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It never rains but it pours: Austerity and mortality rate in peripheral areas

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Abstract

Austerity policies have been widely adopted in advanced countries to reduce public deficits. However, they can have unintended consequences, including negative impacts on population health. In this paper, taking advantage of temporal and geographical discontinuity of regional healthcare recovery plans (RPs) adopted in Italy since 2007 and employing a matching estimator in a discrete spatial non-stationarity framework, the impact of RPs on mortality rates at the municipal level has been tested for the period 2003 to 2018. We find that austerity has had unintentional negative effects on the mortality rate, particularly in peripheral areas and for the most vulnerable population.

Keywords: Austerity, Health outcomes, Mortality rate, Spatial non-stationarity, Difference-in-difference
JEL: C23, E32, I10, I18

Austerity measures, which involve reducing public spending on various programs and services[1], have become increasingly popular in recent years, particularly during times of economic recession. While the goal of austerity measures is to reduce public debt, they can have unintended consequences, including negative impacts on population health. Austerity measures can

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[1]According to Stuckler et al. (2017), "*the majority of deficit reduction policies (>80%) involved budget cuts rather than tax increases*".

impact health in a variety of ways (Stuckler et al., 2017). One of the most direct ways is through reductions in healthcare spending, cuts in health services, reductions in health-care coverage and in access to care that disproportionately affect the most fragile and vulnerable part of the population, by widening pre-existing socio-economic gaps in access to healthcare services (Karanikolos et al., 2013; Quaglio et al., 2013; Kentikelenis et al., 2014). A second way is related to the economic effects of austerity during economic recessions. Economic recessions generally lead to increased unemployment, poverty, homelessness and other socio-economic risk factors. However, austerity measures can worsen the negative effects economic recessions and can have disproportionate impacts on vulnerable populations, such as those with low socioeconomic status, minorities, and individuals with chronic health conditions. These populations may already face barriers to accessing healthcare and social services, and austerity measures can exacerbate these issues, leading to even greater health disparities (McKee et al., 2012; Quaglio et al., 2013; Stuckler et al., 2017).

Furthermore, austerity measures can have a greater impact on people already vulnerable or with existing health problems. Indeed, they are also associated to a worsening of mental health and, consequently, an increase in suicides (De Vogli et al., 2013; Branas et al., 2015; Franklin et al., 2017a), alcohol and drug abuse mortality (Stuckler et al., 2009; Franklin et al., 2017a) and infectious diseases such as HIV (Franklin et al., 2017a).

It is generally believed that these and other similar factors have a dominant impact on human mortality trends. A large part of the literature has focused on the effects of austerity on the general mortality rate (e.g. Franklin et al., 2017a; Golinelli et al., 2017; Depalo, 2019; Lomas et al., 2019; Toffolutti and Suhrcke, 2019; Arcà et al., 2020; Bordignon et al., 2020; Borra and Pons-Pons, 2020; Cirulli and Marini, 2023), on mortality rates of specific population groups (e.g., Franklin et al., 2017a; Bordignon et al., 2020; Cirulli and Marini, 2023) or on avoidable mortality (e.g., Arcà et al., 2020; Cirulli and Marini, 2023).

However, the relationship between austerity measures, economic recession, and mortality is complex, and the literature on this topic is still evolving. While there is broad consensus that austerity measures have affected health care, health and social welfare, the results in the literature are less conclusive on the impact on mortality.

Some studies point to a pro-cyclical trend of mortality risks (i.e. death rates tend to fall in economic recessions and rise in economic upturns[2]) even in the presence of austerity policies (e.g. Granados and Ionides, 2017; Toffolutti and Suhrcke, 2019). In particular, cross-country studies in developed economies tend to confirm that, even in the presence of austerity policies, mortality rates, with the exception of suicides, tend to be pro-cyclical, that is when unemployment rates increase mortality tends to decrease. In their study, Granados and Ionides (2017) examine how mortality-based health indicators have changed in 27 European countries before and after the Great Recession. They discovered that in countries where the recession was particularly severe, there were significantly greater reductions in mortality rates from 2007-2010 compared to 2004-2007. Granados and Ionides (2017) conclude that, on average, recessions have short-term positive effects on mortality rates of the adult population in Europe, but the long-term impacts of economic downturns on population health are complex and require further investigation. In the same line of reasoning, Toffolutti and Suhrcke (2019) show that, although austerity policies are associated to an increase in all-cause mortality, this is offset by the mortality decreasing effects of recessions, with the notable exception for suicides, which receive a 'double boost' from both recession and austerity.

However, considering cross-regional studies, the results appear less clear-cut (Golinelli et al., 2017; Depalo, 2019; Lomas et al., 2019; Arcà et al., 2020; Bordignon et al., 2020; Borra and Pons-Pons, 2020; Cirulli and Marini, 2023). This paper represents a contribution to this second strand of literature, which reports a prevalence of studies indicating an unintended negative impact of austerity policies on mortality rates.

We focus on a specific austerity policy implemented in Italy since 2007, whose main objective is reducing the budget deficit of regional governments originated by healthcare expenditure, under the control of central government. The policy focuses on the arrangement of financial Recovery Plans (RPs) - *Piani di Rientro* - by those regions experiencing high financial deficits for

[2]Several studies conducted in the U.S. and other developed countries have observed that there are more deaths during economic upturns and fewer deaths during economic downturns by analyzing variations across different geographic regions (e.g. Ruhm, 2000; Ruhm, 2003; Ruhm, 2005; Miller et al., 2009; Stevens et al., 2015; Haaland and Telle, 2015 van den Berg et al., 2017). There have been various explanations proposed in the literature for the procyclical pattern of mortality evolution, including a decrease in environmental pollution, driving, and occupational deaths resulting from reduced economic activity and employment.

their provision of healthcare services. This represents an interesting context for a counterfactual analysis of the differences between regions subject to a RP programme and those that are not. In broad terms, there is some consensus that austerity measure have been effective in bringing spending under control in the regions subjected to RPs. However, efforts to achieve economic sustainability and fiscal balance have had an impact on health indicators, resulting in a reduction of healthcare resources, an increase in taxes and a general weakening of regional healthcare systems. In this paper, we provide evidence on the effects of RPs on the mortality rate of populations living in municipalities of the regions where the plans have been implemented, based on a quasi-experiment at the local level, using as a control group the populations living in similar municipalities of the regions where the policy has not been enacted. Moreover, we test how the differential effect of austerity policies on mortality changes with the geographical remoteness of municipalities, which we define in terms of the distance of municipalities from crucial healthcare facilities, like hospitals. Using monthly data relative to mortality rates of the about 8,000 Italian municipalities for the period 2003-2018 (for a total of about 1,500,000 observations) we find that the policy had a detrimental effect on mortality rates in the municipalities located in regions subject to the policy. Moreover, we also find that this effect is increasing with the distance of the municipalities from the closest hospital and for the population most vulnerable to seasonal diseases.

We believe that this paper offers several contributions to the existing literature. First, we use a very large longitudinal dataset on the monthly mortality rate of all Italian municipalities. To the best of our knowledge, this dataset is among the largest ones ever used in the literature. This dataset offers several advantages and unique features. This allows us to better assess the distributional impact of austerity policies across different geographical areas and different population groups. Unlike previous studies that employ regional data, we are able to assess the impact of austerity policies on local areas, by differentiating the impact between urban and peripheral areas. By using monthly data on the dynamics of municipal mortality rates, we are able to gain two significant advantages in understanding the phenomenon, as compared to previous studies using annual average data. In particular, the use of monthly data allows us both to detect whether the policy had an effect on seasonal mortality and to assess whether the policy had a greater impact on the population most vulnerable to seasonal diseases. Second, we explicitly take into account that austerity policies involving cuts in healthcare services have a different impact at the local level, depending on the geographical distance from emergency services. Assuming as a proxy for the availability of emergency healthcare services the distance from a hospital, we classify Italian municipalities on the basis of their geographical distance from such services. This allows us to better assess the relative impact of austerity policies on peripheral versus urban areas. Third, we employ an identification strategy to assess the effects of the policy. which we believe to be more plausible than the one used in previous studies. Specifically, after classifying municipalities on the basis of their distance to emergency services, we construct a counterfactual setting, based on propensity score and separately by type of neighbouring municipalities, to assess the impact of austerity policies at the local level through interaction between time and treatment. This allows us to robustly assess the relative impact of the policy on the municipal mortality rates.

The paper proceeds as follows. In section 1, we provide some information on the policy implemented in Italy since 2007, aimed at recovering the deficit arising from healthcare spending in regions with a considerable deficit, and we briefly survey the main contributions on the analysis of the impact of this policy. At the end of the section, we state the research questions to be investigated in the following empirical analysis, whose results represent our addition to the empirical literature on the effects of RPs on health. In section 2, we depict the model to be estimated. In section 3, we outline the empirical estimation of the model and its results. Section 4 discusses some concluding remarks.

1. The control of regional healthcare deficits in Italy

1.1. The institutional features of the policy

The Italian National Health Service (NHS) has undergone a progressive devolution process since the 1990s, with the goal of enhancing healthcare efficiency and quality. However, administrative and fiscal autonomy was only officially granted to regions and autonomous provinces in 2001, leading to the federalisation and decentralisation of the healthcare system (Arcà et al., 2020). Since then, the central government has collected healthcare funding, which has been redistributed to regions based on local population size and age composition. This decentralisation process has resulted in significant regional disparities in outputs, resource allocation, and healthcare spending, posing a threat to the sustainability of the system (Giancotti et al., 2020).

