Adige. All in all, Lombardy appears indeed to have experienced higher mortality in the 81+ population of between 1 and 1.9 pp compared to all its neighbouring regions than Trentino Alto Adige. The DiD-GRDD point estimates are always smaller in any considered bandwidth when compared with DiD coefficients (1.07–1.86 pp with DiD-GRDD vs. 1.84–2.99 with DiD). By not restricting the comparison to close-to-border municipalities, the DiD estimates include in the analysis those municipalities in Lombardy which were first and heavily affected by COVID-19 (e.g. Alzano Lombardo). These municipalities reported higher mortality rates, especially if compared to those belonging to the control regions. This is clear when comparing Figure 1 with Figure D2 in Appendix D. The DiD estimates, which generally point to a more than 2 pp mortality premium for Lombardy, may be misleading because the estimated differences in mortality rates may be due to the different spread of the COVID-19 virus during the emergency phase. This result supports therefore our choice of relying on the more rigorous DiD-GRDD strategy.

Figure 5 shows the estimates for the 71–80 age bracket. The DiD estimates are again positive (0.46–0.96 pp) and always statistically significant at conventional levels in all pairwise comparisons. However, the DiD-GRDD differences in mortality obtained comparing only municipalities

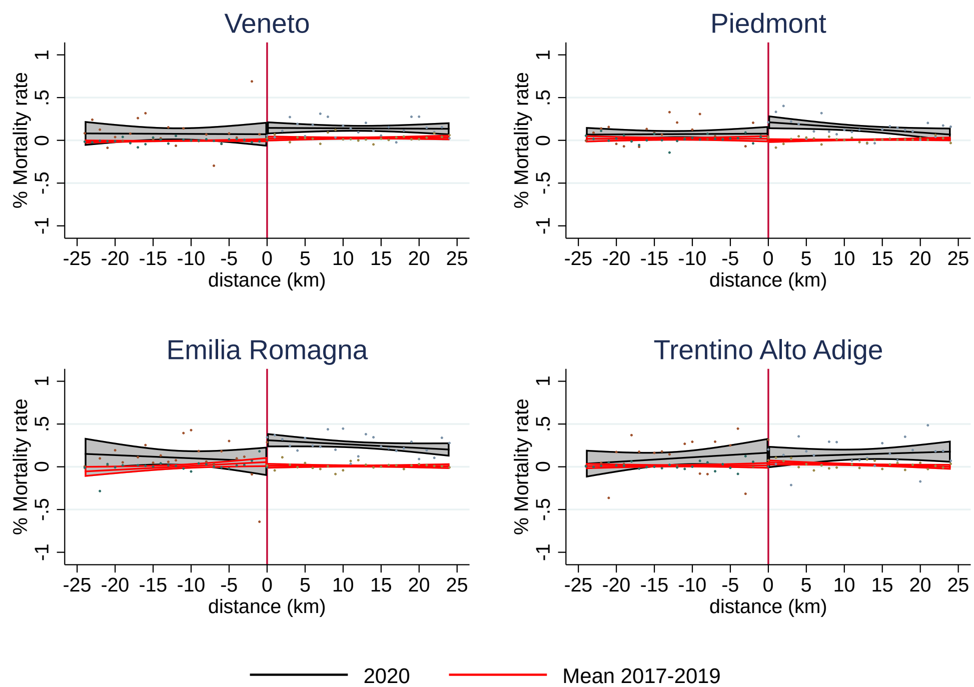

Figure 3. Regression discontinuity at the border: Mean 2017–2019 vs. 2020 mortality rates. *Note.* Plots of the average mortality rates computed using those municipalities included in a 1 km distance range between 0 and 25 km from the administrative border, which is indicated as a red vertical line at zero. Positive values of the distance correspond to Lombardy while negative ones correspond to the 'control' regions. Each dot represents the average mortality rate of all municipalities in a given distance range and linear polynomial fit (allowed to differ on each side of the border) is superimposed.

located near the border are always smaller, and only significant (at 10%) for the Lombardy vs. Emilia Romagna comparison, with an excess mortality of the former in the range of 0.5–0.6 pp. Thus, the higher mortality of the elderly for Lombardy, compared to its neighbouring regions, appears to have occurred only for the oldest age group.

As shown in Figures D3 and D4 in Appendix D, excess mortality in Lombardy is generally not statistically different from neighbouring regions in younger age groups (namely, in the 0–50 and 51–70 groups). Even in the few cases in which the estimates are statistically significant, the point estimates are small. This is consistent with younger age groups having been only marginally exposed to COVID-19 related mortality (Onder et al., 2020).

Clustering the standard errors at the municipality level, our estimates account for time serial correlation in the error term. However, unobservables in the error term may also be correlated across space. For this reason, Table D2 reports the baseline estimates (for the 81+ and 71–80 age groups and within the 25-km bandwidth) both with clustered and spatial heteroskedasticity and autocorrelation consistent (HAC) standard errors (Conley, 1999), which turn out to be remarkably similar.

5 Checks of the DiD-GRDD identifying assumptions

In this section, we report some falsification checks for the DiD-GRDD identifying assumptions.

In the first check, we set a fake border within Lombardy's regional territory and compare municipalities on each side of this border. Since in this falsification exercise all municipalities are ruled by the same regional administration and subject to the same regional health system, we do not expect significant differences in mortality to emerge.

In a second check, by adopting an event-study-like setting, we test whether the excess mortality across the Lombardy administrative border differed also before the COVID-19 crisis outbreak,

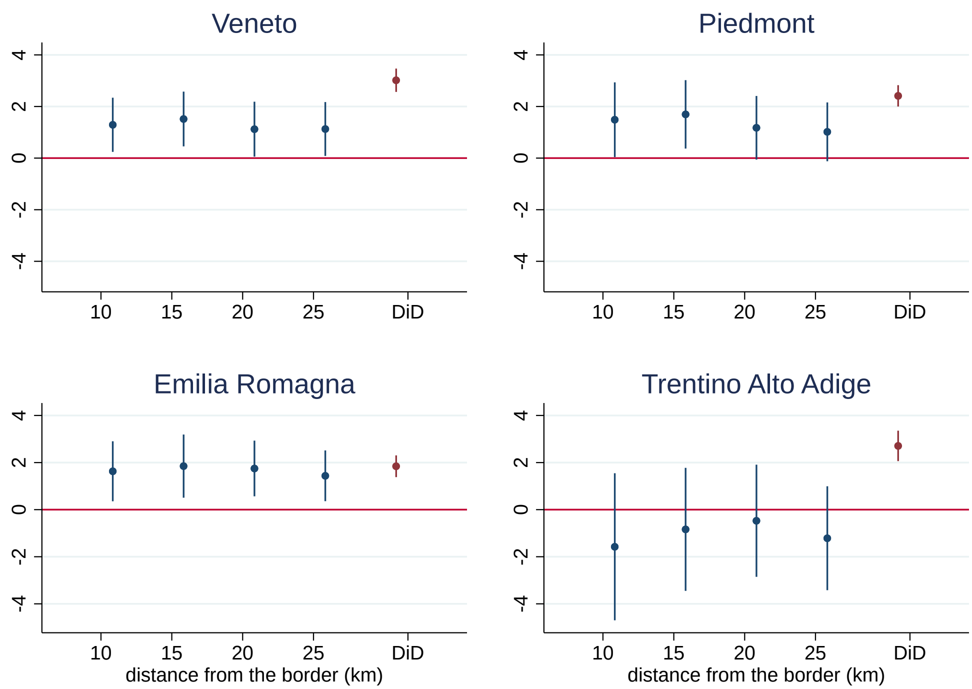

Figure 4. Lombardy's excess mortality compared to neighbouring regions—age 81+ population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at the municipality level) of the DiD-GRDD estimates obtained with different distance bandwidths (in km) from the administrative border indicated on the horizontal axis, including the DiD estimates on all municipalities.

which can be considered a check of the 'parallel trend assumption'. In the case of parallel trends before COVID-19, we can be sure that differential changes in excess mortality were induced by regions' different abilities to cope with the COVID-19 crisis rather than by pre-existing trends in regional administrations' or health systems' performances.

5.1 Event-study analysis and the parallel trend assumption

This section describes the results of the event-study DiD-GRDD analysis. For the sake of brevity, we only comment on the results for the 81+ age group, for which we found statistically significant differences in the baseline DiD-GRDD analysis.

The red horizontal line in the graph of Figure 6 indicates the DiD-GRDD coefficient (the interaction between $Lombardy_i$ and the year indicator) for the year preceding the COVID-19 onset (i.e. 2019, the omitted year). In principle, in the presence of the 'parallel trend assumption', we could observe differences in mortality at the border across regions (e.g. due to the higher quality of a region's health system compared to the other), but these differences should have remained constant over time. This entails that for the years 2017 and 2018, the $Lombardy \times D_t$ interactions should be zero (implying the same difference in mortality as of 2019) because in 2017–2019 municipalities were not affected by the COVID-19 health shock. In this regard, Figure 6 is quite reassuring. Indeed, the 2017 and 2018 estimates are often close to the red line, while the coefficient for 2020 is significantly above it in all the cases in which the DiD-GRDD detected higher excess mortality for Lombardy compared to neighbouring regions (namely, Veneto, Piedmont, and Emilia Romagna). In some cases, owing to the addition of new parameters to be estimated, estimates for 2020 are not very precise but the graph shows quite clearly that their magnitude is above the pre-2020 interactions. Only in the case of Trentino Alto Adige 2019 appears to be a peculiar year, that is Lombardy seems to have experienced lower mortality both before 2019 and after 2019, but similar mortality to Trentino Alto Adige in 2019. For Trentino Alto Adige, therefore, our results are to be taken with caution, given a potential violation of the parallel trend

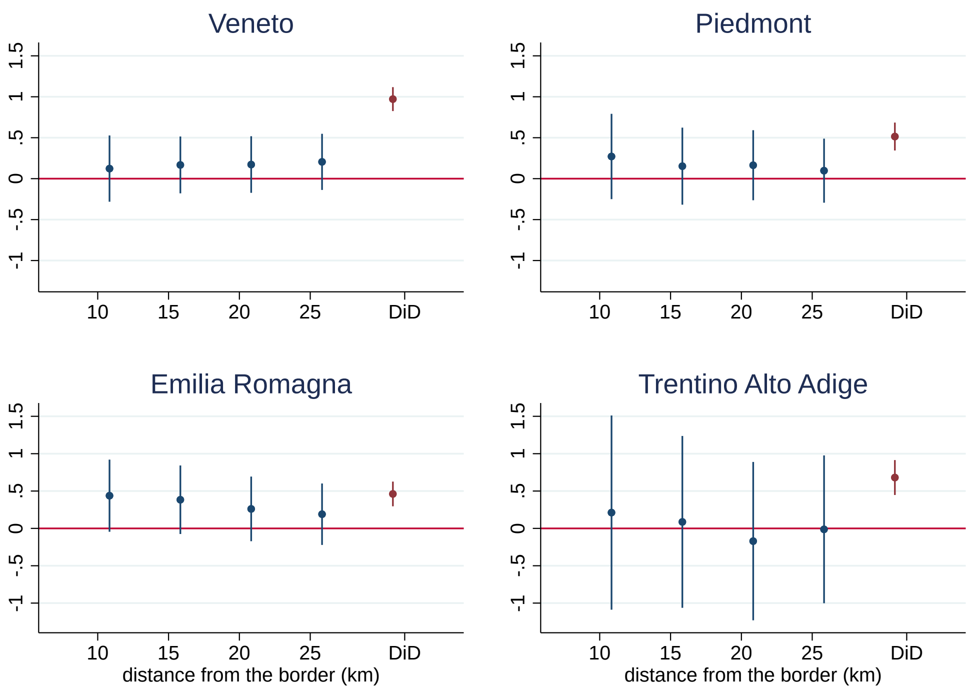

Figure 5. Lombardy's excess mortality compared to neighbouring regions—age 71–80 population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at the municipality level) of the DiD-GRDD estimates obtained with different distance bandwidths (in km) from the administrative border indicated on the horizontal axis, including the DiD estimates on all municipalities.

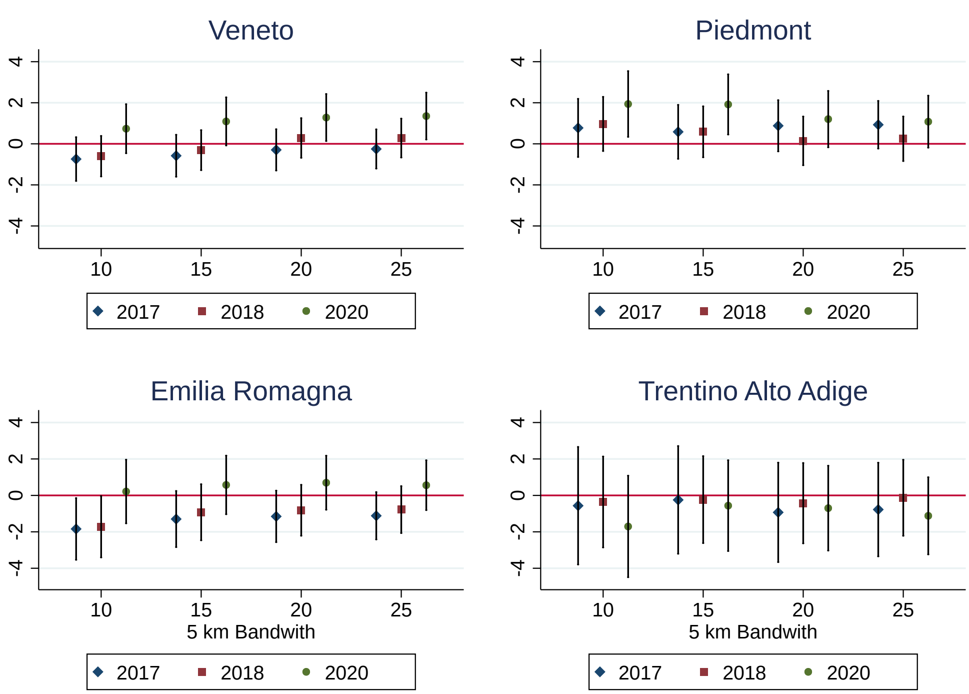

Figure 6. Lombardy's excess mortality compared to neighbouring regions—event-study DiD-GRDD, age 81+ population. *Note.* Plots of the year-specific coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the event-study DiD-GRDD estimates obtained with different distance bandwidths (in km) from the administrative border indicated on the horizontal axis.

assumption. We already stressed that Trentino Alto Adige was a peculiar region also in terms of health expenditures given its status as a special-statute region.

All in all, the analysis in this section supports the validity of our research design and shows that excess mortality for Lombardy at the border, compared to its neighbouring regions, only appeared in 2020.