Certain regions have struggled more than others to balance their budgets, owing to limited managerial capacity and inadequate performance. Moreover, given that the "*public health policy is the result of the interaction of several layers of government*" (Bordignon and Turati, 2009), since the 1990s the regions presumably inflated their expenditure and expected the central government to pay off their annual deficits in the belief that it would cover the remaining costs. Public healthcare expenditure has exhibited a strong upward trend until 2010, increasing from 5% of GDP in 1998 to 6.6% of GDP in 2010. As a consequence, according to de Belvis et al. (2012), in the period 2000-2010, the cumulative deficit from healthcare spending generated by regions reached over 38 billion Euros, most of which was originated in a very few regions[3]. The national Budget Law for the year 2005 marked a transition from a soft-budget constraint system to one based on a strong empowerment principle, introducing an obligation for regions with financial deficits larger than 5% of the overall level of funding to submit a three-year RP program to be approved by the Ministry of Health together with the Ministry of Economy and Finance (Bordignon et al., 2020). RPs thus represent an extraordinary mechanism to re-centralise the control of healthcare spending to the State and reorganise healthcare services, intervening on the factors responsible for the economic and financial imbalances (Giancotti et al., 2020), since they have to be prepared and submitted by regions, exclusively for financial reasons connected with the level of their deficit. In particular, a RP is part of a formal agreement between a region and the central government, which commits the region to lay out a consolidation path to be implemented over a three-year period to restore regional accounts. The actual realisation of the plan will be closely monitored by the central government. If a region successfully achieves the plan's objectives, it "exits" the plan; otherwise, it will be renewed for another three-year period. In addition, if the region fails to achieve the objectives set for the first year, the central government has the power to appoint a commissioner responsible for overseeing the effective implementation of the program. The commissioner acts on behalf of the central government and supervises the regions in making health-related decisions, particularly those relating to the plan's fulfilment. This strict measure is accompanied by an additional increase in regional taxes and the cessation

[3] According to Chisari and Lega (2022), 69% of the overall accumulated debt of Italian regions was attributable to very few ones, mainly Campania, Lazio and Sicilia.

of non-mandatory transfers from the central government (Bordignon et al., 2020).

The cost containment strategy to be implemented through RPs, with the constraint of maintaining the so-called essential levels of care uniformly established for all the regions, is based on several measures: institutional reorganisation through hospital mergers (*e.g.* reduction of the 40% in the number of local health authorities, OASI, 2021); strict standards in terms of hospital beds allocation and hospitalisation rates (*i.e.* de-hospitalisation policy); labour force rationing through freezing of personnel turn-over and a block on hiring; control over pharmaceutical consumption through direct distribution of drugs; reduction in the volume of services provided by private accredited facilities; introduction of centralised purchase to avoid further rise in spending; use of health insurance card system to ensure the appropriateness of community prescribing (General State Accounting Office, 2009). Whatever the specific objectives of each regional RP, altogether they determined a reduction in public spending per capita, as recently shown by Chisari and Lega (2022). Moreover, measures connected with the reduction of the number of hospital beds or the freezing of the personnel turn-over reduced the supply capacity of regions under RPs and potentially the level of satisfaction of demand, whenever the reduction of supply was not limited to the elimination of pure waste.

The first plan was signed by Region Lazio in February 2007. For the first round (2007-2009) five regions were enrolled in RP because of their large deficits: Abruzzo, Campania, Lazio, Liguria and Molise. In mid-2007 also Sicilia and Sardegna were introduced to RPs, preceding Calabria at the end of 2009. Piemonte and Puglia signed their RPs in 2010. Lazio was the first to be commissioned in 2008, soon followed by Abruzzo, Campania and Molise in 2009, and Calabria in 2010. Liguria and Piemonte were successful in implementing RPs, restoring their balances and left the plans in 2010 and 2017, respectively. Sardegna also exited from the RP thanks to its special statute (Bordignon et al., 2020). Currently, 7 regions are still implementing their RPs (Abruzzo, Calabria, Campania, Lazio, Molise, Puglia, Sicilia) with two of them (Calabria and Molise) commissioned[4].

[4] This is the update of the situation at June 2022, which can be found in the website of the Italian Ministry of Health, https://www.salute.gov.it/portale/pianiRientro/dettaglioContenutiPianiRientro.jsp?lingua=italiano&id=5022&area=pianiRientro&menu=vuoto. Accessed the 18th of January, 2023.

1.2. Empirical findings on the impact of RPs

There is large consensus on the effectiveness of RPs on regions' economic and fiscal balance (Italian Ministry of Health, 2014; Atella et al., 2019). According to Aimone Gigio et al. (2018), the measures adopted, mainly cuts in medical staff and reduction in the number of hospital beds per thousands of inhabitants, allowed to align cost structures of regions in RPs to non-RPs regions. However, RPs' effects on healthcare outcomes are still under question. Depalo (2019), using a bound inference method, shows that the containment of health spending resulting from RPs' adoption came at a cost, in terms of mortality rate. In particular the author provides robust evidence of a small increase in mortality rates, at least for Lazio, Abruzzo, Campania and Sardegna. Additionally and strictly correlated to the above-mentioned indicator, the study highlights a drop in total hospitalisation for the second cycle of the policy. Similarly, Arcà et al. (2020), by means of an IV approach coupled with two-way fixed effects for region and time, find that cuts in annual spending, following RPs, increased avoidable deaths, mostly cancer-related, by 3%. According to the authors, RPs also had an impact on regional migration, as witnessed by the rise in the search for hospital care in regions without RPs, by residents in RPs regions, questioning the equity in the access to services. As a confirmation of this, Chisari and Lega (2022) underline that in order to reach a sustainable economic performance, regions under RPs face a reduction in public healthcare expenditure and an increase in regional taxes, which create disparities across the country. The financial benefits from the plan, arising from the rationalisation of the supply structure, are also stressed by Bordignon et al. (2020). However, contrarily to the above-mentioned studies, in their analysis Bordignon et al. (2020), using an IV-DID approach, do not detect substantial consequences on health outcomes (mortality and infant mortality rates) and on the use of health care services, at least for the services under investigation. As a confirmation of this, Giancotti et al. (2020) show that not only RPs did not impact on overall hospital efficiency but even improved technological progress and total factor productivity. However, their results cannot be generalised given the restricted number of hospitals included in the analysis and, actually, more recently, Guccio et al. (2022) show, by means of a counterfactual analysis, that RPs had a negative impact on technical efficiency of hospitals. In a very recent paper, Cirulli and Marini (2023) use an IV fixed-effects approach to test the impact of RPs on different health outcomes (mortality rate, amenable and preventable deaths) and also on morbidity rates, finding a significant detrimental effect on all these health related measures.

1.3. The research issues and empirical challenges

In order to make our empirical approach to assessing the impacts of recovery plans clearer, in this section we define the main issues and empirical challenges that we seek to address in the following sections.

The Italian case is certainly relevant and interesting from a research point of view, even in an international perspective, since the focus on local policies such as RPs allows to disentangle the effects of austerity policies from the ones related to the general economic context. Even if the existing studies, briefly surveyed in the previous section, provide interesting results on the effects of RPs, we believe that the empirical analysis of the Italian case may offer more insights, and a more refined information for policy purposes.

The current research, indeed, shows that RPs were successful in containing regional fiscal deficits, but, with the only exception of Bordignon et al. (2020), it also finds that the policy had a negative impact on the health of the population of the regions where it was implemented. However, it does not provide any evidence of how this effect has eventually originated and how it is distributed across the population living in the regions under RPs. In particular, the different cost-containment measures of RPs, as depicted in the previous section, especially those related to the downsizing of capital and labour resources of relevant healthcare facilities like hospitals, reduced the supply potential of healthcare services. However, given the non-uniform spatial distribution of this potential within each region and, moreover, the search-for-efficiency imprint in the implementation of the policy, most of the structural interventions of the RPs ended up in focusing on small facilities, located in peripheral geographic areas and, therefore, the downsizing of the supply capacity hit relatively more these areas (Aimone Gigio et al. (2018)). If RPs and, in particular, their structural downsizing measures, had an impact on population health, we expect that it would have been relatively more severe in local communities more far away from supply facilities like hospitals, given that it would have been increasingly difficult for them to access essential services. The first research issue we wish to address is, therefore, the following: provided that our empirical evidence show a detrimental effect of RPs on the health of the population living in municipalities located in regions implementing the plans, does the extent of this effect, within those regions, depend on the distance of a municipality from the nearest hospitals? Using an appropriately large panel of mortality rates, computed at the municipal level, on a monthly basis, with a total of about 1.5 million records, we try to understand the effects of the austerity policy from the point of view of the spatial distribution of supply and demand for healthcare services. Employing a homogeneous classification of all Italian municipalities according to their distance from emergency facilities (i.e. hospitals), we assess whether peripheral areas in regions under RP showed different dynamics of mortality rates, as compared to areas with the same characteristics in regions without RP.

Limitations to access, and their consequential impact on health, if any, may not only be asymmetrically distributed across space, but also along time. It is, indeed, reasonable to think that if the restriction of the supply capacity is severely hitting access to services and, as a consequence, it is having a substantial detrimental effect on health, this effect has to be stronger in those months when the demand is relatively high and the limitations of supply are, therefore, more impactful. The rationale is that many diseases have different seasonal incidences that lead to peaks in demand for health services, putting them under pressure with higher risks of unmet needs and increased mortality risks[5]. Our second research issue, then, is: does the extent of the impact of RPs on health of populations living in regions implementing the policy, if any, change along the different months of the year? Unlike previous studies that employ annual mortality data, we employ monthly municipal mortality data that allow us to assess the effects of austerity policies on the seasonal dynamics of mortality, which the use of annual data may mask.

A further concern about austerity policies in the health sector is that they disproportionately affect the most fragile and vulnerable members of society (Franklin et al., 2017b). Indeed, the fatal effects on health of limitations to access arising from the implementation of RPs may be different for different individuals, in connection with their health conditions. More vulnerable individuals have a higher risk of a fatal consequence of a delay or a lack of access to healthcare facilities. Our third research issue is: does the extent of the impact of RPs on health of populations living in regions implementing the policy, if any, change across different groups of individuals, in relation to their health conditions? We try to investigate this question, using municipal

[5] For instance, climate variability is a well-established factor that affects human health, with clear seasonal patterns observed in fatalities resulting from influenza and other respiratory illnesses (Ballester et al., 2016).

mortality rates by gender. The use of mortality by gender does not only depend on the nature of our data, which differentiate mortality only by gender, but it also has an epidemiological rationale. Indeed, according to Pinkhasov et al., 2010, men tend to postpone care and give less priority to prevention than women, which may result in higher mortality and earlier morbidity for men than women. Furthermore, studies on mortality amenable to healthcare services (Nolte and McKee, 2008) indicate that the Italian male population reported higher amenable mortality than the female population (e.g. Lenzi et al., 2013; Fantini et al., 2013), indicating the presence of underlying factors that potentially make the male population more vulnerable to healthcare cuts. It is plasuible to assume, then, that the Italian male population potentially has a higher prevalence of vulnerable individuals. Therefore, we can consider the changes in male mortality rates (in comparison to females) as a means of estimating the marginal effects of the policy on the more vulnerable population.

Finally, the effects of RPs on health, if originated by limitations to access arising from structural interventions on the supply capacity of regions, may not be temporary and they may reveal to be persistent along the years. The fourth research issue is then: does the extent of the impact of RPs on health of populations living in regions implementing the policy, if any, change along the years, after the implementation of the policy? Using a sufficiently long time series of mortality rates, we attempt to understand whether the effects of austerity policy have been temporary or appear to be permanent, all other things being equal.

In the following section we explain in detail our empirical strategy and the data used to investigate the research questions outlined above.

2. Empirical framework

Differently from previous counterfactual analyses of the effects of the Italian RPs, which are based on regional data and, therefore, cannot set up a natural experiment to estimate the causal effect of austerity on health (see *e.g.* Cirulli and Marini, 2023 or Depalo, 2019 that stated that DID method is not valid for regional data because the parallel trend assumption is not fulfilled), we use municipal level data, given that the regional financial deficits are not directly linked with the municipal mortality rates in the pre-treatment years. In fact, regions were obliged to join an RP only if their budget deficit exceeded a threshold (in terms of total healthcare expenditure financing),

and not on the basis of health or demand satisfaction criteria.
The general model, at the basis of our empirical analysis, is represented by a regression specification, which binds the outcome of interest (the mortality rate) to a set of control variables, within a difference-in-difference counterfactual, where the treated group includes the municipalities belonging to a region under RP. The model is represented by the following equation:

$$Outcome_{it} = \alpha + \boldsymbol{X}_{it}\beta + \gamma TR_i + \delta T_i + \phi D_i + \epsilon_{it}, \tag{1}$$

where i is the i^{th} municipality, t represents the month of observation of the variable, within the period from 1 January 2003 to 1 December 2018, $\boldsymbol{X}$ is a matrix of control variables, TR is the fixed effect relative to the different treatment states, T is the fixed effect for the different time periods and, finally, the D term ($TR \cdot T$) is a dummy equal to 1 for treatment observations in the after-treatment period (otherwise it is zero).
One of the key aspects we want to check - linked with our first research issue - is the spatial stationarity of the estimates; in other terms, can the ϕ parameter, i.e. the effect of the policy on the outcome, be considered as stationary across the different municipalities in the treated regions? To answer this question, we need to discretise the regional jurisdiction into j parts (see section 3.1 for a more detailed description of this functional subdivision of the regional territory) in order to highlight the distance of each municipality from the nearest hospital. Equation (1) thus becomes:

$$Outcome_{jit} = \alpha_j + \boldsymbol{X}_{jit}\beta_j + \gamma_j TR_{ji} + \delta_j T_{ji} + \phi_j D_{ji} + \epsilon_{jit}, \tag{2}$$

where j is the j^{th} typology of the i^{th} municipality in terms of distance from the nearest hospital.

3. Application

3.1. Data

In order to investigate our research questions, an extensive database was constructed to check whether the financial recovery policy had a differentiated effect between treated and non-treated regions, and whether this effect had differentiated characteristics depending on the distance from hospital care units.
In practice, this meant constructing the outcome measure as spatially accurate as possible, and comparing it to the location of hospitals, so as to

construct a counterfactual that controlled for the observable characteristics of the territories.
From an empirical point of view, the following dimensions of analysis were explored:

- **Dependent variable**: we use the `Total deaths` per month (for the years 2003 to 2018) to build the monthly mortality rate at the municipality level. The use of monthly data allowed us to obtain a time series of 192 months. The source for the data is the Italian Statistical Institute (ISTAT)[6]. This information has been collected for the approximately 8,000 Italian municipalities distinctly by gender, thus producing a dataset of 1,473,897 records.

- **Control variables**: The matching procedure prior to the difference-in-difference analysis, as well as the subsequent analysis itself, required the selection of similar municipalities also in terms of social and demographic characteristics, which we represent through the `Life expectancy at 65 years` and the `Age structure of the population` (65 years and over) - collected by province and year[7]. Finally, the `Population` (total and by gender) by municipalities and year (2003-2018), source ISTAT, has been collected in order to normalise deaths per municipality size.

- **Geography**: For each municipality, the `latitude and longitude` of the municipal centroid were calculated and, in a second step, these data were compared to the `location of the hospital` provided by the Italian Ministry of Health. In particular, 880 public acute hospitals and private accredited hospitals (year 2010) have been geocoded via Google Maps API through their name and their address[8]. The location

[6] For more info please see: https://demo.istat.it/tavole/?t=seried&l=en.

[7] Source: Italian Statistical Institute, ISTAT, 1^{st} of January, 2003-2018; https://demo.istat.it/tavole/?t=indicatori&l=en

[8] We assume that the number and location of hospitals do not change in the years after 2010, because of data availability reasons. However, we consider this to be a conservative hypothesis, as some hospitals were closed in the following years, reducing the healthcare provision even at a greater extent than we calculate in this study. The differential effect between RP municipalities and the others could therefore have been greater or equal to the calculated effect, but certainly not smaller.

of the hospitals and of municipalities jointly allowed us to segment the regional territory into 4 `typologies of municipalities`:

- "*0 - Same city*": the municipality hosts one or more hospitals;
- "*1 - Neighb. level 1*": the municipality does not host any hospital, but it is contiguous[9] with a municipality that does; it is, therefore, a level 1 neighbour.
- "*2 - Neighb. level 2*": the municipality does not host any hospital, but it is contiguous with a level 1 municipality neighbour; it is, therefore, a level 2 neighbour.
- "*3 - Neighb. more than level 2*": the municipality does not host any hospital, but it is contiguous with a level 2 municipality neighbour; it is, therefore, a level 3 neighbour.

• **Treatment**: The dummy variable `treatment` has a value of 1 for all the municipalities belonging to regions under RP in the months within the period reported in Table 1 (first day of the following month) and 0 otherwise.

Table 1: Overview of signature, entry and exit from RP by Region

Region	Date of RP signature	Resolution of approval	Date of exit from RP
Lazio	28-Feb-2007	DGR n. 149 - March 6, 2007	-
Abruzzo	6-Mar-2007	DGR n. 224 - March 13, 2007	-
Liguria	6-Mar-2007	DGR n. 243 - March 9, 2007	10-Apr-2010
Campania	13-Mar-2007	DGR n. 460 - March 20, 2007	-
Molise	27-Mar-2007	DGR n. 362 - March 30, 2007	-
Sicilia	31-Jul-2007	DGR n. 312 - August 1, 2007	-
Sardegna	31-Jul-2007	DGR n. 30/33 - August 2, 2007	31-Dic-2010
Calabria	17-Dec-2009	DGR n. 908/09 - December 23, 2009	-
Piemonte	29-Jul-2010	DGR n. 1/415 - August 2, 2010	21-Mar-2017
Puglia	29-Nov-2010	DGR n. 2624 - November 30, 2010	-

[9]Please see the next section for a more precise definition of contiguity.