5.2 Manipulation of the running variable and spatial placebo

As well known, an important identification assumption in RDD, and consequently also in our DiD-GRDD, is the absence of manipulation of the running variable (distance from the border in our case). In principle, there is very little room for differential 'manipulation' of the treatment between the geographic areas around each shared border, especially during the COVID-19 first wave. In the context of our study, a potential form of manipulation of the 'treatment' (i.e. exposure to a specific regional health system) could occur if a patient in a municipality close to the border had the freedom to choose the region for healthcare. However, due to the stringent national restrictions imposed by the sudden implementation of confinement measures starting from March 9, 2020, in Italy, such instances should be very rare, especially during the initial wave of COVID-19. This would likely be limited to highly severe and critically ill patients, specifically those requiring transfer to an Intensive Care Unit (ICU), and only in cases where the ICU department of the patient's current hospital and the overall availability of ICU beds in the entire region are saturated. Figure D5 in Appendix D shows indeed a sudden drop in people's mobility starting from the beginning of March (10th week of the year). Moreover, changes of residence during the pandemic were unlikely given that they entailed registering with a new general practitioner (after finding him/her) in the middle of a health emergency.

Another concern related to the potential manipulation of the running variable is that sorting before the onset of COVID-19 of individuals on each side of the border could be motivated by characteristics of the regional health systems. We do not have data to test this kind of selection, but we provide some indirect evidence.

Using data from Berta et al. (2022), we estimate the difference in health expenditure—measured via the per-capita regional reimbursement (defined according to the Lombardy tariffs) of all the 2016 hospitalizations of patients with residence in those municipalities lying around the regional border—regressing it against distance from the border, a Lombardy indicator and their interaction term. Figure D6 shows that using small bandwidths (10 and 15 km) in all cases but Trentino Alto Adige, we do not find a discontinuity in health expenditures at the border. So, there was little scope for population sorting along this dimension. Trentino Alto Adige is, in many respects, a peculiar region since it has special statute and its two provinces (Trento and Bolzano) benefit from very large legislative, administrative, and financial autonomy. For this reason, the comparison between Lombardy and Trentino Alto Adige should be taken with a grain of salt.

In any case, to correctly attribute the geographic differences in mortality detected with the DiD-GRDD analysis to differences in the management of the COVID-19 crisis, we must check that similar differences do not emerge between nearby municipalities belonging to the same region. To test for this potential threat to identification, we implemented a *spatial placebo* where we only focus on mortality (separately by age group) among clusters of municipalities around a fake border that is set within the Lombardy territory. We create a new *fake border* within the region at different bandwidths from the real one. We then estimate again our preferred specification, equation (5). The fake border is set by moving the real border towards the interior of the Lombardy region and retaining in the analysis all of Lombardy's municipalities within a given distance bandwidth from the 'artificial' border. Just to give an example, if we set a bandwidth of 10 km, the border is moved by 20 km from the original one (so that we can consider municipalities within 10 km on each side of this new border). So, *de facto*, in this analysis, the fictitious border changes with the bandwidth choice.

The spatial placebo estimates in Figure 7 do not show any statistical difference between the average mortality rates of municipalities on each side of the fictitious border.

5.3 Additional robustness checks

We carried out additional robustness checks. First, following Carrell et al. (2018), we assessed how much of the mortality differences across municipalities are accounted for by differences in

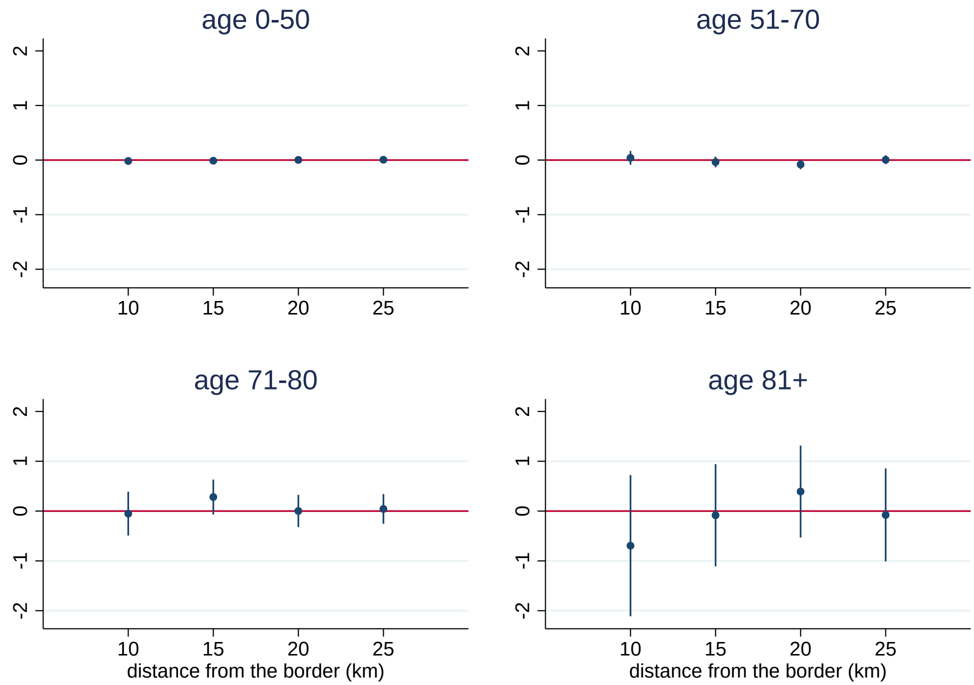

Figure 7. Lombardy's excess mortality compared to neighbouring regions—'Fake border'. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at the municipality level) of the DiD-GRDD estimates obtained with different distance bandwidths (in km) from a 'fake' administrative border—set within the Lombardy region—indicated on the horizontal axis. For the age brackets 0–50 and 51–70, the effects are precisely estimated zeroes.

the covariates, e.g. socio-economic and demographic characteristics, eventually changing sharply across the administrative borders. This is a balancing test run on the linear predictor of mortality based on a regression model, which weights the covariates according to their importance in predicting mortality. Second, we re-estimated the models omitting control variables. Under the validity of the DiD-GRDD, covariates should not significantly impact our estimates but only affect precision. Third, we checked the sensitivity of the DiD-GRDD model to the inclusion of municipality fixed effects. In all cases, the results are in line with our baseline estimates and are commented on in more detail in Appendix C.

A key assumption in the DiD-GRDD is that closer municipalities should be more comparable, e.g. in terms of virus diffusion, than two municipalities taken at random. However, recent research has shown that the intensity of COVID-19 circulation was partly related to commuting flows (e.g. Gu et al., 2022; Kuebart & Stabler, 2020; McMahon et al., 2022; Mitze & Kosfeld, 2022). In principle, two bordering municipalities may be characterized by different commuting flows partly depending on the features of the transport network. To take into account this potential confounder, we made two checks. In a first check, we estimated gravity models (Beine et al., 2016; Head & Mayer, 2014) for commuting flows measured in the 2011 Population Census using region pairs. The most recent available data refer to the 2011 Census; however, a simple correlation between the commuting flows in 2011 and 2001 at the municipality level returns a coefficient of 0.98 suggesting that commuting flows are quite persistent over time. The gravity models include as control variables the distance between the origin and destination municipalities, the distance from the border, the population at origin, old-age and young-age dependency ratios, destination fixed effects, and a dummy variable for the Lombardy region, which captures potential discontinuities in commuting at the border. Table C1 in online Appendix C shows that the Lombardy indicator is generally non-significant in the commuting models, with few exceptions, namely, Trentino Alto Adige considering the largest bandwidth and Emilia-Romagna with bandwidths larger than 10 km. Although the one using 10 km, the smallest bandwidth, is also our preferred specification since it reduces the bias due to potential unobservables and commuting flows do not appear to cause problems to these estimates, we tried to incorporate mobility in our baseline estimates. Indeed, in a second robustness check, we included in the main specification of equation (5), the predicted out-of-sample (i.e. using the values of the covariates in the different years) outward and inward commuting flows obtained from the gravity models, and their interactions with the $post_t$ indicator, which allow mobility to have differential effects on mortality in the presence of COVID-19. The results are plotted in the usual way in Figure C7 in online Appendix C. Reassuringly, the estimates are not significantly affected. All in all, we conclude that differences in commuting are unlikely to have an important impact on our estimates.

6 What did go wrong? An analysis of potential mediators

In general, it is difficult to determine all factors that may be responsible for the statistically robust differences in mortality that we observe at the border using only the administrative data we have. A thorough analysis of the mechanisms would require hospital-level or nursing home data for all the five regions considered, which are not publicly available.

Despite these limitations, we attempt to explore some possible mechanisms. First, we investigate whether, in addition to having differently managed health services, regional administrations may also have differently enforced mobility restrictions. In order to test this hypothesis, we carried out the DiD-GRDD on an indicator of people's mobility (see Appendix B for the data description) measured at the municipality level. We performed a GRDD using this measure of mobility as the dependent variable to formally test whether the reduction (compared to the pre-pandemic baseline) in mobility differed at the border during the first wave of the pandemic. Unfortunately, mobility data are measured as index numbers, so only variations and not levels can be compared across locations (we cannot apply a DiD-GRDD model since the mobility indicator is only available for 2020). The GRDD coefficients, reported in Table D4 in Appendix D, show how for most of the pairwise regional comparisons there was no statistically significant difference in changes in mobility across the border. In a few cases, for larger distance bandwidths, a quite small negative and marginally significant effect emerges, suggesting that Lombardy was more effective in restricting mobility (or that Lombardy's population complied more with the restrictions). Thus, through this channel, we should have observed a *lower* mortality for Lombardy, if anything. All in all, these results point towards the exclusion of differential reductions in mobility at the border (due to differences in regional policies) as a primary cause of the larger excess mortality in Lombardy.

Second, we seek to explore the possible mediating role of some structural features of Lombardy's health system management of nursing homes during the first phase of the emergency. To this end, we use a simplified version of the DiD-GRRD model, which despite including distance as a control, omits the distance interactions. So, we do to avoid multicollinearity problems (between interaction terms involving the $Lombardy_i$ and $post_t$ indicators) and to retain some statistical power, as in the mediation analysis we interact certain regressors (one at a time) with the $Lombardy_i$, $post_t$ and $Lombardy_i \times post_t$ indicators. These specifications allow for the effect of the characteristic x on mortality to differ not only after COVID-19, and in Lombardy (compared to other regions), but also for the role of these features to differently change in Lombardy following the pandemic. In the spirit of mediation analysis, we are primarily interested in the effect of including these additional terms on the estimates of excess mortality at the border [i.e. the coefficient α_3 in equation (5)]. These differences are displayed in Figure 8, which plots the baseline DiD-GRDD estimates, the estimates of the DiD-GRDD 'simplified' model, and how the latter change including interactions with the variables x indicated on the horizontal axis. As for the x's, we consider a dummy for hosting nursing homes in the municipality (and the number of beds when it is available), the number of ICU beds in public and private hospitals, and the number of ordinary beds in public and private hospitals. First, we observe that the baseline DiD-GRDD and the DiD-GRDD 'simplified' models lead to very similar estimates (except for Trentino Alto Adige, for which differences in excess mortality are lower when using the more parsimonious model). Second, only the inclusion of nursing home interaction terms appears to reduce Lombardy's higher excess mortality at the border, but exclusively in the comparison with Emilia Romagna (by about 1 pp). Table D3 in Appendix D shows that although more municipalities in

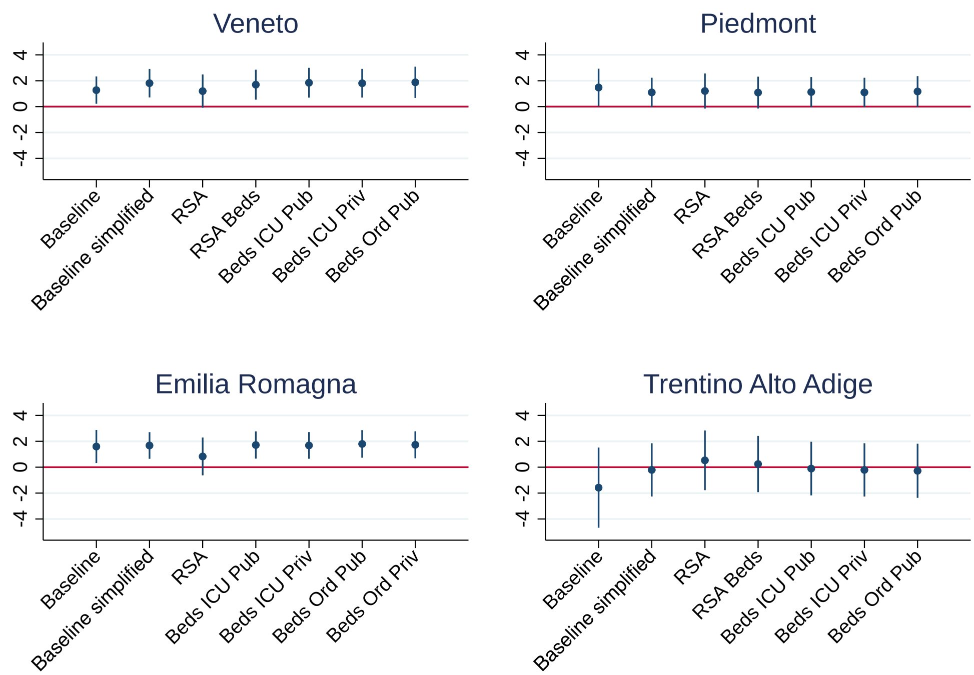

Figure 8. Mediation analysis (81+ age bracket, municipalities within 10 km from the border). *Note.* Plots of the of the DiD-GRDD coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) obtained with a 10-km bandwidth. The coefficients reported are respectively that of the baseline model of equation (5), the simplified model described in this section, and models including interactions between presence of nursing homes in the municipality, the number of RSA beds (whenever available) and the number of beds (ordinary or ICU) in private or public hospitals with the $post_t$, the $Lombardy_i$ and the $Lombardy_i \times post_t$ indicators. RSA (*Residenza Sanitaria Assistenziale*) stands for nursing homes.

Lombardy host nursing homes, focusing on the 10-km bandwidth, proportions are very similar in all regions but Veneto. After controlling for the interaction between the post-COVID-19 indicator with this potential mediating factor, Lombardy did not experience significantly higher mortality than Emilia Romagna in the 81+ population. Yet, estimates are not precise enough to be statistically different from our baselines.

7 Discussion and concluding remarks

The analysis in this paper shows that municipalities in Northern Italy, located near the regional borders, had different mortality rates during the first wave of the COVID-19 pandemic in 2020, depending on their administrative region. This result is significant despite considering geographical areas that should have been broadly subject to the same virus diffusion, environmental conditions (humidity, wind speed, pollution levels, etc.), labour market, socio-economic conditions, demographic and epidemiological characteristics of the resident populations, and similar mobility levels both before and during the lockdown, but were ruled by different regional administrations.

Our DiD-GRDD-based comparison accounts for ‘baseline’ differences in mortality rates among the selected areas during the years preceding the pandemic (2017–2018–2019) allowing us to estimate the deviations in mortality rates from this baseline.

Regional administrations are shown to be potentially responsible for between 1 and 1.9 pp first-semester excess mortality rates at the border compared to previous years and neighbouring regions. Such effect, which is only observed for the 81+ age group, is statistically significant and similar in magnitude across different bandwidths of the DiD-GRDD estimates for all comparisons with the other regions than Trentino Alto Adige (for which mortality among municipalities is not statistically different from the one experienced in Lombardy). Results are generally robust to many placebo tests and robustness checks as well as to an event-study analysis confirming the validity of the parallel trend assumption (key for DiD-GRDD) for all regional-pair comparisons but Trentino Alto Adige, which is a special-statute region enjoying larger autonomy from the central government.

Differences in elderly mortality between the Lombardy region and the bordering regions may derive from the structural characteristics of Lombardy's health system or poor management of the pandemic during the first emergency phase. A simple mediation analysis points to differential management of the health emergency in nursing homes as a possible factor in explaining Lombardy's higher mortality compared to Emilia Romagna during the first wave of the pandemic while it does not identify the larger diffusion of private health structures in Lombardy as a key factor for higher excess mortality.

Our results confirm and integrate earlier evidence that the management of nursing homes might have played a key role in the exceptional mortality observed in Lombardy (Alacevich et al., 2021). Ancidoni et al. (2020), using data from a survey run by the ISS (*Institute Superiore di Sanità*) in March 2020, document higher mortality rates in the nursing homes in Lombardy (7.5%) compared to the neighbouring regions (1.2% in Veneto, 3.3% in Piedmont, 4.2% in Emilia Romagna, and 6.4% in the Autonomous Province of Trento). A high mortality in nursing homes was also observed in other countries during the first wave of COVID-19 (Schultze et al., 2022). Although it is not possible with our municipality-level data to delve into which aspects of nursing homes' management contributed to higher mortality, an article by Notarnicola et al. (2021) provides important insights. The authors use a qualitative survey to investigate regional differences in policies adopted by nursing homes during the pandemic and report some differences in the ways health emergency was tackled, especially since May 2020. A striking difference between Lombardy and the other regions was the lack of measures for the management of residents in home care and positive cases and for workforce management (safety and training). A first reaction to an unprecedented pandemic outbreak required an immediate ability to act under scarce information, to be able to implement and quickly scale successful and effective decision-making strategies. Examples of such policies are the coordination of human and economic resources across different parts of the health care system, especially in nursing and care homes, implementation of testing facilities, support to primary care physicians, implementation of dual track systems in hospitals to preserve non-COVID patients in response to the crisis. This proved to be difficult in Lombardy during the first COVID-19 wave.

Acknowledgments

The authors would like to acknowledge the GSM Association of Mobile Network Operators (GSMA) for providing access to aggregated and anonymized mobile positioning data to the European Commission, Joint Research Centre, in the framework of the Data4Good initiative. Data have been used within the scope of the Letter of Intent of Cooperation (https://www.gsma. com/gsmaeurope/wp-content/uploads/2021/02/Letter-of-Intent_final_16-April-2021.pdf). The authors would also like to thank colleagues from Eurostat and European Centre for Disease Prevention and Control (ECDC) for their input in drafting the data request and from the Joint Research Centre, in particular Michele Vespe, Umberto Minora and Stefano Iacus for their valuable contribution and data assistance. We also thank Cinzia Di Novi for her useful comments and suggestions on an early draft of this paper. Three reviewers, the joint Editor and the Associate Editor, whose comments gave us inputs to greatly improve the paper, are also gratefully acknowledged. The information and views set out in this paper are those of the authors and do not reflect the official opinion of the European Union. Neither the European Union institutions and bodies nor any person acting on their behalf may be held responsible for the use which may be made of the information contained therein.

Conflicts of interest: None declared.

Funding

None.

Data availability

All the data used in the paper are publicly available as reported in Table B1. Data to reproduce results in Table D4 and Figure D5 in Appendix concerning mobility of residents were provided by the GSM Association of Mobile Network Operators (GSMA) to the European Commission, Joint Research Centre in the framework of the Data4Good initiative and cannot be shared publicly.

Appendix A: The Italian National Healthcare Service and Heterogeneity Across Regions

The Italian National Healthcare Service (INHS) was established in 1978 with the aim of providing free-of-charge, uniform, and comprehensive care, replacing the existing system based on health insurance funds. The INHS is a typical Beveridge system, financed through general taxation, which guarantees equitable access and a uniform provision of healthcare services to all citizens without any discrimination.

Over the last 40 years, two major reforms were introduced, one in 1992–1993 and one in 1998–1999, aimed at containing costs and increasing the responsibility and autonomy of regional authorities (France et al., 2005). INHS is currently structured in three main levels: (i) the national state with the Ministry of Health; (ii) the regions with their health departments (21 regional governments, namely 19 Regions and two Autonomous Provinces); and (iii) the Local Health Authorities (LHAs), interacting with municipalities. LHAs are vertically integrated organizations funded by regions and are responsible for a wide range of hospital and community services in a given geographical area. LHAs directly manage most public hospitals, coordinate primary care, and territorial services, assess the appropriateness of health services and their distribution, and improve the integration of social and health services. Regions are allowed to adopt different strategies and governance models, allowing them significant autonomy in organizing their healthcare system under a balanced-budget constraint and the requirement of delivering the core and essential health benefit package (*Livelli Essenziali di Assistenza*, LEA), to all citizens free-of-charge or upon a co-payment. The LEAs are set by the central government to preserve a core uniform set of services, throughout the country. The recent reforms aimed at making the public sector more efficient, effective, and accountable. However, this process produced a large heterogeneity across regions that developed financial, administrative, and political responsibility for the provision of health care, often employing different governance models and management tools (see Neri, 2011; Tediosi et al., 2009, among others).

In this paper, we focus on Lombardy, the epicentre of the first wave of the COVID-19 crisis and its neighbouring Italian regions, namely, from northwest to north-east, Piedmont, Emilia Romagna, Veneto, and Trentino Alto Adige. Altogether, the five regions we consider in this paper account for over 40% of the Italian population (Table A1, column A) and an average income above the country's average. According to the Italian National Statistical Institute (ISTAT) data, in 2019 in Italy, the per capita GDP was 29,700€, whereas among the five regions considered it ranged from a maximum of 39,700€ of Lombardy to a minimum of 31,700€ of Piedmont. Although relatively homogeneous from an economic point of view, they are heterogeneous concerning the governance of the healthcare system.

Complementing (Nuti et al., 2016) taxonomy of the Italian governance models with Bobini et al. (2020), which is based on interviews with some key informants, Lombardy emerges as a stand-alone healthcare system in the Italian context. Lombardy is the only region that opted for the 'choice and competition' model, stressing the role of patients' choices to boost competition by splitting purchasers and providers, including private institutions. It is based on the assumption that, upon fulfilling the rules and standards set by the regional government, the market will regulate itself, promoting competition between public and private health service providers. It combines elements of the 'pay for performance' (P4P) model, as general managers of LHAs are rewarded according to the achievements of targets negotiated with the regional administration, though the variability of managers' rewards and performance results is low, with limited public information on hospitals' performances. Lombardy does not use a regional public ranking, which limits information available to citizens and the possibility of hospitals learning from their relative performance (Berta et al., 2013).

The other four Italian regions bordering Lombardy opted for models of governance with a relevant role of the regional government to plan activities and set standards to be implemented by

Table A1. Descriptive statistics on Regional Health Systems (RHSs)

	Population	Average number of residents covered by LHSs	RHSs' expenditures for GPs	Number of GPs	Numbe of GPs on out-of-hours services	People using ER within 3 months before interview	People using GPs out-of-hours services within 3 months before interview	Beds in acute care, accredited private institutions	Accredited private in-ordinary-regime discharge	Accredited private day-hospital discharges over total discharges
	thousands	thousands	€	for 10,000 inhabitants	for 10,000 inhabitants	out of 1,000	out of 1,000	%	% over total	% over total
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(L)
Year	2019	2019	2019	2018	2018	2019	2019	2019	2019	2019
Lombardy	10,011	370.8	64.6	6.2	9.4	96.7	28.1	36.5%	36.4%	42.8%
Piedmont	4,329	360.7	81.5	6.9	10.2	89	40.1	8.7%	19.3%	10.6%
Veneto	4,885	542.7	82.7	6.5	14.4	87.4	36.5	12.4%	17.2%	27.8%
Emilia Romagna	4,459	557.4	85.4	6.6	10.6	93.2	33.5	17.1%	19.3%	25.7%
Trento, A. P.	544	543.7	76.0	6.6	11.6	82	51.1	14.5%	20.9%	14.1%
ITALY	59,817	543.8	76.1	7.1	19.6	78.6	38.9	30.4%	26.0%	28.3%

Sources: (A) ISTAT, resident population on Jan. 1st 2019 (B) Our calculations using ISTAT and Ministry of Health data (C) Ministry of Health (D-L) ISTAT, Healthcare sector data *Note.* GPs stands for 'general practitioners'.

LHAs overlooking the service providers. In these regions, the presence of private providers is limited, with the percentage of beds in acute care supplied by accredited private institutions well below Lombardy and the national average. Some specificity, however, applies. The Piedmont RHS is better described by a 'command and control' model, following the recovery plan introduced in 2010 to have access to the national bail-out fund. Although the central government specifies financial targets, there is no systematic benchmarking of clinical results nor public disclosure of performance data. Following the recovery process, the number of LHAs was reduced to 12, with an average coverage of 360.7 thousand people, which is still one of the lowest in Italy, with 3 AOUs and 3 AOs. Veneto, Emilia Romagna, and Trento Autonomous Province (the province in the Trentino Alto Adige region sharing the border with Lombardy) have adopted a mixed governance model that combines 'hierarchy and targets' with 'transparent public ranking' and P4P, however, specificities apply according to the governance models and the staff's managerial skills. Trento's RHS is relatively simple, due to the small size of the resident population, and with a local tradition of sound management.

In Emilia Romagna's RHS, the Department of Health is supported by a regional health agency for technical and scientific matters, is responsible for the overall planning and coordination of activities, and leaves large discretionality to public service providers, including 8 LHSs, 4 AOUs and 3 IRCCS. Emilia Romagna was one of the first regions to increase the population coverage of LHAs, which currently count over 550 thousand residents. The peculiarity of Emilia Romagna's RHS is the strong interconnection with local administrative authorities, including municipalities, in a typical network model (Rhodes, 1997).

The existing differences among the RHS, aimed at increasing the overall efficiency of the INHS, may represent a critical issue when facing an unprecedented pandemic such as COVID-19. Autonomy and independence in the organization and delivery of healthcare services may be a problem when the response to an epidemic outbreak requires strong coordination among the different actors regardless of their local context. Such a scattered picture may also be reflected in subsequent substantial differences in the strategies adopted by the different regional governments to face the COVID-19 emergency (OECD, 2020).

During the first wave, When responding to the health emergency at the onset of the COVID-19 epidemic, Veneto largely relied on home care assistance, limiting hospital admissions to the most severe cases, and started early testing of healthcare workers operating in the community and in hospitals. In Emilia Romagna, the network model of the RHS helped, allowing it to adapt promptly, relying on home care assistance and active surveillance systems, on GPs with phone calls to patients to monitor their symptoms, and strengthening primary care assistance, as suggested also in OECD (2021). On the contrary, Lombardy chose a hospital-centred approach at the expense of community-based services, with intensive use of emergency rooms as a consequence of reduced territorial services provided by GPs and GPs on out-of-hours services. This might have contributed to exacerbating the stress on the health system generated by COVID-19 (Usuelli, 2020). The dramatic inflow of patients quickly saturated the intensive care units, forcing doctors to decide how to allocate resources (Rosenbaum, 2020). In the hospital setting, the virus was spread not only by patients but also by healthcare workers, who could not always rely on appropriate personal protective equipment, risking their lives while doing their job (Gibertoni et al., 2021).

As for the second COVID-19 wave (starting from October 2020), the Italian government implemented several progressive restrictions, initially applied homogeneously over the country, and then after November 6, 2020 adopted a colour-labelled scheme with four different colours (coded as white, yellow, orange, and red with increasing levels of restrictions to mobility and economic activities), which were imposed on a regional basis to reflect existing regional heterogeneity in the virus transmission and hospital stress. For all details regarding the adopted measures, see https://www.agenas.gov.it/covid19/web/index.php. Regional restrictions were automatically assigned centrally depending on the value of the reproduction number (R_t).

As described in detail in Manica et al. (2021), according to these measures, a stay-home mandate between 10 pm and 5 am (except for work, health, and other certified reasons) was implemented in yellow and orange regions, while the stay-home mandate plus a ban on movements between municipalities and to/from other regions was in place in the red ones. For what concerns retail and service shopping, malls were closed during weekends and holidays (except for essential retail and services) in both yellow and orange regions while all shops not selling essential goods were always closed (again except for essential retail and services) in red ones. Bars serving food, cafes, and restaurants were allowed to be open until 6 pm while take-away activity was only allowed between 6 pm and 10 pm in yellow regions. In orange and red regions, only take-away activity until 10 pm was allowed. Distance learning in high schools and universities was mandatory in yellow and orange regions, including the second and third grades of lower secondary schools in red ones. For all colour-labelled restrictions, public transport was reduced to 50% of its capacity (except for school service) and indoor recreational and cultural venues were closed. Gyms, pools, and leisure venues were closed except for outdoor sport centres in yellow and orange regions while in red regions, individual outdoor training only was allowed (except for sport events of national interest like the national football league).

Differences in adopted colours among the five selected regions during the second wave may be summarized as follows: Lombardy and Piedmont were classified as red zones up to November 28, orange afterwards up until December 13, and yellow before Christmas; Emilia Romagna spent the first week (up to November 14) in yellow then moved to orange for 14 days (December, 5) and went back to yellow afterwards; Trento Autonomous Province and Veneto remained yellow all the time. During the Christmas period up to the end of the year, restrictions have been applied uniformly in all regions. Because of this heterogeneity in mobility restrictions, which might have affected both virus spread and mortality, we limit our empirical analysis to the first COVID-19 wave, i.e. the first semester of 2020.

Appendix B: Control Variables

A rich body of work is becoming available as to the main determinants of COVID-19 diffusion and mortality. We start from this evidence to select (conditional on availability) the covariates to be included in our empirical analysis.

The extant literature has identified a clear demographic profile for COVID-19 victims (Jordan et al., 2020; Zheng et al., 2020). COVID-19 counts victims particularly among the oldest, and proportionally hits fewer females than males. Underlying health conditions such as respiratory and Cardiovascular disease, diabetes, hypertension, and cancer are important predictors of COVID-19 related mortality (Robilotti et al., 2020).