3.2. Constructing the counterfactual setting

The construction of the counterfactual setting essentially involves testing all possible causes of pre-treatment misalignment between units, so as to select a control group such that the difference in trend between treated and untreated units could be attributed to the policy alone. A key issue is the identification of the contiguity relationship, as outlined in the previous section, characterising municipalities, in terms of the distance from the nearest hospital.

As stated by Bivand et al. (2013), creating neighbours is "*not an unambiguous step in spatial analysis*", given that proximity between two points can be defined in terms of mere contiguity between the boundaries of two shapefiles, minimum radius or maximum number of neighbours. This subjective choice clearly has an impact on the definition of level 1, 2 and 3 neighbours. For this reason, we have taken a conservative approach by defining the neighbourhood very narrowly in order to capture the effects of distance from the treatment centre more accurately. In technical terms, we have defined neighbours as two municipalities that have at least one point in common in their border, *i.e.* the points in common lie in at least one boundary.

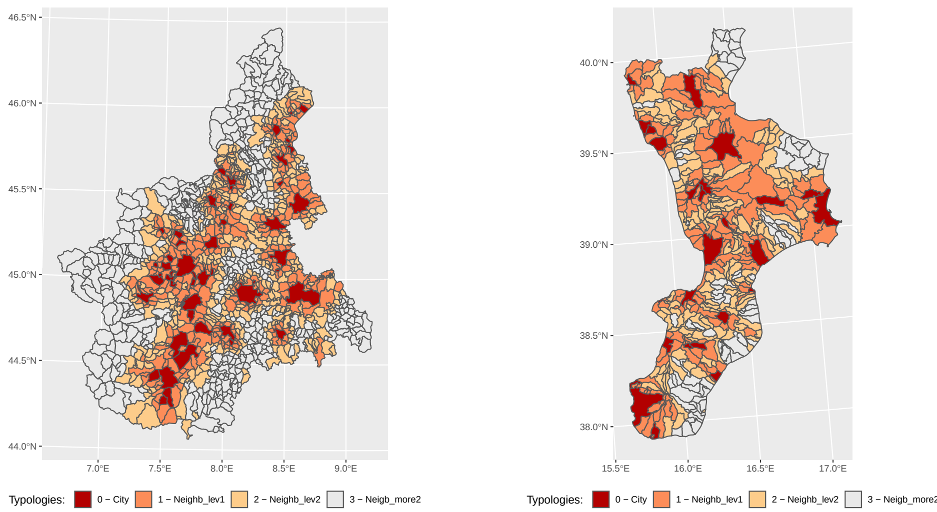
Figure 1 shows, as an example, the classification of municipalities for two regions, Piedmont and Calabria, according to their distance from hospitals. In such a way, it is possible to identify, for each treated municipality, its corresponding untreated municipality of the same neighbouring typology.

Other neighbourhoods have been defined using the radius criterion[10] to test the robustness of the results.

Combining the dummy variable relative to the month in which the treatment started (see before, `treatment`) and the dummy variable for identifying the group under treatment (the municipalities of a region in Table 1), the interaction between time and treatment, called 'DID', has been computed.

In order to take into account also the exit of individual regions from RPs (and to test the robustness of our results), two specifications of the interac-

[10]We have tried for different values of the radius, and graphical representations can be found in the Appendix A. *(a)* Radius 5 km for level 1 neighbours, between 5 and 10 km for level 2 neighbours and over 10 km for level 3 neighbours, see *e.g.* Figure A.1; *(b)* radius 10 km for level 1 neighbours, between 10 and 20 km for level 2 neighbours and over 20 km for level 3 neighbours, see *e.g.* Figure A.2; *(c)* radius 15 km for level 1 neighbours, between 15 and 30 km for level 2 neighbours and over 30 km for level 3 neighbours, see *e.g.* Figure A.3.



(a) Region Piedmont

(b) Region Calabria

Figure 1: Municipalities by typology

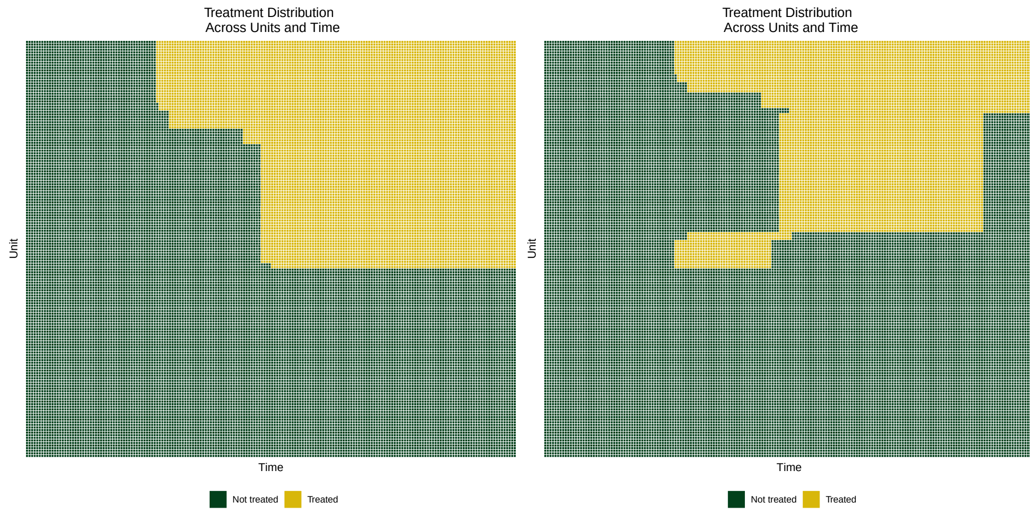
tion term were constructed: the first one (`DID1`, Figure 2 on the left) in which we do not consider exit of regions from their RP, and the second one (`DID2`, Figure 2 on the right) where also the exit from treatment is considered.

After constructing the geographical and treatment variables, our matching rationale, from an empirical point of view, was to identify the closest untreated units, based on the propensity score, separately by neighbouring typology of municipalities.

The matching method[11] for time-series cross-sectional (TSCS) data proposed by Imai et al. (2021) allows to match each treated observation for a given unit in a particular time period with control observations from other non-treated units in the same time period that have a similar covariate history. One of the main advantages of this method is the ability to estimate causal effects, which makes it possible to control for multiple treatments occurring at different times.

More precisely, the PanelMatch method can be illustrated in two main steps: in the first one, a subset of potential control observations with identical treatment history at time t is extracted from the sample (we set 45 months as

[11]Thanks to PanelMatch R package: `https://cran.r-project.org/web/packages/PanelMatch/index.html`.



(a) Without exit from treatment (DID1)

(b) With exit from treatment (DID2)

Figure 2: Treatment distributions by units and time (192 months), extract (10%) from group "*3 - Neighb. more than level 2*"

the pretreatment lag), while in the second one, the initial control group is further refined in terms of outcome and a set of covariates. In our case, this step has been carried out using the propensity score procedure, including the `life expectancy at 65`, the `age structure of the population`, the `population` and their 45-month time lags as control variables. This refinement is crucial as it allows for controlling for relevant confounders (apart from the municipality typology, as seen above) that are expected to influence the treatment.

The estimation of DiD models depends mainly on two critical assumptions: the "Stable Unit Treatment VAlue" (SUTVA) and the the "parallel trends". The SUTVA assumption implies that there should be no spillover effects between the treatment and control groups, as the treatment effect would then not be identified (Duflo et al., 2007). This assumption cannot be fully met in the healthcare sector, as people may move from their own region as a result of reduced supply and be cured in other regions, including those not under RPs. However, we believe that even if the SUTVA assumption may not be met in our case and, therefore, there may exist (limited) spillovers, our analysis is, anyway, probably underestimating the effect of the policy since, if mobility had not occurred, there would certainly have been a larger effect on

mortality.
As for the "parallel trends" hypothesis, however, after identifying the matching set of untreated units the final step is to check the balance between treated and untreated units in the pre-treatment months (45 months before treatment to 0) by geography and by pre/post matching.

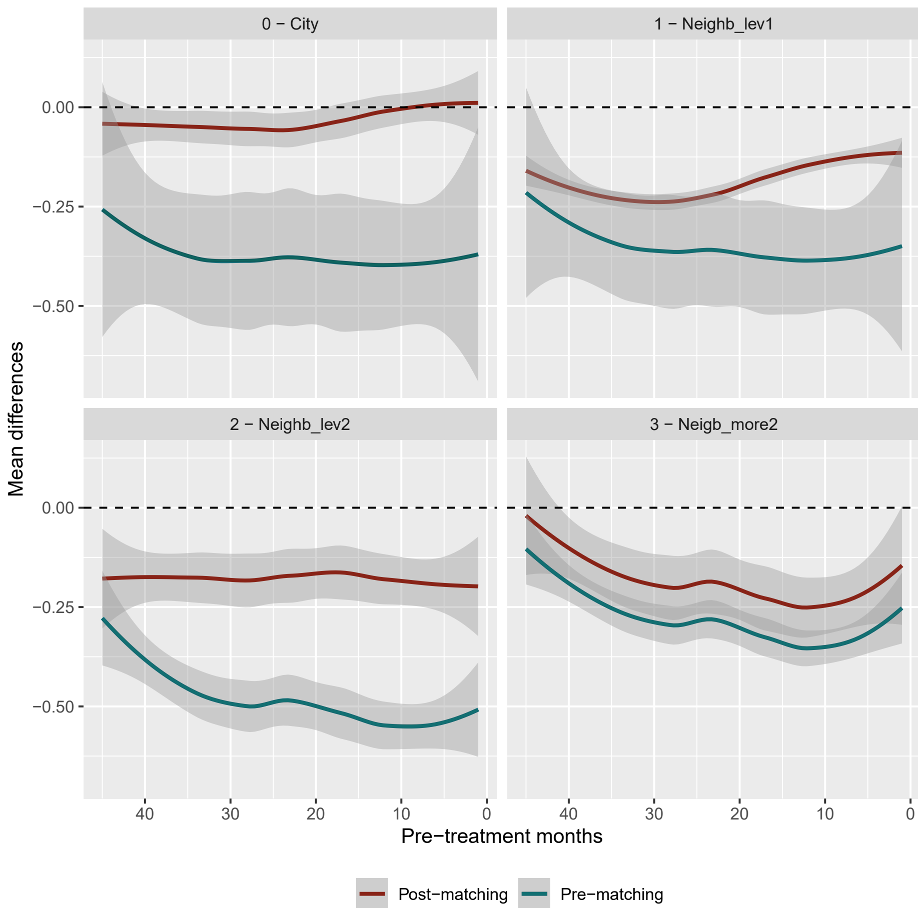


Figure 3: Balance (average difference of population) between pre and post matching by typology of municipality

Figure 3 and Table 2 report this comparison for the resident population, whereas an optimal balance is obtained when the average difference between the size of treated and untreated municipalities (in terms of population) approaches zero throughout the pre-treatment period. It can be seen how the matching procedure has improved this balance for all types of municipalities.

Table 2: Descriptive statistics (year 2007) - after matching procedure

Statistic	Mean	St. Dev.	Min	Max
Municipalities within treated Regions				
Monthly deaths (males)	3.617	24.405	0	1,220
Male population	4,392	28,851	35	1,213,734
Monthly deaths (females)	3.672	26.740	0	1,367
Female population	4,712	32,365	30	1,372,295
Monthly deaths (total)	7.289	51.059	0	2,587
Total population	9,104	61,214	85	2,586,029
Life expectancy at 65 years (years)	19.42	0.52	17.90	20.30
Age structure of the population (> 65 years) (%)	20.61	3.29	13.80	27.30
Municipalities within untreated Regions				
Monthly deaths (males)	3.540	16.725	0	595
Male population	4,234	19,146	50	586,578
Monthly deaths (females)	3.798	19.645	0	689
Female population	4,530	21,678	49	666,637
Monthly deaths (total)	7.338	36.259	0	1,256
Total population	8,765	40,823	99	1,253,215
Life expectancy at 65 years (years)	19.93	0.37	19.00	20.70
Age structure of the population (> 65 years) (%)	20.56	2.24	16.20	27.40

3.3. The impact of RPs on mortality rates

Did the RPs have an impact on the mortality differential between treated and untreated municipalities? Is this difference spatially stationary or does it increase with distance from hospitals? We will try to answer these questions both through a first trend analysis and, more formally, by estimating the average treatment effect on the treated (ATET) by typology of municipality.

3.3.1. Introductory insights

Trends in mortality rates over time for treated and untreated municipalities allow us to obtain initial, albeit imprecise, results.
In Figure 4, in order to remove statistical noise, a moving average filter is

applied to the mortality rates, using a symmetric moving average[12] with an interval of 5. In addition, for the sake of comparability, the data are standardised to 100, with the average of the first year of the historical series as the reference period.

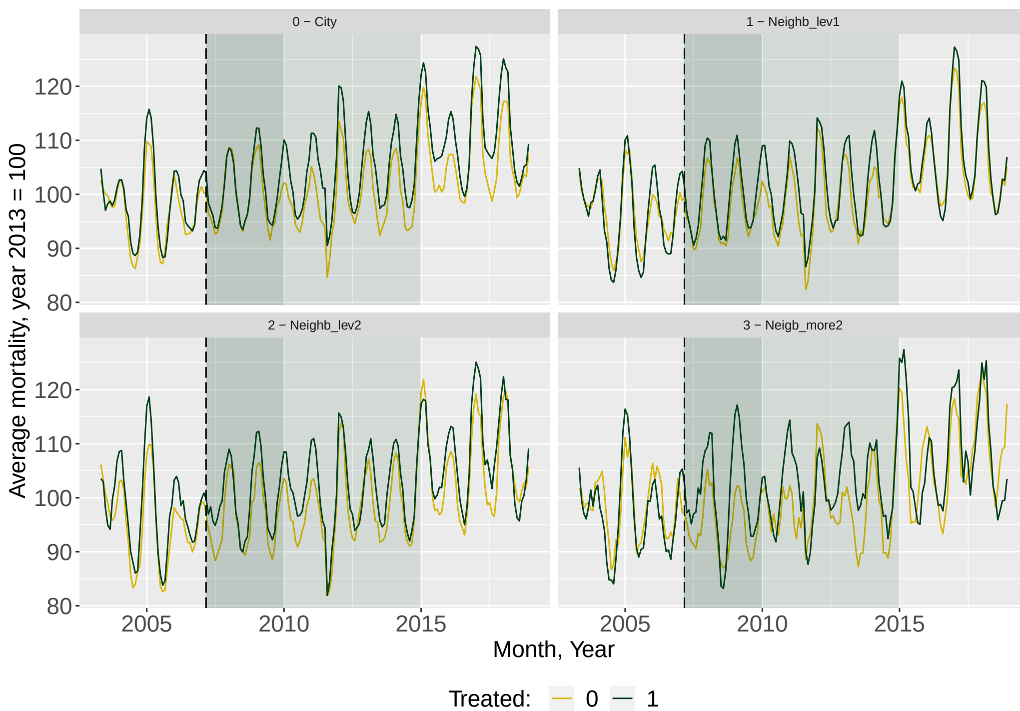


Figure 4: Mortality trends over time by treatment and typology of municipality, Average mortality, year 2003 = 100

Some results can be glimpsed. First, the presence of a strong seasonality, as it was to be expected for both the treated and untreated groups. Second, the differences between the two curves increase with increasing distance from hospitals, especially at the peaks. Third, there is a general increase in the mortality rates of the population also due to the decrease in the total population due to lower births, relative to the beginning of our observation period, that is 2003.

[12]This means that the first two lagged values, the current value and the first two forward terms of the series are averaged, with each term of the average given a weight of 1.

3.3.2. A more analytical approach

Against this background, a more analytical approach is needed to assess the average differences in mortality rates between the two groups. Table 3 reports the estimates of the average treatment effect on the treated (ATET) by fitting a linear model with time and panel fixed effects[13], and adjusting for covariates (`Life expectancy at 65 years` and the `Age structure of the population`) (Standard error are adjusted by province). The differential effect is computed without considering exit from RPs (`DID1`), and with exit (`DID2`) as well.

Table 3: Estimated ATET by DID

	Robust Coefficient	Std. err.	t	P>t	[95% conf. interval]	
ATET (1 vs 0) DID1	0.2653	0.0989	2.68	0.0090	0.0692	0.4614
ATET (1 vs 0) DID2	0.1895	0.0759	2.50	0.0140	0.0386	0.3405

Figure 5 shows the Difference in Difference model extended to include time interactions with the treatment indicator, and plots the predicted values of this extended model for treatment and control. The vertical line clearly indicates the time period of treatment onset. The figure shows a very good alignment of the outcome variable between the control and treatment groups during the 45 months pre-treatment period, an alignment that is also confirmed by the parallel-trends test (pretreatment time period) ($F(1, 102) = 0.47, Prob > F = 0.4925$) showing that we do not have sufficient evidence to reject the null hypothesis of parallel trend. As we have already seen, the two curves begin to diverge after the start of treatment, with the treatment group gradually deviating from the control group. The stationary model estimated in Table 3 confirms that the policy has had the effect of increasing the overall mortality rate in the recovery plan regions. Table 4 shows the estimated ATET by reference group, estimation model, DID and typology of municipality, pointing out that this effect cannot be said to be spatially stationary.

More precisely, the estimates by typology of municipality are reported both for the total population and separately for men and women, both with and

[13] `xtdidregress` STATA function has been used.