Environmental factors, such as air pollution, and weather conditions, such as temperature and humidity, have been found to be associated with mortality (Becchetti et al., 2022; Ma et al., 2020; Wu et al., 2020).

Restrictions in economic activity and individual mobility (lockdowns) contribute to reducing the diffusion of the virus and mortality. This has been observed, *inter alia*, for China, Italy, and Spain (Ciminelli & Garcia-Mandicó, 2020; Lau et al., 2020; Qiu et al., 2020; Tobías, 2020), which were among the first countries to be hit by the pandemic and to implement lockdowns. However, evidence is not limited to these countries. Evidence on Europe has been reported in Flaxman et al. (2020).

Recent studies also demonstrate how hospital resources' availability had an impact on COVID-19 mortality. In particular, geographic areas with fewer intensive care unit (ICU) beds, nurses, and general medicine/surgical beds were statistically significantly associated with more deaths in the USA and the UK (Lin, 2021; Wood et al., 2020).

Moreover, previous Influenza-like illness in COVID-19 hospitalized patients and previous influenza vaccination in 2019 were associated with larger COVID-19 incidence and reduced rate of COVID-19, respectively (see Ceccarelli et al., 2020; Green et al., 2021 among others).

In addition, recent evidence from Sweden using individual-level registry data demonstrates that gender (being male), individual income, education, married status (being single), and being an immigrant from a low- or middle-income country all independently predict a higher risk of death from COVID-19 (Drefahl et al., 2020). Similar evidence of a disproportionate impact of COVID-19 on immigrant communities has been reported in USA (Clark et al., 2020).

Finally, a strand of the enormous COVID-19 literature currently available found that mobility habits represented one of the variables that explain the number of COVID-19 infections jointly with other factors and some environmental variables (i.e. PM pollution and temperature) (Cartenì et al., 2020). So, Governments' emergency measures aimed at human-mobility containment have been proven to have a direct impact on the number of COVID-19 related deaths (Hadjidemetriou et al., 2020) and should be taken into account when studying COVID-19 mortality.

Table B1. Control variables description and sources

Description	Year	Source
Percentage of population in age class 51–60	2017–2020	ISTAT
Percentage of population in age class 61–70	2017–2020	ISTAT
Percentage of population in age class 71–80	2017–2020	ISTAT
Percentage of population in age class 81+	2017–2020	ISTAT
Percentage of migrant citizens	2017–2020	ISTAT
Population density	2017–2020	ISTAT
Hospitalization rate for COPD	2017–2020	AGENAS
Hospitalization rate for influenza	2017–2020	AGENAS
Relative Humidity	2017–2020	Copernicus Climate Service
Temperature at 2mt	2017–2020	Copernicus Climate Service
Total precipitations	2017–2020	Copernicus Climate Service
Wind Speed	2017–2020	Copernicus Climate Service
Particulate matter 2.5	2017–2020	Copernicus Atmosphere Service
Number of beds (per capita) in public hospital	2017–2019	Ministry of Health
Number of beds (per capita) in ICU in public hospital	2017–2019	Ministry of Health
Number of beds (per capita) in private hospital	2017–2019	Ministry of Health
Per capita taxable income	2017–2019	ISTAT
Number of nursing homes	2019	Regional Healthcare Directorate
Distance from airport	Time invariant	Google Maps
Distance from nursing homes	Time invariant	Google Maps
Distance from red zone	Time invariant	Google Maps
Size ICU in private hospitals	2017–2019	Ministry of Health
Size ICU in public hospitals	2017–2019	Ministry of Health
Size private hospitals	2017–2019	Ministry of Health
Size public hospitals	2017–2019	Ministry of Health
Distance from ICU in private hospital	Time invariant	Google Maps
Distance from ICU in public hospital	Time invariant	Google Maps
Distance from private hospital	Time invariant	Google Maps
Distance from public hospital	Time invariant	Google Maps
Mobility index (inward, outward, internal)	2020	Mobile Network Operators

Note. This table reports the description, year in which they are measured and the sources of the control variables included in the DiD-GRDD regression models. ISTAT is the Italian National Statistical Office (*Istituto Nazionale di Statistica*) and AGENAS is the National Agency for the Regional Health Services (*Agenzia Nazionale per i Servizi Sanitari Regionali*.

B.1 Description of Control Variables

We include in the $\mathbf{X}_{it}$ vector of equations (5) and (6) several controls at the municipality level that are likely to be associated with, or potential determinants of, mortality. In short, we collected data on the following groups of variables (data sources are reported in Table B1):

Demographic and socioeconomic characteristics: population structure by age and gender; percentage of immigrants; population size; population density; average taxable income;

Infrastructure variables: distance to the closest airport, distance to the closest care home, distance from the closest early declared 'red zones' (February-March 2020);

Healthcare system variables: number of (ordinary and ICU) beds per capita in public hospitals, number of (ordinary and ICU) beds per capita in private hospitals; closest distance from closest ICU in private/public hospital (two separate variables); closest distance from private/public hospital (two separate variables);

Table B2. Descriptive statistics by region and pre/post covid period

	Lombardy 2017–29		Lombardy 2021		Veneto 2017–29		Veneto 2021		Piedmont 2017–29		Piedmont 2021	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Mortality overall (%)	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.01	0.00	0.01	0.00
Mortality 0–50 (%)	0.02	0.06	0.03	0.07	0.02	0.04	0.02	0.04	0.03	0.10	0.02	0.09
Mortality 51–70 (%)	0.28	0.32	0.39	0.38	0.25	0.20	0.25	0.20	0.33	0.48	0.32	0.48
Mortality 71–80 (%)	1.20	1.08	1.92	1.40	1.14	0.70	1.13	0.70	1.33	1.71	1.40	1.48
Mortality 81+ (%)	5.92	3.04	8.61	4.54	5.77	2.12	5.99	2.38	6.41	4.02	6.76	3.82
% of pop in age class 51–60	0.15	0.02	0.16	0.02	0.16	0.01	0.16	0.01	0.16	0.02	0.16	0.02
% of pop in age class 61–70	0.13	0.02	0.13	0.02	0.12	0.02	0.13	0.02	0.14	0.02	0.14	0.02
% of pop in age class 71–80	0.09	0.02	0.10	0.02	0.09	0.02	0.10	0.02	0.11	0.02	0.11	0.02
% of pop in age class 81+	0.06	0.02	0.06	0.02	0.06	0.02	0.06	0.02	0.08	0.03	0.08	0.03
% of migrant citizens	0.08	0.04	0.08	0.04	0.08	0.04	0.08	0.04	0.07	0.04	0.07	0.04
Population density	573.90	814.13	569.02	810.27	301.07	285.42	299.33	284.98	158.58	316.48	156.16	310.31
Hospitalization rate for COPD	1.71	0.34	1.59	0.31	1.40	0.23	1.29	0.20	1.38	0.19	1.40	0.21
Hospitalization rate for influenza	0.13	0.07	0.13	0.07	0.17	0.16	0.20	0.18	0.08	0.10	0.13	0.13
Per capita taxable income	20.87	3.23	21.24	3.30	19.62	2.21	19.98	2.22	19.62	2.71	19.93	2.74
Relative Humidity (Jan-Mar)	−0.45	0.73	−0.55	0.63	−0.11	0.48	0.23	0.48	−0.67	0.81	−0.77	1.02
Temperature at 2mt (Jan-Mar)	−0.33	0.80	−0.40	0.80	−0.18	0.74	−0.23	0.77	−0.56	0.83	−0.54	0.82
Total precipitations (Jan-Mar)	−0.69	0.49	−0.38	0.65	−0.69	0.44	−0.38	0.78	−0.12	1.02	−0.27	0.85
Wind Speed (Jan-Mar)	−0.33	0.53	−0.20	0.71	0.09	1.06	−0.20	0.58	−0.45	0.51	−0.46	0.55
Relative Humidity (Apr-Jun)	−0.13	0.93	−0.42	0.97	0.27	1.00	−0.23	1.16	0.17	0.85	0.42	0.72
Temperature at 2mt (Apr-Jun)	0.01	1.00	0.07	1.02	0.24	1.01	0.19	1.03	−0.42	1.07	−0.34	1.06
Total precipitations (Apr-Jun)	0.70	0.77	0.67	0.79	0.59	0.82	0.34	0.97	0.72	1.03	0.83	0.95
Wind Speed (Apr-Jun)	−0.41	0.54	−0.55	0.52	0.70	1.26	0.66	1.24	−0.25	0.65	−0.31	0.73

(*continued*)

Table B2. Continued

	Lombardy 2017–29		Lombardy 2021		Veneto 2017–29		Veneto 2021		Piedmont 2017–29		Piedmont 2021	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Particulate matter 2.5	17.94	4.52	17.94	4.52	17.26	3.60	17.26	3.61	13.99	3.55	13.99	3.55
Distance from airport	30.68	15.59	30.68	15.59	40.84	17.44	40.84	17.45	37.52	14.54	37.52	14.54
Distance from red zone	61.45	27.71	61.45	27.72	53.69	31.60	53.69	31.62	135.35	36.05	135.35	36.06
Per capita beds in priv hosp	0.81	13.36	0.83	13.85	0.27	2.33	0.27	2.33	0.96	13.57	0.95	13.37
Per capita beds in pub hosp	0.69	4.76	0.69	4.65	1.08	4.91	1.08	4.94	0.36	3.75	0.36	3.75
Per capita ICU beds in priv hosp	0.01	0.11	0.01	0.11	0.00	0.03	0.00	0.03	0.00	0.01	0.00	0.01
Per capita ICU beds in pub hosp	0.01	0.11	0.01	0.10	0.03	0.16	0.03	0.16	0.01	0.08	0.01	0.08
Dist. from private hospital	12.04	10.32	12.04	10.33	18.33	12.88	18.33	12.89	13.55	8.62	13.55	8.63
Dist. from public hospital	7.33	3.88	7.33	3.88	8.20	4.30	8.20	4.30	10.94	6.17	10.94	6.18
Dist. from ICU in priv hosp	22.16	15.02	22.16	15.03	28.86	19.29	28.86	19.31	47.39	16.08	47.39	16.09
Dist. from ICU in pub hosp	10.53	6.19	10.53	6.19	10.34	5.77	10.34	5.78	13.70	7.75	13.70	7.75
Dist. from care homes	2.64	2.41	2.64	2.41	5.00	3.95	5.00	3.95	2.65	3.02	2.65	3.02
Number of care homes	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	Emilia Romagna 2017–29		Emilia Romagna 2021		Trentino Alto Adige 2017–29		Trentino Alto Adige 2021	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Mortality overall (%)	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00
Mortality 0–50 (%)	0.02	0.04	0.03	0.06	0.02	0.06	0.03	0.07
Mortality 51–70 (%)	0.27	0.22	0.33	0.38	0.23	0.28	0.25	0.26
Mortality 71–80 (%)	1.13	0.56	1.44	0.76	1.05	1.09	1.33	1.33

(*continued*)

Table B2. Continued

	Emilia Romagna 2017–29		Emilia Romagna 2021		Trentino Alto Adige 2017–29		Trentino Alto Adige 2021	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Mortality 81+ (%)	6.08	1.56	7.03	2.14	5.60	3.18	6.45	3.63
% of pop in age class 51–60	0.15	0.01	0.16	0.01	0.15	0.02	0.16	0.02
% of pop in age class 61–70	0.13	0.02	0.13	0.02	0.11	0.02	0.12	0.02
% of pop in age class 71–80	0.10	0.02	0.11	0.02	0.08	0.02	0.09	0.02
% of pop in age class 81+	0.08	0.03	0.08	0.03	0.06	0.02	0.06	0.01
% of migrant citizens	0.10	0.03	0.10	0.04	0.06	0.04	0.06	0.04
Population density	225.49	329.52	224.59	329.15	111.35	191.91	112.45	193.89
Hospitalization rate for COPD	2.41	0.32	2.32	0.22	1.51	0.20	1.52	0.16
Hospitalization rate for influenza	0.26	0.17	0.29	0.16	0.37	0.32	0.51	0.35
Per capita taxable income	20.25	2.69	20.62	2.67	19.97	2.72	20.46	2.86
Relative Humidity (Jan-Mar)	0.09	0.63	0.30	0.21	−1.68	1.30	−1.88	1.11
Temperature at 2mt (Jan-Mar)	0.10	0.36	0.16	0.31	−2.04	0.93	−2.06	0.99
Total precipitations (Jan-Mar)	−0.47	0.69	−0.69	0.78	−0.55	0.70	0.19	0.48
Wind Speed (Jan-Mar)	−0.66	0.60	−0.51	0.55	−0.79	0.53	−0.69	0.62
Relative Humidity (Apr-Jun)	−0.83	0.81	−1.31	0.90	0.53	1.06	0.28	0.92
Temperature at 2mt (Apr-Jun)	0.46	0.61	0.42	0.62	−2.09	0.98	−2.04	1.06
Total precipitations (Apr-Jun)	−0.23	0.52	−0.71	0.43	0.83	0.78	0.84	0.61
Wind Speed (Apr-Jun)	−0.04	0.77	0.48	0.55	−0.99	0.27	−0.62	0.28
Particulate matter 2.5	14.59	2.65	14.59	2.66	9.11	2.04	9.11	2.05
Distance from airport	32.91	15.23	32.91	15.25	41.91	17.64	41.91	17.66
Distance from red zone	91.00	41.81	91.00	41.85	121.85	30.17	121.85	30.21
Per capita beds in priv hosp	0.42	2.33	0.42	2.33	0.19	1.81	0.18	1.78

(*continued*)

Table B2. Continued

	Emilia Romagna 2017–29		Emilia Romagna 2021		Trentino Alto Adige 2017–29		Trentino Alto Adige 2021	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Per capita beds in pub hosp	1.00	3.56	0.99	3.57	0.58	2.62	0.57	2.59
Per capita ICU beds in priv hosp	0.01	0.15	0.01	0.15	0.00	0.00	0.00	0.00
Per capita ICU beds in pub hosp	0.02	0.09	0.02	0.09	0.01	0.04	0.01	0.04
Dist. from private hospital	14.44	8.02	14.44	8.03	22.61	14.09	22.61	14.11
Dist. from public hospital	9.81	6.05	9.81	6.05	11.45	5.60	11.45	5.60
Dist. from ICU in private hospital	28.46	16.65	28.46	16.67	88.50	30.69	88.50	30.73
Dist. from ICU in public hospital	15.56	9.13	15.56	9.14	19.15	9.15	19.15	9.16
Dist. from care homes	1.17	2.49	1.17	2.49	12.93	13.63	12.93	13.64
Number of care homes	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note. This table reports summary statistics on the samples including all municipalities in the regions.