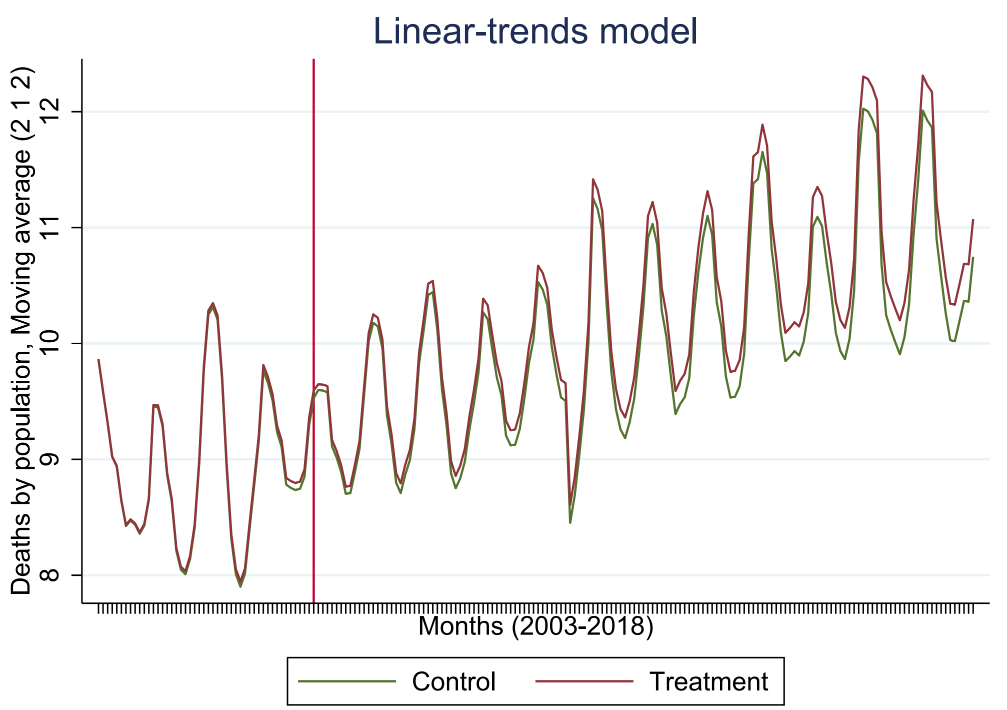


Figure 5: Graphical diagnostics for parallel trends, model DID1

without the control variables.
Some regularities emerge in line with the research issues discussed at the end of section 1.3. *(i)* ATET estimates provide a positive answer to our first research question, that is RPs had a detrimental effect on mortality rates, and they also increase, in a clear and robust way, as the distance of the municipality from the nearest hospitals increases. *(ii)* The inclusion of the control variables attenuates the effect on mortality, when compared to the model without control variables, but the estimates remain significant (see Figure 6). *(iii)* There do not appear to be any significant differences between the DID1 and DID2 models, *i.e.* it appears that the effect of the financial cut has had a lasting and non-transitory negative impact on health.

The results shown in Table A.1 in the Appendix were tested for changes in the neighbourhood criterion and show excellent robustness. By construction, the results are the same for the type 0 municipalities (municipalities with one or more hospitals within it), while for neighbours (calculated as contiguity or within a radius) the estimated ATET increases with increasing distance.

The difference in mortality rates between treated and untreated municipalities has also been examined by gender (see Table 4). Figure 7 highlights the differences in type 0 and type 3 municipalities, showing a clear difference between male and female mortality rates.

Finally, the availability of monthly data makes it possible not only to assess the seasonality of the time series of mortality rates for treated and untreated municipalities in the post-treatment period but, above all, the difference between them. If seasonality of differences is present, it means that not only the absolute level is different, as shown above, but that there are structural factors, related to the supply side, such that, during specific periods of the year, the higher demand in the area cannot be completely satisfied.
The measure to be tested has been constructed as an average mortality rate standardised to 100 against the 1 January 2004 value for both treated and untreated: the difference between treated and untreated is, therefore, equal to 0 if there is no difference, and it is positive if the average standardised rate of treated is greater than that of untreated and vice versa. Two results stand out: *(i)* the presence of a clear positive seasonality in the winter months (December to March) - reflecting the insufficient sizing of hospitals at peak times, especially in peripheral areas - which is almost completely absorbed in the summer months, and *(ii)* an overall positive difference to the treated (as it is also evident in the previous results).

Table 4: Estimated ATET by reference group, estimation model, DID and typology of municipality

Reference group	Estimation model	DID	Typology of municipality	ATET	S.E.	t	p-value	[95% interval]	
Total	No Cov	DID1	0	0.218	0.101	2.165	0.033	0.018	0.418
			1	0.337	0.104	3.237	0.002	0.130	0.543
			2	0.343	0.168	2.044	0.044	0.010	0.676
			3	0.717	0.277	2.593	0.012	0.165	1.269
		DID2	0	0.262	0.094	2.791	0.006	0.075	0.448
			1	0.373	0.098	3.825	0.000	0.180	0.567
			2	0.476	0.158	3.010	0.003	0.162	0.789
			3	1.052	0.297	3.546	0.001	0.460	1.644
	Cov	DID1	0	0.155	0.082	1.893	0.062	-0.008	0.318
			1	0.224	0.089	2.509	0.014	0.047	0.401
			2	0.173	0.153	1.131	0.261	-0.131	0.477
			3	0.622	0.284	2.190	0.032	0.055	1.189
		DID2	0	0.193	0.076	2.526	0.013	0.041	0.345
			1	0.255	0.082	3.114	0.002	0.092	0.417
			2	0.291	0.146	1.993	0.049	0.001	0.580
			3	0.931	0.308	3.021	0.004	0.316	1.545
Male	Cov	DID1	0	0.288	0.095	3.039	0.003	0.100	0.477
			1	0.189	0.119	1.592	0.114	-0.046	0.424
			2	-0.087	0.224	-0.386	0.701	-0.532	0.359
			3	0.672	0.385	1.747	0.085	-0.095	1.440
		DID2	0	0.323	0.088	3.667	0.000	0.148	0.498
			1	0.248	0.108	2.296	0.024	0.034	0.462
			2	0.041	0.223	0.186	0.853	-0.401	0.484
			3	0.990	0.394	2.512	0.014	0.204	1.777
Female	Cov	DID1	0	0.031	0.091	0.339	0.736	-0.151	0.213
			1	0.253	0.110	2.310	0.023	0.036	0.471
			2	0.435	0.175	2.482	0.015	0.087	0.783
			3	0.548	0.369	1.484	0.142	-0.189	1.284
		DID2	0	0.074	0.086	0.852	0.396	-0.098	0.245
			1	0.254	0.111	2.292	0.024	0.034	0.474
			2	0.538	0.155	3.471	0.001	0.230	0.845
			3	0.854	0.342	2.497	0.015	0.172	1.536

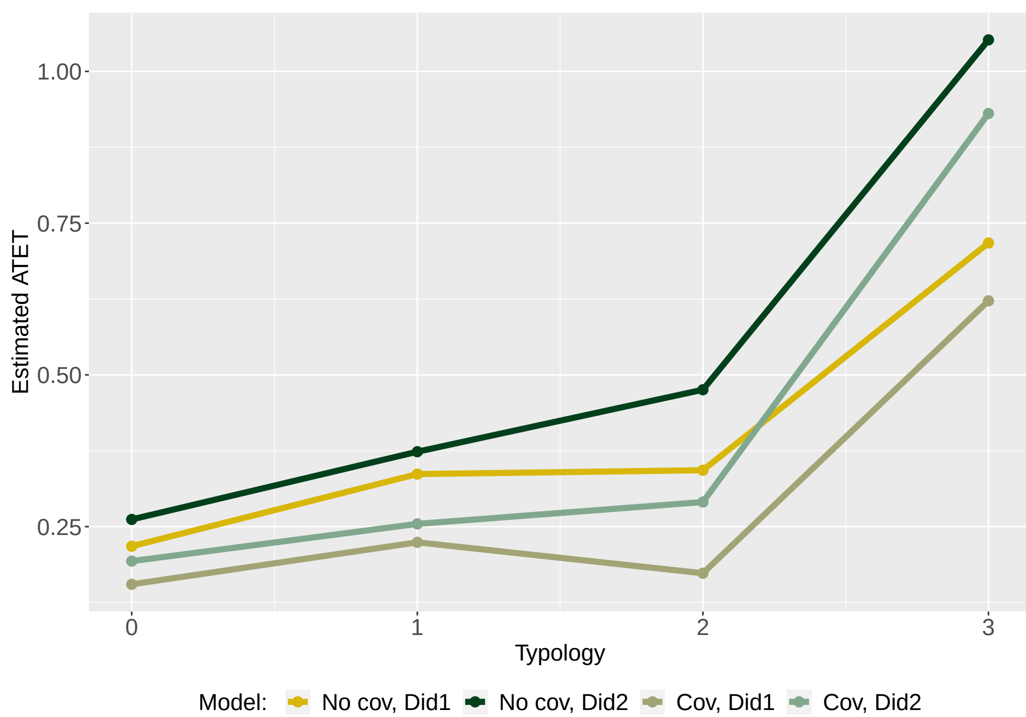


Figure 6: Estimated ATET by estimation model, DID and typology of municipality, Reference group = Total