Environmental and climate variables: air quality (PM2.5 yearly average concentrations from 2014 to 2018), as derived from Copernicus Atmosphere Monitoring Service 'Reanalysis' product (Inness et al., 2019); weather/climate conditions (yearly average wind speed and components, temperature, relative humidity, surface pressure, precipitation, solar radiation), as derived from Copernicus Climate Service 'ERA5' product (Hersbach et al., 2020);

Pulmonary diseases: Chronic obstructive pulmonary disease (COPD) gross municipality rate; Influenza gross municipality rate (obtained by National Outcomes Plan, PNE https://pne.agenas.it);

In addition to the explanatory variables included in the model, we used data on citizens' mobility to test the validity of the identifying assumptions of the proposed GRDD model in 2020, which requires mobility to be balanced at the border and to explore potential mechanisms. Mobility data are aggregated data provided by Mobile Network Operators gathering information on collective mobility behaviours aggregated at the municipality level. Given that mobile phone subscribers represent about 65% of the population in the EU, mobile data provide reliable information to capture the aggregate mobility patterns of the population (Iacus et al., 2021). The mobility indicators provide a daily time series of mobility according to the direction of movements as internal (within the same municipality), inward (to a municipality), outward (from a municipality), and total. More information about the *Mobility Indicators* and their application to the European Commission JRC's live anomaly detection system to spot potential new outbreaks can be found in Santamaria et al. (2020) and Iacus et al. (2021).

Table B1 reports the definition for all variables, timing, and sources, and Tables B2 sample descriptive statistics.

Appendix C: Additional Robustness Checks

C.1 Balancing of Covariates at the Border and the Effect on Mortality

In this section, we implement the test proposed by Carrell et al. (2018) to check for the balancing of covariates that are likely to be important predictors of mortality rates. We first estimate predicted mortality through linear regressions of observed mortality rates on the control variables described in Appendix B, and then estimate equation (5) excluding the control variables, using predicted mortality rates instead of the observed mortality rates as the dependent variables. The results are shown in Figures C1 and C2 in Appendix C for the age groups 81+ and 71–80, respectively. The DiD-GRDD coefficients shown in the graphs are much smaller than those of our baseline estimates, generally very close to zero, and statistically non-significant. This confirms that different covariates alone are not able to explain differences in mortality at the border, especially when one focuses on quite narrow bandwidths, for which the assumption of municipalities' similar observable and unobservable characteristics is more credible.

As a further check, we estimated the DiD-GRDD model for the 81+ age group excluding control variables. Consistent with a substantial balancing of controls across the borders, DiD-GRDD coefficients (shown in Figure C3 and C4) are remarkably similar to our baseline estimates.

C.2 Omitted Variables and Municipality Fixed Effects

One potential caveat with the specification of equation (5) is that we do not control for municipality-level time-invariant unobservable variables through municipality fixed effects.

However, if the assumptions underlying the DiD-GRDD are correct nearby municipalities are comparable in terms of observable and unobservable variables, then the municipality fixed effects should not significantly affect the estimates. In a DID setting using a balanced panel, Wooldridge (2021) demonstrates that a simple OLS model including the *post* and *treatment* indicators produces the same estimates as the Two-Way Fixed Effects (TWFE) model. In our case, the DiD-GRDD model in equation (5) also includes polynomial-in-distance interactions with the above indicators. This is indeed confirmed by Figures C5 and C6.

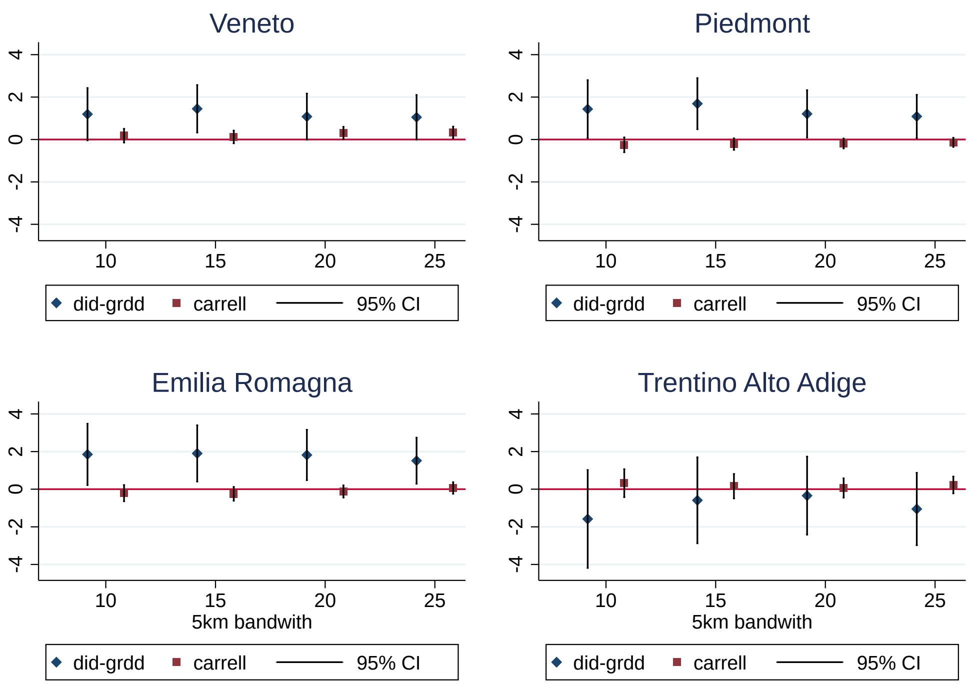

Figure C1. Balancing of covariates test for age 81+ population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the DiD-GRDD estimates obtained with different distance bandwidths (in km) from the administrative border (indicated in the horizontal axis) using as dependent variables predicted mortality rates from a linear regression on the covariates (Carrell et al., 2018).

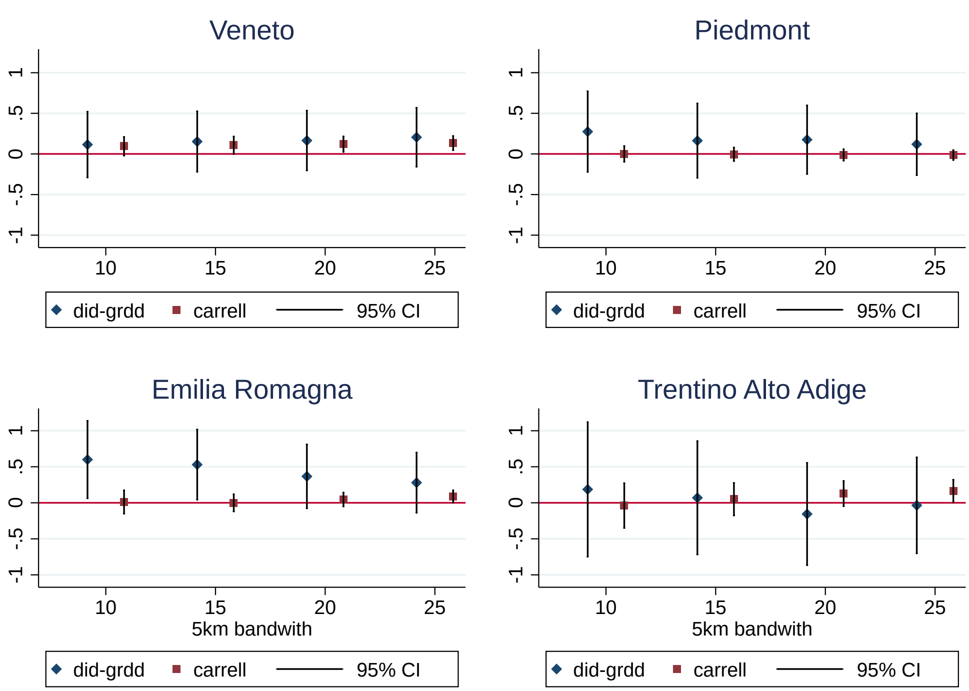

Figure C2. Balancing of covariates test for age 71–80 population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the DiD-GRDD estimates obtained with different distance bandwidths (in km) from the administrative border (indicated in the horizontal axis) using as dependent variables predicted mortality rates from a linear regression on the covariates (Carrell et al., 2018).

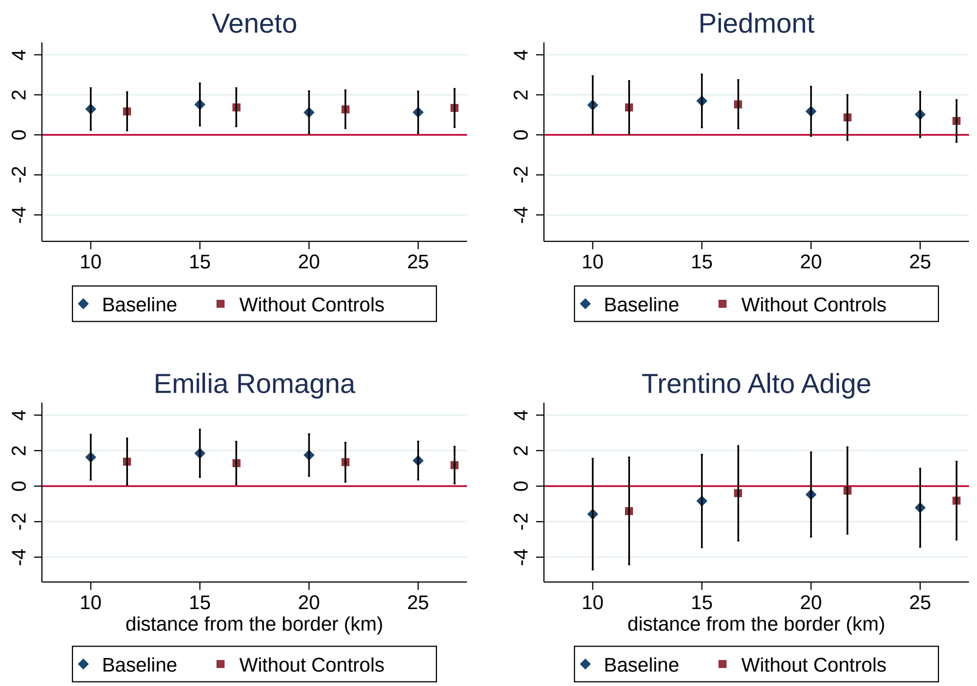

Figure C3. Sensitivity to excluding covariates—81+ population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the DiD-GRDD estimates with and without covariates obtained with different distance bandwidths (in km) from the administrative border indicated on the horizontal axis.

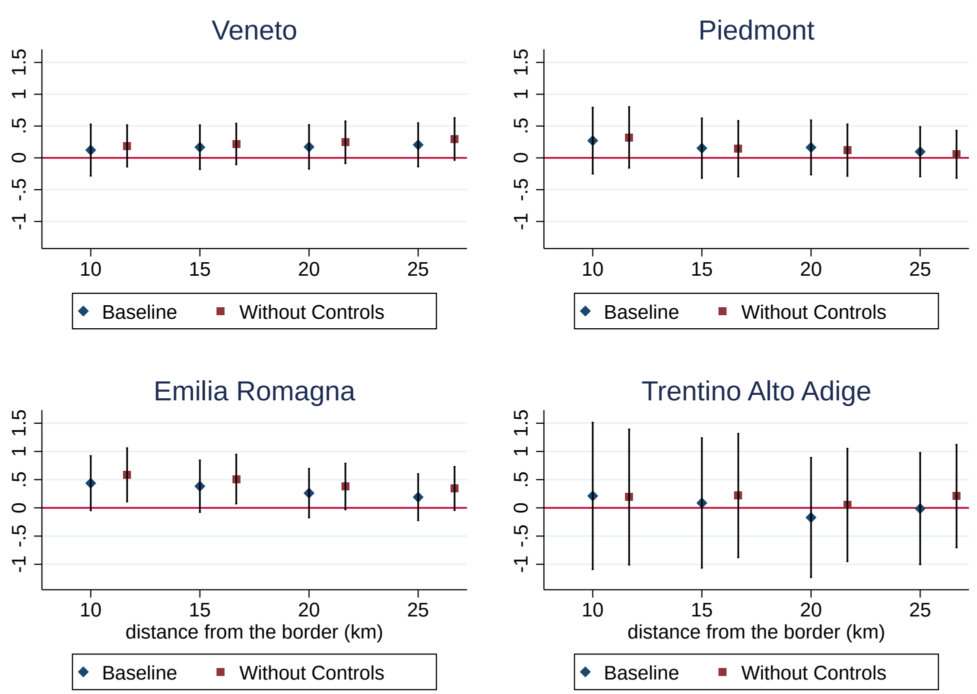

Figure C4. Sensitivity to excluding covariates—71–80 population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the DiD-GRDD estimates with and without covariates obtained with different distance bandwidths (in km) from the administrative border indicated on the horizontal axis.

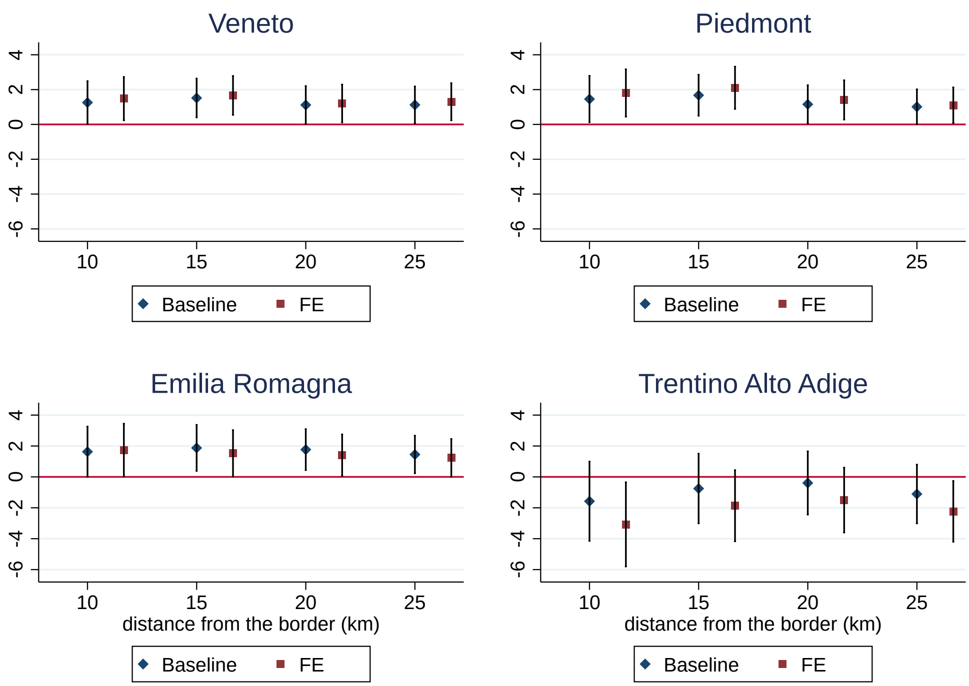

Figure C5. Sensitivity to the inclusion of municipality fixed effects (FE) for the 81+ population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the DiD-GRDD estimates with fixed effects obtained from different distance bandwidths (in km) from the administrative border indicated on the horizontal axis.