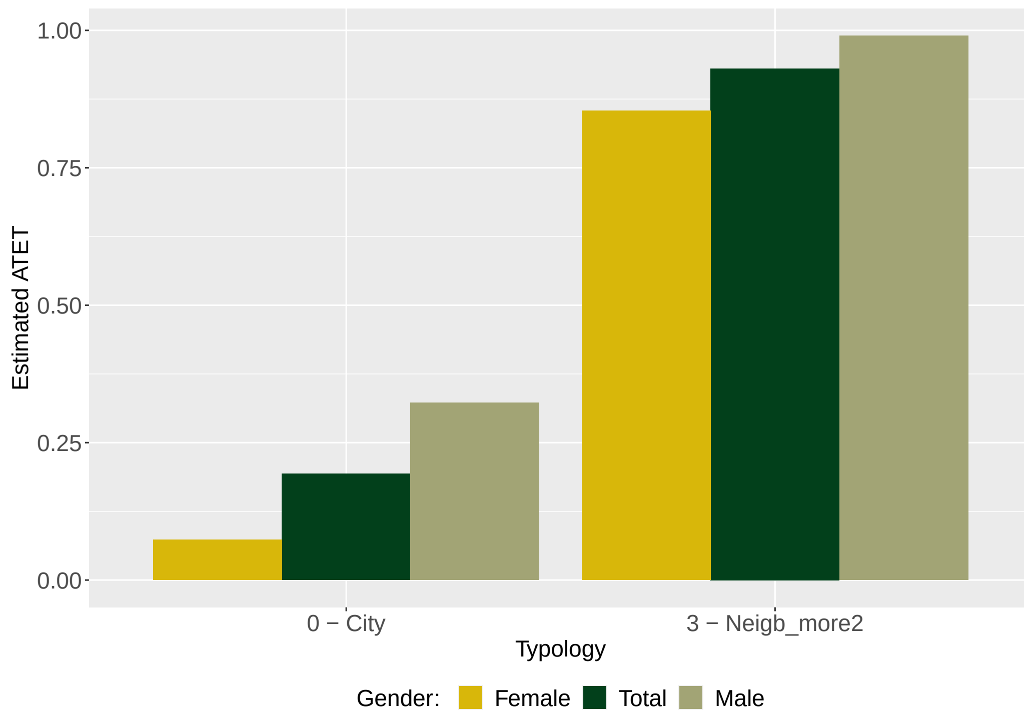


Figure 7: Estimated ATET by reference group and typology of municipality, estimation model = Cov, DID = DID2

male) and typology of municipality (Municipalities in which at least one hospital is located (level 0) versus level 3 municipalities.).

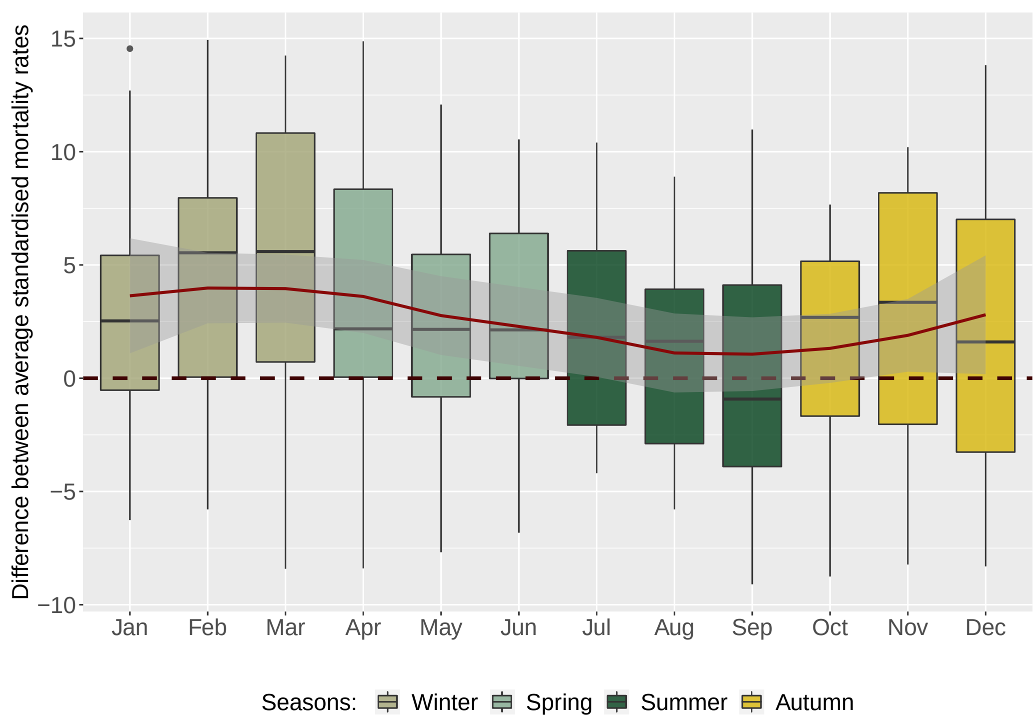


Figure 8: Seasonality of the differences between standardised average mortality rates (Treated - Untreated) by month, group "3 - Neighb. more than level", year 2007-2018

4. Final remarks

In this paper we contribute to the broad debate on the impact of austerity policies, introduced in many European countries as a reaction to the financial crisis, on several dimensions of social welfare. We focus on healthcare, and we carry out an articulate empirical analysis of the effects of RPs, implemented in some Italian regions since 2007 to contrast their excess budget deficits, on the health of their populations, as measured by general mortality rates. The focus on the RP policy, and the exploitation of the spatial and temporal discontinuity in the adoption of RPs, allow to test the specific impact of austerity policies, disentangling this effect from any other potential concurrent effects of the general economic context (e.g., economic recession). Even if our first result, that is austerity carries out a detrimental effect on health, is in line with (most of) previous international literature and, above all with studies on Italian RPs, it needs to be emphasised that the higher level of granularity of our data (monthly mortality data at the municipal level, for a total of about 1.5 million records) with respect to previous studies on the same topic (using yearly regional data, for a total of a few hundred records) guarantees a stronger robustness of our results and a much more conclusive evidence. Unfortunately, policy measures too much centred on the achievement of short-term financial goals, like cost-savings, prove not to be able to control for wider social welfare consequences, which, as we also show, can be of a long-term nature. If public policy is concerned with social welfare, then, public debt is certainly an issue but there are several other issues to be considered and weighed upon, and it may prove dangerous to regard each single issue as a sort of absolute priority, above all when there are such relevant "interests" at stake, like the health and life of people. Our contribution, however, goes behind a robust confirmation of previous results. What we believe is more relevant in the outcome of our empirical analysis is the "localisation" of the impact of austerity policies, which is not uniform across the population affected by the policy. The relevance of this perspective is not only in terms of an addition to the knowledge of the effects of austerity policies but mainly in terms of a refinement of the information needed for the design of effective policies. We show that the detrimental effects on mortality are concentrated on male population, living in communities more far away from hospitals, in the winter months. It does not seem improper to think that these results relate to the downsizing of healthcare supply caused by the different interventions included in regional RPs and, specifically, to the consequential limitations of access to relevant facilities like hospitals, mainly due to distance and to the overload of demand in winter months. These limitations of access may prove to be fatal especially for the male population who is, in general, comparatively more fragile than women. While the health conditions of these groups of individuals are, in general, worse than for similar groups living closer to core healthcare facilities like hospitals, our analysis provides evidence that austerity measures make these conditions even worst. The spending cuts involved by RPs may have further impoverished the supply potential for the communities living at a distance from hospitals, weakening the access opportunities of their populations. The main policy implication is that any structural reorganisation of the supply of services cannot just be evaluated in terms of efficiency improvement or, even worst, for its short-terms financial benefits (cost-savings), but it must also consider how it impacts on the distribution of the access opportunities across the communities of a jurisdiction. Moreover, it may not be enough, for cutting hospital care supply, to argue about its inappropriate use, if hospital care is the only form of access to medical care. In addition, during the first waves of the Covid-19 pandemic we have also learned that some inefficient sizing of hospitals may represent an acceptable cost to be borne just to be able to face demand peaks.

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Appendix A. Appendix A: Robustness checks

In this appendix, we provide further estimates and robustness tests.

Table A.1: Estimated ATET by typology of neighbourhoods between municipalities (contiguity and radius), DID=DID1, No control covariates

Typology	Neighbourhood criteria	ATET	S.E.	t	p-value	[95% interval]	
0 - City	Contiguity	0.218	0.101	2.165	0.033	0.018	0.418
	Radius 5-10 km	0.218	0.101	2.165	0.033	0.018	0.418
	Radius 10-20 km	0.218	0.101	2.165	0.033	0.018	0.418
	Radius 15-30 km	0.218	0.101	2.165	0.033	0.018	0.418
Level 1	Contiguity	0.337	0.104	3.237	0.002	0.130	0.543
	Radius 5-10 km	0.194	0.140	1.38	0.171	-0.085	0.474
	Radius 10-20 km	0.267	0.115	2.32	0.022	0.039	0.495
	Radius 15-30 km	0.359	0.114	3.14	0.002	0.133	0.587
Level 2	Contiguity	0.343	0.168	2.044	0.044	0.010	0.676
	Radius 5-10 km	0.299	0.143	2.09	0.040	0.015	0.586
	Radius 10-20 km	0.492	0.168	2.92	0.004	0.158	0.826
	Radius 15-30 km	0.355	0.261	1.36	0.178	-0.165	0.874
Level 3	Contiguity	0.717	0.277	2.593	0.012	0.165	1.269
	Radius 5-10	0.508	0.169	3.01	0.003	0.174	0.843
	Radius 10-20	0.575	0.415	1.39	0.171	-0.256	1.406
	Radius 15-30	2.910	0.914	3.18	0.005	0.998	4.823