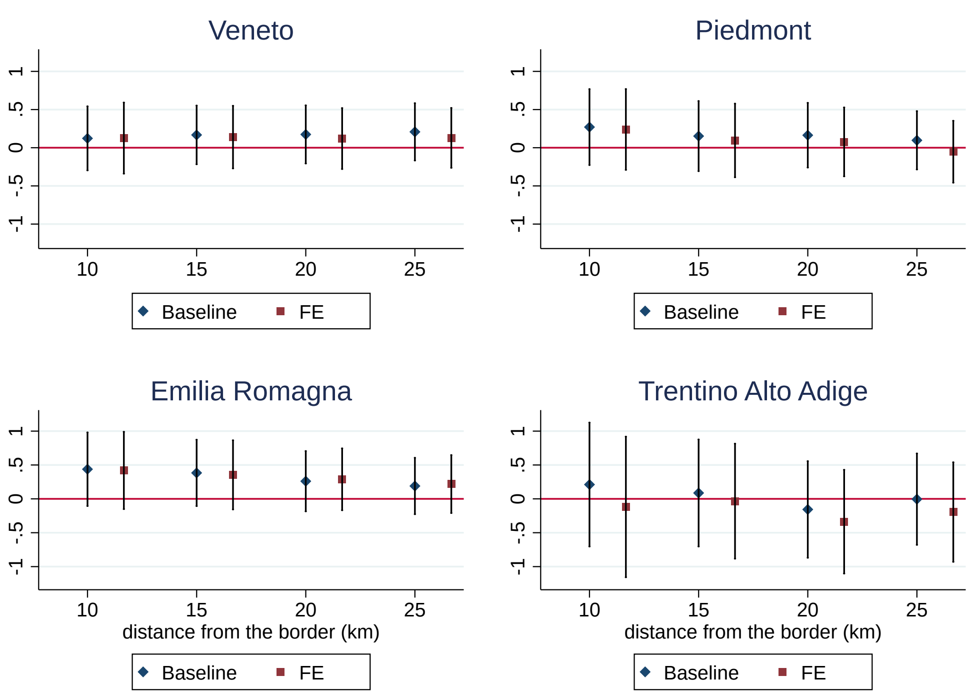

Figure C6. Sensitivity to the inclusion of municipality fixed effects (FE) for the 71–80 population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the DiD-GRDD estimates with fixed effects obtained with different distance bandwidths (in km) from the administrative border indicated on the horizontal axis.

Table C1. Gravity models for commuting flows

	Veneto				Piedmont			
Variables	10 km	15 km	20 km	25 km	10 km	15 km	20 km	25 km
$distance_{ij}$	−0.150***	−0.123***	−0.122***	−0.117***	−0.129***	−0.129***	−0.093***	−0.093***
	(0.004)	(0.010)	(0.010)	(0.011)	(0.008)	(0.006)	(0.008)	(0.008)
d_i	−0.000	−0.000	−0.000***	−0.000*	−0.000*	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pop_i	0.042***	0.010***	0.010***	0.010***	0.023***	0.024***	0.002***	0.002***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
$olddep_i$	−0.008	0.018	0.018	0.009	0.023***	0.024***	0.036**	0.041***
	(0.007)	(0.014)	(0.013)	(0.014)	(0.009)	(0.009)	(0.017)	(0.013)
$youngdep_i$	−0.002	0.052**	0.057**	0.037	−0.015	−0.035	−0.002	−0.023
	(0.026)	(0.026)	(0.023)	(0.027)	(0.043)	(0.032)	(0.040)	(0.043)
$Lombardy_i$	0.074	0.069	0.069	0.093	−0.169	−0.101	0.003	0.073
	(0.107)	(0.094)	(0.091)	(0.088)	(0.135)	(0.149)	(0.462)	(0.502)
Obs.	9925	14050	17621	21058	30072	42587	55061	65455
	Emilia Romagna				**Trentino Alto Adige**			
	10 km	**15 km**	**20 km**	**25 km**	**10 km**	**15 km**	**20 km**	**25 km**
$distance_{ij}$	−0.090***	−0.092***	−0.095***	−0.096***	−0.145***	−0.147***	−0.135***	−0.132***
	(0.010)	(0.009)	(0.006)	(0.006)	(0.017)	(0.017)	(0.014)	(0.010)
d_i	−0.000***	−0.000***	−0.000***	−0.000***	0.000	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
pop_i	0.015***	0.013***	0.011***	0.011***	0.083***	0.054***	0.057***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.012)	(0.005)	(0.005)	(0.002)
$olddep_i$	0.013*	0.027***	0.027**	0.032***	0.022*	−0.022	−0.014	0.027*
	(0.008)	(0.007)	(0.011)	(0.010)	(0.012)	(0.014)	(0.012)	(0.015)

(*continued*)

Table C1. Continued

	Emilia Romagna				Trentino Alto Adige			
	10 km	15 km	20 km	25 km	10 km	15 km	20 km	25 km
$youngdep_i$	0.038	0.044	0.005	−0.001	0.040*	0.018	0.016	0.063**
	(0.041)	(0.033)	(0.049)	(0.044)	(0.021)	(0.023)	(0.020)	(0.027)
$Lombardy_i$	−0.059	−0.231**	−0.281***	−0.334***	−0.596	−0.630	−0.515	−1.441***
	(0.098)	(0.111)	(0.099)	(0.093)	(0.400)	(0.408)	(0.356)	(0.499)
Obs.	16198	22781	30845	38463	2494	3958	5984	8244

Note. Gravity models of commuting flows using (ISTAT) Population Census 2011 data. Estimates are weighted using the population of the municipality of origin. Models are estimated for different distance bandwidth (10, 15, 20, and 25 km). Each estimate by region includes the municipalities located in the region indicated in the table's headline and in Lombardy. pop_i is the population of the origin municipality i (divided by 1,000); $dist_{ij}$ is the geodesic distance between i and j; d_i is distance from the Lombardy's border; $youngdep_i$ is municipality i's percent young dependency ratio in the population (population aged 0–14 over the population 15–64); $olddep_i$ is municipality i's percent old dependency ratio in the population (population aged 65 and more over the population 15–64); $Lombardy_i$ is an indicator for Lombardy's municipalities. Municipality of destination fixed effects are included. *, **, ***, statistically significant at the 10%, 5%, 1% level, respectively.

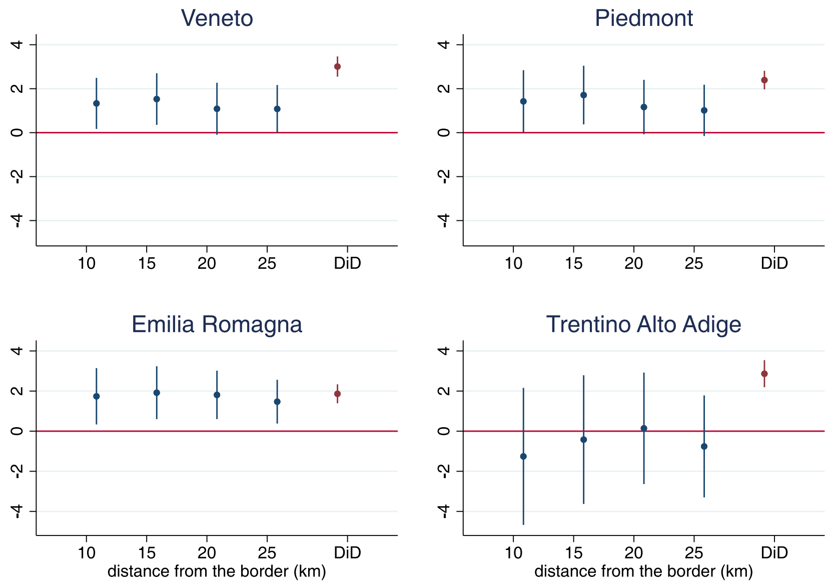

Figure C7. DiD-GRDD estimates including predicted inflows and outflows of commuters. *Note.* Plots of the coefficients (points) and bootstrapped 95% confidence intervals with 1,000 replicates (bars, observations clustered at municipality level) of the DiD-GRDD estimates obtained with different distance bandwidths (in km) from the administrative border indicated on the horizontal axis, including the DiD estimates on all municipalities. The baseline model in equation (5) is augmented with commuters' outflows and inflows, predicted out-of-sample from the gravity models estimated on 2011 Population Census data (Table C1), and their interactions with the post-COVID-19 indicator. Confidence intervals are bootstrapped since commuters' inflows and outflows are predicted from a gravity model.

C.3 Commuting Flows

Table C1 shows the estimates of a gravity model,

$$C_{ij} = \alpha + \alpha_0 pop_i + \alpha_1 dist_{ij} + \alpha_3 d_i + \alpha_4 youngdep_i + \alpha_5 olddep_i + \alpha_6 Lombardy_i + D_j, \qquad (7)$$

where C_{ij} is the number of commuters from municipality i to municipality j; pop_i is the population of the origin municipality i; $dist_{ij}$ is the geodesic distance between i and j; d_i is distance from the Lombardy's border; $youngdep_i$ is municipality i's young dependency ratio in the population (population aged 0–14 over the population 15–64); $olddep_i$ is municipality i's old dependency ratio in the population (population aged 65 and more over the population 15–64); $Lombardy_i$ is an indicator for Lombardy's municipalities; D_j are destination municipalities fixed effects (absorbing all destination municipalities covariates). The model is estimated using the Poisson Pseudo Maximum Likelihood Estimator (PPML). Estimates are weighted by the population in the municipality of origin, and standard errors are clustered at the municipality of origin.

The model is estimated using data from the 2011 Italian Population Census (ISTAT), which provides the commuting flows and the control variables. We estimate commuting models using pairs of regions, each pair includes Lombardy.

Table C1 shows that commuters' flows generally do not show a discontinuity at the border. Exceptions are Trentino Alto Adige, with the largest bandwidth, and Emilia Romagna, with bandwidths larger than 10 km. Since 10 km is also our preferred bandwidth, since it increases the likelihood that unobservables are balanced at the border, this evidence is not very problematic.

However, as a further robustness check, we re-estimated the baseline model in equation (5) augmenting it with the predicted (out-of-sample) commuters' inflows and outflows estimated from the gravity models just described for 2011 commuter flows, along with their interaction terms with the $post_t$ indicator, which allows for the impact of commuting on mortality to differ between the pre- and the post-pandemic periods. The estimates are plotted in Figure C7 and confirm the results of our baseline model.

Appendix D: Additional Figures and Tables

Table D1. DiD-GRDD main Results

	71–80					81+				
	10 km	15 km	20 km	25 km	DiD	10 km	15 km	20 km	25 km	DiD
Piedmont										
Lomb#Post	0.271	0.153	0.164	0.0974	0.514***	1.488**	1.695**	1.175*	1.018*	2.412***
	(0.266)	(0.240)	(0.218)	(0.200)	(0.0870)	(0.739)	(0.677)	(0.629)	(0.582)	(0.211)
# Municipalities	347	484	597	705	2,660	347	484	597	705	2,660
Tot. Obs.	1388	1936	2388	2820	10640	1388	1936	2388	2820	10636
Trentino Alto Adige										
Lomb#Post	0.212	0.0869	−0.170	−0.0124	0.681***	−1.576	−0.837	−0.472	−1.214	2.708***
	(0.663)	(0.587)	(0.541)	(0.505)	(0.119)	(1.593)	(1.333)	(1.215)	(1.126)	(0.330)
# Municipalities	78	114	154	194	1,768	78	114	154	194	1,768
Tot. Obs.	312	456	616	776	7072	312	456	616	776	7071
Veneto										
Lomb#Post	0.123	0.168	0.172	0.205	0.972***	1.290**	1.515***	1.121**	1.128**	3.017***
	(0.207)	(0.177)	(0.176)	(0.175)	(0.0745)	(0.536)	(0.541)	(0.543)	(0.532)	(0.231)
# Municipalities	109	150	198	236	2,040	109	150	198	236	2,040
Tot. Obs.	436	600	792	944	8160	436	600	792	944	8159
Emilia Romagna										
Lomb#Post	0.438*	0.383	0.261	0.190	0.461***	1.630**	1.849***	1.749***	1.437***	1.843***
	(0.246)	(0.234)	(0.221)	(0.210)	(0.0843)	(0.650)	(0.685)	(0.603)	(0.550)	(0.236)
# Municipalities	211	291	366	437	1,815	211	291	366	437	1,815
Tot. Obs.	844	1164	1464	1748	7260	844	1164	1464	1748	7259

Note. The table only reports the DiD-GRDD coefficients of equation (5). Observations clustered and the municipality level. *, **, ***, statistically significant at the 10%, 5%, 1% level, respectively.

Table D2. Spatial correlation: HAC standard errors

Regional comparison	Method (SE)	age 81+ coef.	age 81+ SE	age 81+ t-stat	age 71–80 coef.	age 71–80 SE	age 71–80 t-stat
Piedmont	Clustered	0.684	(0.507)	1.350	0.056	(0.187)	0.299
	Spatial HAC	0.684	(0.577)	1.186	0.056	(0.191)	0.293
Trentino Alto Adige	Clustered	−0.818	(0.955)	−0.857	0.209	(0.331)	0.631
	Spatial HAC	−0.818	(1.208)	−0.678	0.209	(0.428)	0.488
Veneto	Clustered	1.355	(0.527)	2.571	0.298	(0.180)	1.650
	Spatial HAC	1.355	(0.538)	2.519	0.298	(0.174)	1.709
Emilia Romagna	Clustered	1.179	(0.613)	1.922	0.344	(0.207)	1.663
	Spatial HAC	1.179	(0.567)	2.079	0.344	(0.211)	1.626

Note. The table reports the baseline estimates of the DiD-GRDD model with the 25-km bandwidth and compares (municipality level) cluster-robust with Conley's Spatial HAC standard errors (Conley, 1999). SE stands for standard error. *, **, *** refer to coefficients statistically significant at the 10%, 5%, 1% level, respectively.

Table D3. Percentage of municipalities with nursing homes at different kilometres from the border in each comparison Region vs. Lombardy (in parentheses)

Distance	Piedmont	Veneto	Trentino Alto Adige	Emilia Romagna
10 km	49.65	36.01	48.01	47.79
	(50.35)	(64.00)	(52.00)	(52.21)
15 km	48.13	35.82	44.44	46.58
	(51.87)	(64.18)	(55.56)	(53.42)
20 km	48.93	38.37	36.54	46.02
	(51.07)	(61.63)	(63.46)	(53.98)
25 km	49.65	37.62	38.1	46.02
	(50.35)	(62.38)	(61.90)	(53.96)

Table D4. GRDD estimates using municipality outward mobility index as dependent variable

Region	10 km	15 km	20 km	25 km
Lombardy vs Veneto	−0.000	0.001	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Lombardy vs Piedmont	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Lombardy vs Emilia Romagna	−0.001	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Lombardy vs Trentino Alto Adige	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)

Note. This table shows the estimates of a GRDD model using the outward mobility indicator during lockdown (aggregated and anonymized measure obtained from GSMA mobile positioning data) as dependent variable. The GRDD model includes a treatment variable (dummy variable for Lombardy against other control regions), and distance from the border as running variable. Only the GRDD coefficient of interest is reported in the table. Standard errors (in parentheses) are clustered by municipality. *, **, *** refer to coefficients statistically significant at the 10%, 5%, 1% level, respectively.

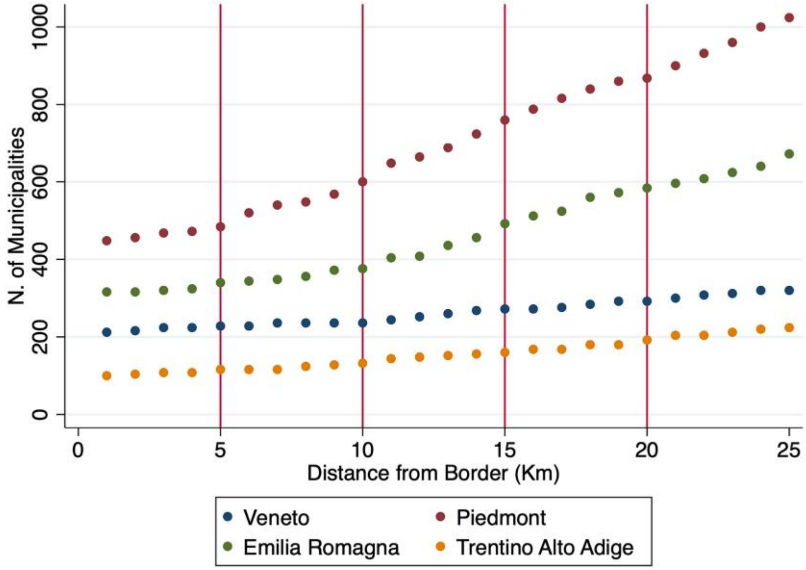

Figure D1. Number of municipalities by bandwidth (in km). *Note.* The Figure shows the sample sizes (number of municipalities) in each pairwise regional comparison obtained by changing the distance bandwidth from Lombardy's administrative borders.

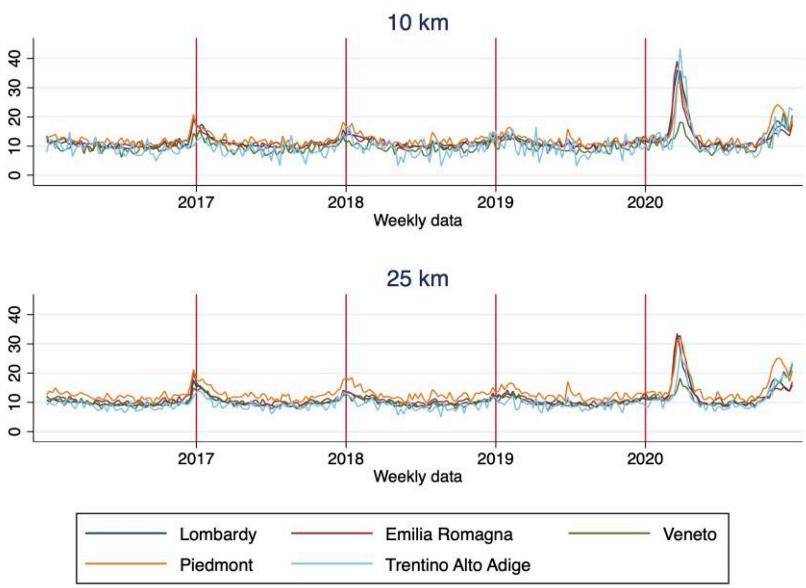

Figure D2. Weekly mortality rates (per 100,000 individuals)—10-km and 25-km bandwidths. *Note.* Weekly mortality rates computed using ISTAT (Italian National Statistical Institute) data only on the municipalities within 10 km or 25 km from Lombardy's administrative borders.

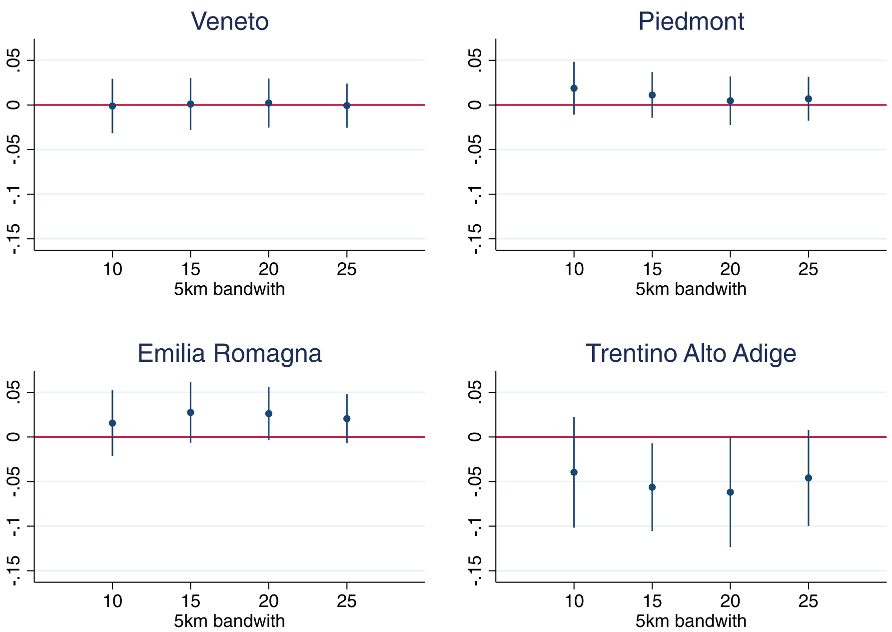

Figure D3. Lombardy's excess mortality compared to neighbouring regions—age 0–50 population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the DiD-GRDD estimates obtained with different distance bandwidths (in km.) from the administrative border indicated on the horizontal axis.

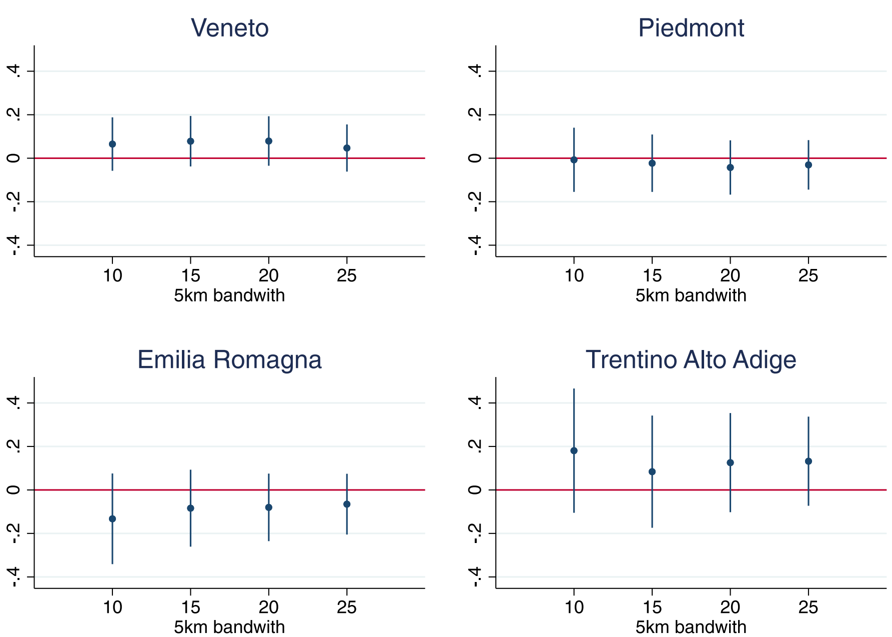

Figure D4. Lombardy's excess mortality compared to neighbouring regions—age 51–70 population. *Note.* Plots of the coefficients (points) and 95% confidence intervals (bars, clustered standard errors at municipality level) of the DiD-GRDD estimates obtained with different distance bandwidths (in km) from the administrative border indicated on the horizontal axis.

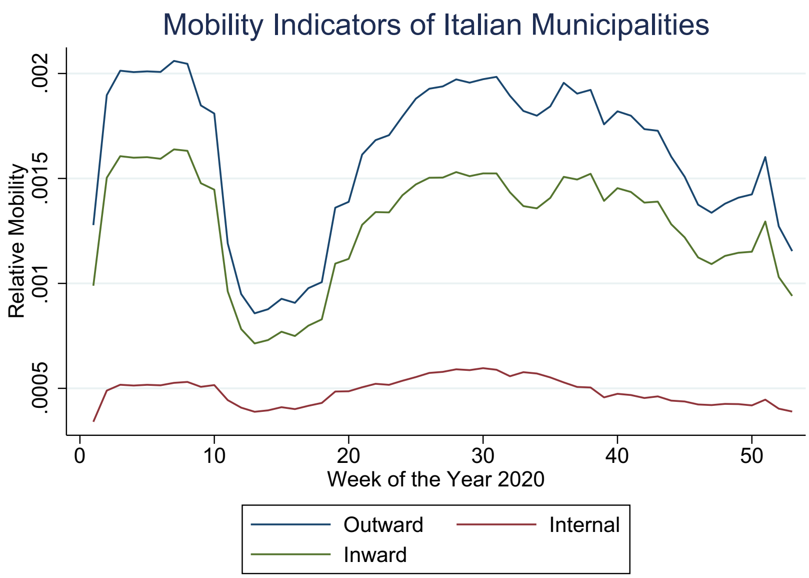

Figure D5. Mobility patterns over time in 2020. *Note.* See Appendix B for the description of the mobility indicators.

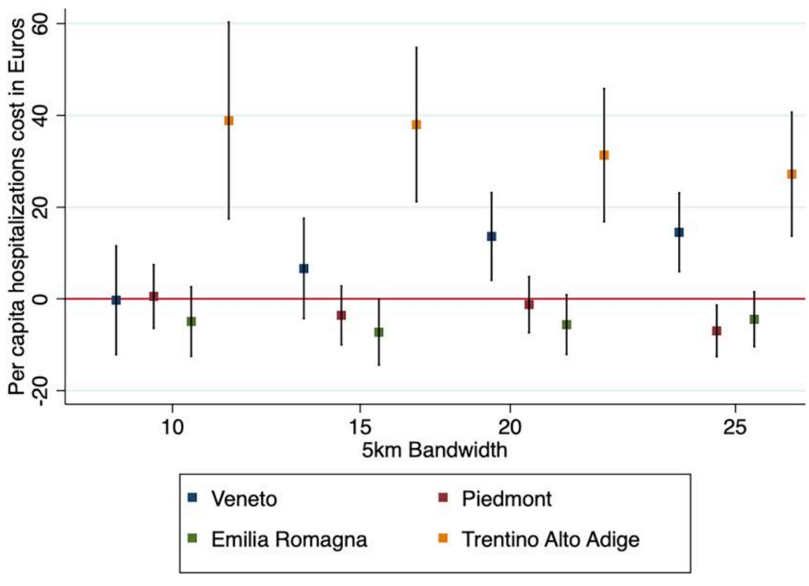

Figure D6. Balancing of healthcare expenditures at the border. *Note.* The figures show the effect of the distance from the border between Lombardy and the other Italian regions on per capita hospitalization costs in Euros, using individual administrative data from Berta et al. (2022) on hospitalizations in 2016 for cardiac, orthopaedic, and oncological diseases. The balance test is carried out by estimating a model that regresses the per capita costs on the distance from the border, the dummy for the Lombardy region against other control regions, and their interaction.

References

Alacevich C., Cavalli N., Giuntella O., Lagravinese R., Moscone F., & Nicodemo C. (2021). The presence of care homes and excess deaths during the covid-19 pandemic: Evidence from Italy. *Health Economics*, *30*(7), 1703–1710. https://doi.org/10.1002/hec.v30.7

Ancidoni A., Bacigalupo I., Bellomo G., Canevelli M., Carbonari P., Carella M. G., Confaloni A., Crestini A., D'Ancona F. P., Faralli C., & Fiaccavento S. (2020). *Survey nazionale sul contagio COVID-19 nelle strutture residenziali e sociosanitarie. Report Finale* (Technical report). Istituto Superiore di Sanitá, Roma.

Bartoszek K., Guidotti E., Iacus S. M., & Okrój M. (2020). Are official confirmed cases and fatalities counts good enough to study the covid-19 pandemic dynamics? A critical assessment through the case of Italy. *Nonlinear Dynamics*, *101*(3), 1951–1979. https://doi.org/10.1007/s11071-020-05761-w

Becchetti L., Conzo G., Conzo P., & Salustri F. (2022). Understanding the heterogeneity of COVID-19 deaths and contagions: The role of air pollution and lockdown decisions. *Journal of Environmental Management*, *305*, Article 114316. https://doi.org/10.1016/j.jenvman.2021.114316

Beine M., Bertoli S., & Fernández-Huertas Moraga J. (2016). A practitioners' guide to gravity models of international migration. *The World Economy*, *39*(4), 496–512. https://doi.org/10.1111/twec.2016.39.issue-4

Bello P., & Rocco L. (2022). Education and covid-19 excess mortality. *Economics & Human Biology*, *47*, Article 101194. https://doi.org/10.1016/j.ehb.2022.101194

Berta P., Martini G., Spinelli D., & Vittadini G. (2022). The beaten paths effect on patient inter-regional mobility: An application to the Italian NHS. *Papers in Regional Science*, *101*(4), 945–977. https://doi.org/10.1111/pirs.12678

Berta P., Seghieri C., & Vittadini G. (2013). Comparing health outcomes among hospitals: The experience of the lombardy region. *Health Care Management Science*, *16*(3), 245–257. https://doi.org/10.1007/s10729-013-9227-1

Bertuzzo E., Mari L., Pasetto D., Miccoli S., Casagrandi R., Gatto M., & Rinaldo A. (2020). The geography of COVID-19 spread in Italy and implications for the relaxation of confinement measures. *Nature Communications*, *11*(1), 1–11. https://doi.org/10.1038/s41467-020-18050-2

Bobini M., Cinelli G., del Vecchio M., & Longo F. (2020). *Regioni e Aziende: Modelli di coordinamento a confronto* (Chapter 8, pp. 347–378). Collana CERGAS.