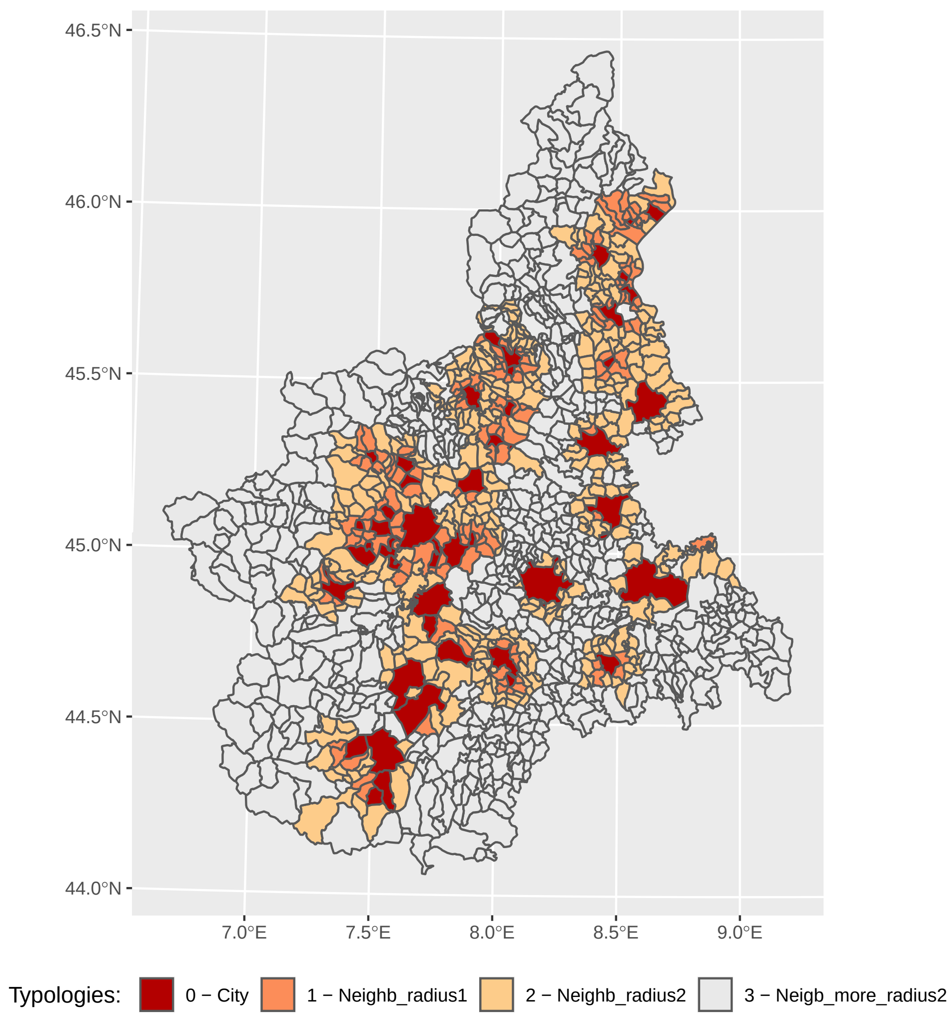

Figure A.1: Municipalities by typology and radius, radius = 5 and 10 km, region Piedmont

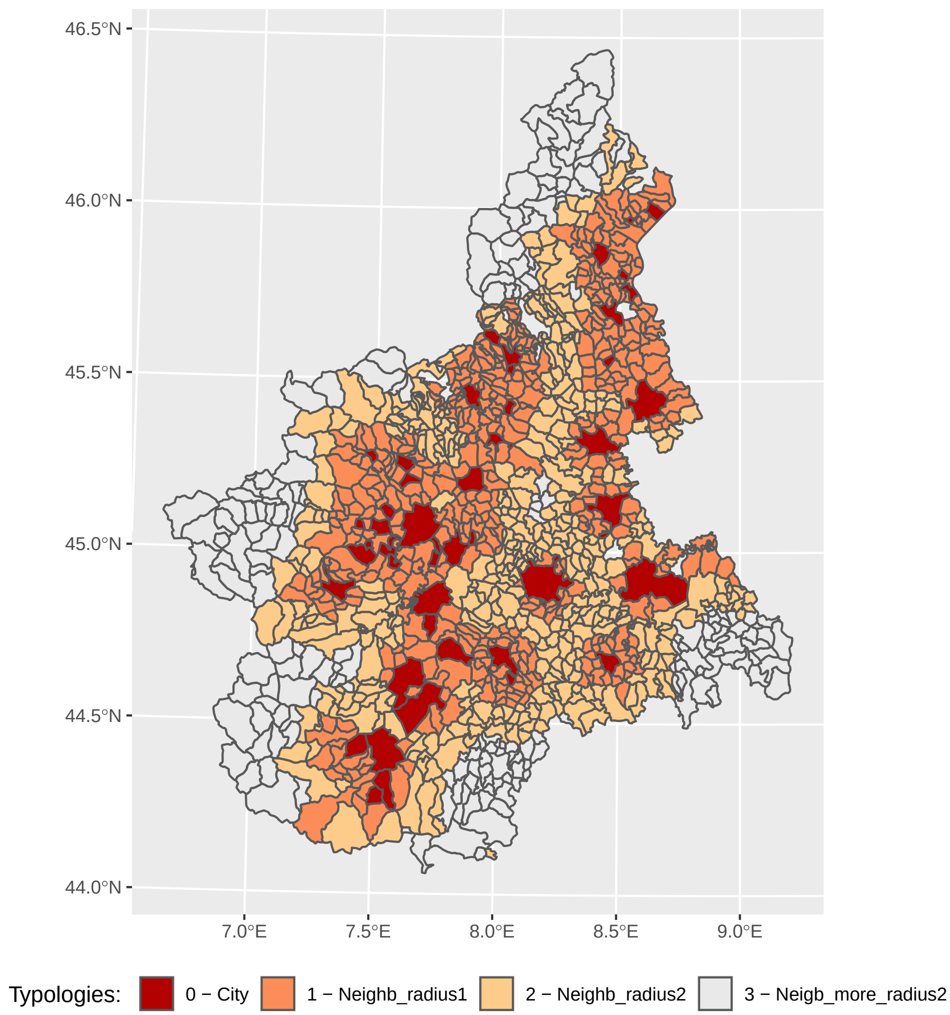

Figure A.2: Municipalities by typology and radius, radius = 10 and 20 km, region Piedmont

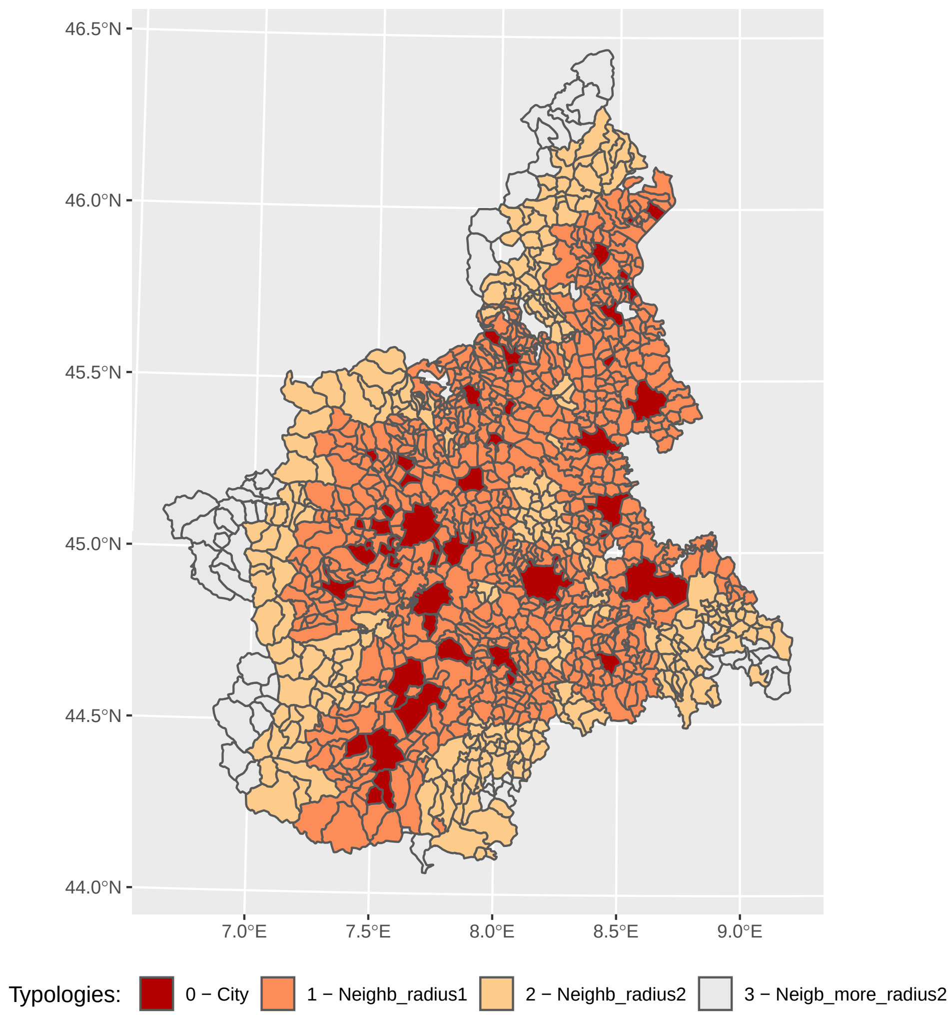

Figure A.3: Municipalities by typology and radius, radius = 15 and 30 km, region Piedmont