Buonanno P., Galletta S., & Puca M. (2020). Estimating the severity of COVID-19: Evidence from the Italian epicenter. *PLoS One*, *15*(10), e0239569. https://doi.org/10.1371/journal.pone.0239569

Carrell S. E., Hoekstra M., & Kuka E. (2018). The long-run effects of disruptive peers. *American Economic Review*, *108*(11), 3377–3415. https://doi.org/10.1257/aer.20160763

Cartenì A., Francesco L. D., & Martino M. (2020). How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study. *Science of the Total Environment*, *741*, Article 140489. https://doi.org/10.1016/j.scitotenv.2020.140489

Castaldi S., Luconi E., Rivieccio B. A., Boracchi P., Marano G., Pariani E., Romano L., Auxilia F., Nicolussi F., Micheletti A., Manzi G., Salini S., Galli M., & Biganzoli E. (2021). Are epidemiological estimates able to describe the ability of health systems to cope with COVID-19 epidemic? *Risk Management and Healthcare Policy*, *14*, 2221–2229. https://doi.org/10.2147/RMHP.S290801

Ceccarelli G., d'Ettorre G., Innocenti G. P., Mastroianni C. M., Ciccozzi M., & d'Ettorre G. (2020). Is previous influenza-like illness a potential Trojan horse for COVID-19? *Critical Care*, *24*(1), 1–2. https://doi.org/10.1186/s13054-020-03226-5

Chernozhukov V., Kasahara H., & Schrimpf P. (2021). Causal impact of masks, policies, behavior on early covid-19 pandemic in the US. *Journal of Econometrics*, *220*(1), 23–62. https://doi.org/10.1016/j.jeconom.2020.09.003

Ciminelli G., & Garcia-Mandicó S., Mitigation policies and emergency care management in Europe's ground zero for covid-19. *medRxiv 20106575*. https://doi.org/10.1101/2020.05.19.20106575, May, 2020, preprint: not peer reviewed.

Clark E., Fredricks K., Woc-Colburn L., Bottazzi M. E., & Weatherhead J. (2020). Disproportionate impact of the COVID-19 pandemic on immigrant communities in the United States. *PLoS Neglected Tropical Diseases*, *14*(7), e0008484. https://doi.org/10.1371/journal.pntd.0008484

Conley T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics*, *92*(1), 1–45. https://doi.org/10.1016/S0304-4076(98)00084-0

De Blasio G., & Poy S. (2017). The impact of local wage regulation on employment: A border analysis from Italy in the 1950s. *Journal of Regional Science*, *57*(1), 48–74. https://doi.org/10.1111/jors.2017.57.issue-1

Dell M. (2010). The persistent effects of Peru's mining Mita. *Econometrica*, *78*(6), 1863–1903. https://doi.org/10.3982/ECTA8121

Drefahl S., Wallace M., Mussino E., Aradhya S., Kolk M., Brandén M., Malmberg B., & Andersson G. (2020). A population-based cohort study of socio-demographic risk factors for COVID-19 deaths in Sweden. *Nature Communications*, *11*(1), 1–7. https://doi.org/10.1038/s41467-020-18926-3

Eurostat (2024). Excess mortality by month. https://ec.europa.eu/eurostat/cache/metadata/en/demo_mexrt_esms.htm.

Flaxman S., Mishra S., Gandy A., Unwin H. J. T., Mellan T. A., Coupland H., Whittaker C., Zhu H., Berah T., Eaton J. W., Monod M., Perez-Guzman P. N., Schmit N., Cilloni L., Ainslie K. E. C., Baguelin M., Boonyasiri A., Boyd O., Cattarino L., … Bhatt S. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature*, *584*(7820), 257–261. https://doi.org/10.1038/s41586-020-2405-7

France G., Taroni F., & Donatini A. (2005). The Italian health-care system. *Health Economics*, *14*(S1), S187–S202. https://doi.org/10.1002/(ISSN)1099-1050

Gelman A., & Imbens G. (2019). Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics*, *37*(3), 447–456. https://doi.org/10.1080/07350015.2017.1366909

Gibertoni D., Adja K. Y. C., Golinelli D., Reno C., Regazzi L., Lenzi J., Sanmarchi F., & Fantini M. P. (2021). Patterns of COVID-19 related excess mortality in the municipalities of Northern Italy during the first wave of the pandemic. *Health & Place*, *67*, Article 102508. https://doi.org/10.1016/j.healthplace.2021.102508

Green I., Ashkenazi S., Merzon E., Vinker S., & Golan-Cohen A. (2021). The association of previous influenza vaccination and coronavirus disease-2019. *Human Vaccines & Immunotherapeutics*, *17*(7), 2169–2175. https://doi.org/10.1080/21645515.2020.1852010

Grembi V., Nannicini T., & Troiano U. (2016). Do fiscal rules matter? *American Economic Journal: Applied Economics*, *8*(3), 1–30. https://doi.org/10.1257/app.20150076

Gu L., Yang L., Wang L., Guo Y., Wei B., & Li H. (2022). Understanding the spatial diffusion dynamics of the COVID-19 pandemic in the city system in China. *Social Science & Medicine*, *302*, Article 114988. https://doi.org/10.1016/j.socscimed.2022.114988

Hadjidemetriou G. M., Sasidharan M., Kouyialis G., & Parlikad A. K. (2020). The impact of government measures and human mobility trend on COVID-19 related deaths in the UK. *Transportation Research Interdisciplinary Perspectives*, *6*, Article 100167. https://doi.org/10.1016/j.trip.2020.100167

Head K., & Mayer T. (2014). Gravity equations: Workhorse, toolkit, and cookbook. In *Handbook of international economics* (Vol. 4, pp. 131–195). Elsevier.

Hersbach H., Bell B., Berrisford P., Hirahara S., Horányi A., Muñoz-Sabater J., Nicolas J., Peubey C., Radu R., Schepers D., Simmons A., Soci C., Abdalla S., Abellan X., Balsamo G., Bechtold P., Biavati G., Bidlot J., Bonavita M., … Villaume S. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, *146*(730), 1999–2049. https://doi.org/10.1002/qj.v146.730

Hsiang S., Allen D., Annan-Phan S., Bell K., Bolliger I., Chong T., Druckenmiller H., Huang L. Y., Hultgren A., Krasovich E., Lau P., Lee J., Rolf E., Tseng J., & Wu T. (2020). The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature*, *584*(7820), 262–267. https://doi.org/10.1038/s41586-020-2404-8

Iacus S. M., Sermi F., Spyratos S., Tarchi D., & Vespe M. (2021). Anomaly detection of mobile positioning data with applications to covid-19 situational awareness. *Japanese Journal of Statistics and Data Science*, *4*(1), 763–781. https://doi.org/10.1007/s42081-021-00109-z

Inness A., Ades M., Agustí-Panareda A., Barré J., Benedictow A., Blechschmidt A.-M., Dominguez J. J., Engelen R., Eskes H., Flemming J., Huijnen V., Jones L., Kipling Z., Massart S., Parrington M., Peuch V.-H., Razinger M., Remy S., Schulz M., & Suttie M. (2019). The CAMS reanalysis of atmospheric composition. *Atmospheric Chemistry and Physics*, *19*(6), 3515–3556. https://doi.org/10.5194/acp-19-3515-2019

Jordan R. E., Adab P., & Cheng K. K. (2020). Covid-19: Risk factors for severe disease and death. *BMJ*, *368*. https://doi.org/10.1136/bmj.m1198

Kraemer M. U., Yang C.-H., Gutierrez B., Wu C.-H., Klein B., & Pigott D. M., Open COVID-19 Data Working Group†, Du Plessis L., Faria N. R., Li R. & Hanage W. P. (2020). The effect of human mobility and control measures on the covid-19 epidemic in China. *Science*, *368*(6490), 493–497. https://doi.org/10.1126/science.abb4218

Kuebart A., & Stabler M. (2020). Infectious diseases as socio-spatial processes: The Covid-19 outbreak in Germany. *Tijdschrift Voor Economische en Sociale Geografie*, *111*(3), 482–496. https://doi.org/10.1111/tesg.v111.3

Lau H., Khosrawipour V., Kocbach P., Mikolajczyk A., Schubert J., Bania J., & Khosrawipour T. (2020). The positive impact of lockdown in Wuhan on containing the COVID-19 outbreak in China. *Journal of Travel Medicine*, *27*(3), taaa037. https://doi.org/10.1093/jtm/taaa037

Lin Z. (2021). Analysis of hospital resource availability and COVID-19 mortality across the United States. *Journal of Hospital Medicine*, *16*(4), 211–214. https://doi.org/10.12788/jhm.3539

Ma Y., Zhao Y., Liu J., He X., Wang B., Fu S., Yan J., Niu J., Zhou J., & Luo B. (2020). Effects of temperature variation and humidity on the death of covid-19 in Wuhan, China. *Science of the Total Environment*, *724*, 138–226. https://doi.org/10.1016/j.scitotenv.2020.138226

Manica M., Guzzetta G., Riccardo F., Valenti A., Poletti P., Marziano V., Trentini F., Andrianou X., Urdiales A. M., Del Manso M., & Fabiani M. (2021). Impact of tiered restrictions on human activities and the epidemiology of the second wave of COVID-19 in Italy. *Nature Communications*, *12*(1), 4570. https://doi.org/10.1038/s41467-021-24832-z

McMahon T., Chan A., Havlin S., & Gallos L. K. (2022). Spatial correlations in geographical spreading of COVID-19 in the United States. *Scientific Reports*, *12*(1), 699. https://doi.org/10.1038/s41598-021-04653-2

Mesas A. E., Cavero-Redondo I., Álvarez-Bueno C., Sarriá Cabrera M. A., Maffei de Andrade S., Sequí-Dominguez I., & Martínez-Vizcaíno V. (2020). Predictors of in-hospital COVID-19 mortality: A comprehensive systematic review and meta-analysis exploring differences by age, sex and health conditions. *PLoS One*, *15*(11), e0241742. https://doi.org/10.1371/journal.pone.0241742

Mitze T., & Kosfeld R. (2022). The propagation effect of commuting to work in the spatial transmission of COVID-19. *Journal of Geographical Systems*, *24*(1), 5–31. https://doi.org/10.1007/s10109-021-00349-3

Neri S. (2011). The evolution of regional health services and the new governance of the NHS in Italy. In *Health studies: Economic, management and policy* (pp. 269–282). Atiner.

Notarnicola E., Perobelli E., Rotolo A., & Berloto S. (2021). Lessons learned from Italian nursing homes during the COVID-19 outbreak: A tale of long-term care fragility and policy failure. *Journal of Long-Term Care*, 221–229. https://doi.org/10.31389/jltc.73

Nuti S., Vola F., Bonini A., & Vainieri M. (2016). Making governance work in the health care sector: Evidence from a 'natural experiment' in Italy. *Health Economics, Policy and Law*, *11*(1), 17–38. https://doi.org/10.1017/S1744133115000067

OECD (2020). *Beyond containment: Health systems responses to COVID-19 in the OECD* (Technical report). OECD Policy Responses to Coronavirus (COVID-19).

OECD (2021). *Strengthening the frontline: How primary health care helps health systems adapt during the COVID 19 pandemic* (Technical report). OECD Policy Responses to Coronavirus (COVID-19).

Onder G., Rezza G., & Brusaferro S. (2020). Case-fatality rate and characteristics of patients dying in relation to COVID-19 in Italy. *JAMA*, *323*(18), 1775–1776. https://doi.org/10.1001/jama.2020.4683

Pisano G. P., Sadun R., & Zanini M. (2020). Lessons from Italy's response to coronavirus. In *Harvard business review* (Vol. 27). https://hbr.org/2020/03/lessons–from–italys–response–to–coronavirus.

Qiu Y., Chen X., & Shi W. (2020). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics*, *33*(4), 1127–1172. https://doi.org/10.1007/s00148-020-00778-2

Rhodes R. A. W. (1997). *Understanding governance: Policy networks, governance, reflexivity, and accountability / R.A.W. Rhodes*. Open University Press.

Robilotti E. V., Babady N. E., Mead P. A., Rolling T., Perez-Johnston R., Bernardes M., Bogler Y., Caldararo M., Figueroa C. J., Glickman M. S., Joanow A., Kaltsas A., Lee Y. J., Lucca A., Mariano A., Morjaria S., Nawar T., Papanicolaou G. A., Predmore J., … Kamboj M. (2020). Determinants of severity in cancer patients with COVID-19 illness. *Nature Medicine*, *26*(8), 1218–1223. https://doi.org/10.1038/s41591-020-0979-0

Rosenbaum L. (2020). The untold toll—The pandemic's effects on patients without Covid-19. *New England Journal of Medicine*, *382*(24), 2368–2371. https://doi.org/10.1056/NEJMms2009984

Santamaria C., Sermi F., Spyratos S., Iacus S. M., Annunziato A., Tarchi D., & Vespe M. (2020). Measuring the impact of COVID-19 confinement measures on human mobility using mobile positioning data. A european regional analysis. *Safety Science*, *132*, Article 104925. https://doi.org/10.1016/j.ssci.2020.104925

Schultze A., Nightingale E., Evans D., Hulme W., Rosello A., Bates C., Cockburn J., MacKenna B., Curtis H. J., Morton C. E., Croker R., Bacon S., McDonald H. I., Rentsch C. T., Bhaskaran K., Mathur R., Tomlinson L. A., Williamson E. J., Forbes H., … Leon D. A. (2022). Mortality among care home residents in England during the first and second waves of the COVID-19 pandemic: An observational study of 4.3 million adults over the age of 65. *The Lancet Regional Health—Europe*, *14*, Article 100295. https://doi.org/10.1016/j.lanepe.2021.100295

Tediosi F., Gabriele S., & Longo F. (2009). Governing decentralization in health care under tough budget constraint: What can we learn from the Italian experience? *Health Policy*, *90*(2), 303–312. https://doi.org/10.1016/j.healthpol.2008.10.012

Tobías A. (2020). Evaluation of the lockdowns for the SARS-CoV-2 epidemic in italy and spain after one month follow up. *Science of the Total Environment*, *725*, Article 138539. https://doi.org/10.1016/j.scitotenv.2020.138539

Usuelli M. (2020). The Lombardy region of Italy launches the first investigative COVID-19 commission. *The Lancet*, *396*(10262), e86–e87. https://doi.org/10.1016/S0140-6736(20)32154-1

Wood R. M., McWilliams C. J., Thomas M. J., Bourdeaux C. P., & Vasilakis C. (2020). COVID-19 scenario modelling for the mitigation of capacity-dependent deaths in intensive care. *Health Care Management Science*, *23*(3), 315–324. https://doi.org/10.1007/s10729-020-09511-7

Wooldridge J. M. (2021). Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators. *Available at SSRN 3906345*.

Wu X., Nethery R. C., Sabath M. B., Braun D., & Dominici F. (April, 2020). Air pollution and COVID-19 mortality in the United States: Strengths and limitations of an ecological regression analysis. *Science Advances*, *6*(45). https://doi.org/10.1126/sciadv.abd4049

Zheng Z., Peng F., Xu B., Zhao J., Liu H., Peng J., Li Q., Jiang C., Zhou Y., Liu S., Ye C., Zhang P., Xing Y., Guo H., & Tang W. (2020). Risk factors of critical & mortal COVID-19 cases: A systematic literature review and meta-analysis. *Journal of Infection*, *81*(2), e16–e25. https://doi.org/10.1016/j.jinf.2020.04.021