University of Pavia

Three essays on the consequences of seismic and environmental shocks on society

by Michael Santarossa

supervised by Prof. Giuliano Masiero

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Abstract

Natural disasters and environmental shocks are destructive events that are growing in frequency and severity, driven also by climate change. Despite the large implications of these shocks on society, their impact has been under-investigated in several fields. Moreover, rigorous studies that identify the consequences of natural disasters are lacking because a cross-country perspective is generally adopted rather than a local one. Besides the direct impact of natural disasters, the exogenous nature of these shocks also provides the opportunity to disentangle individuals' and institutions' behavior and mechanisms, which otherwise would not be identifiable due to endogeneity problems. The three essays that compose this thesis contribute to fill this gap by analyzing some implications of seismic and environmental shocks.

In the first essay, we analyze the response of municipalities to the occurrence of natural disasters in terms of spending behavior, use of upper tier transfers and recovery, using balance sheet data of about 8000 Italian municipalities for the period 2000-2015 and the universe of earthquakes events. We find evidence of increasing expenditure for about 12 years after the shocks, with asymmetric responses between earthquake-related and unconditional grants, and heterogeneous flypaper effects across the country. While in Northern municipalities expenditure tends to regress to pre-earthquake levels, Southern municipalities stick to higher expenditure levels when grants drop. This evidence is coupled with a faster recovery of private income and housing prices in Northern municipalities. Moreover, earthquake shocks trigger spillover effects of spending levels and composition in unaffected municipalities that share the border with the disaster area.

In the second essay, we analyze how the occurrence of earthquakes changes voters' behavior at municipal elections and which channels drive this change. We exploit data

from municipal electoral cycles between 1993 and 2015 in Italy and apply an empirical strategy that combines propensity score matching and regression adjustment. We find that the occurrence of destructive earthquakes significantly increases the incumbent chance of being reelected and vote share in municipal elections. We run several placebo tests and robustness checks to corroborate the results. We find that incumbent mayors are rewarded for a high quality response to disaster damages that offsets the partial accountability of incumbent mayors for disaster relief since resources are sent by upper-tier governments and are not completely converted into expenditure. Moreover, incumbents benefit from the mediatic interest of earthquake occurrence since their visibility on the media grows as compared to the main competing candidates.

In the last essay, we analyze the effect of temperatures on monthly mortality rates and hospital admission rates for cardiovascular and respiratory diseases among the elderly and children, and investigate whether municipalities with higher social expenditure face lower mortality and hospitalizations. We use data from monthly mortality for the period 2003-2015 and the universe of hospital admissions aggregated by municipality for the period 2001-2015. We use panel data models of mortality and hospitalization rates that control for temperature level or deviation bins, with deviations being relative to municipality-specific average temperatures, income, precipitation, pollution, province-specific time trends, and municipality, month$\times$year and province$\times$month fixed effects. We find surges in mortality rates when extremely hot days occur independently from the adopted temperature measure. Moreover, we find that both extremely hot and cold temperatures, measured as deviations from the municipality-specific mean temperatures, cause surges in hospital admission rates of the elderly both for cardiovascular and respiratory diseases, and of children for respiratory diseases. Conversely, when using temperature levels, results of hospital admissions are confounding because temperature levels do not account for local resilience to temperatures and offsetting behaviors. Moreover, we find evidence of a mitigating effect of social expenditure on health outcomes with the lowest-spending municipalities facing higher surges in mortality and hospital admission rates when extremely hot or cold days occur as compared to municipalities with higher spending levels.

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Preamble

Natural disasters and environmental shocks are destructive and often unpredictable events that cause devastating direct and indirect damages to economies and societies. Since these shocks are growing in frequency and severity, driven also by climate change, the recent literature has increasingly analyzed the impact of natural disasters on several aspects, such as economic growth, firm productivity, household prices, health and electoral outcomes. One reason why this strand of the literature is of relevance is because efficient and effective damage recovery procedures need to be identified in order to mitigate negative consequences on society in the short and long run. Moreover, the exogenous nature of these events generates natural experiments that allow to perform causal investigation of economic mechanisms and behavior of individuals and institutions which otherwise would be hard to identify due to endogeneity issues. Despite the remarkable consequences of these shocks and the opportunity that their occurrence provides for research, the investigation of social and economic consequences of natural disasters is limited due to the low frequency of extreme disaster occurrences and the necessity to collect data at small-area level. Indeed, the impact of these shocks may be dramatic at local level, but risks to be irrelevant from a wider perspective.

This thesis tries to fill this gap and investigates the impact of seismic and environmental shocks on three outcomes using unique datasets from Italian municipalities. The first essay analyzes the impact of earthquake occurrences on per per capita local government expenditure using a flexible model specification most closely aligned to event-study-like approaches and exploits the variability in transfers from upper-tier governments for recovery from earthquake damages to investigate differences in the response of public expenditure to increasing and decreasing earthquake-specific (matching) and general (unconditional) grants. Then, we analyze how the heterogeneous response to grants affects local economic growth and whether earthquake shocks cause spillover effects on unaffected municipalities that share the border with the disaster area. The second essay investigates the causal impact of earthquake occurrences on the electoral success of incumbent mayors using propensity score matching and weighting combined with regression adjustment. Further, we analyze whether incumbent mayor performance and visibility on the media drive variations in electoral outcomes after earthquake occurrence. The third essay identifies the causal relationship between environmental temperatures and health outcomes (mortality and hospital admission rates) using flexible temperature-bin regression models that control for a large set of fixed effects to account for unobserved geographic- and time-specific determinants of health outcomes. Then, we investigate whether local government social expenditure, which mainly funds the provision of services for children and the elderly, allows to mitigate the adverse effects of extreme temperatures on health.

Each essay provides specific contributions to its economic sub-field that are discussed later in the thesis. However, the three essays are linked together by some broader contributions that apply to all of them. The essays focus on seismic and environmental shocks exploiting data from a country, Italy, that is largely exposed to weak and severe natural disasters, in particular earthquakes. This peculiar setting, together with the availability of detailed historic datasets of disaster occurrences, provides a unique opportunity to investigate social and economic implications of these shocks. Indeed, many past studies are forced to investigate on the impact of single events that affected a small area, or to use very long panels in order to increase disaster frequency, with the drawback that data availability may be limited. Moreover, we consider the impact of disasters on outcomes that have been neglected in previous studies, such as local government expenditure, and use municipal-level data which allows to disentangle effects of shocks which may be irrelevant at country-level, but devastating at local level. As compared to previous studies, this perspective allows to improve the identification of the consequences of shocks on society.

The remainder of the thesis is structured as follows. Essay 1 analyzes the variation in local government expenditure after earthquake occurrences, the heterogeneous response to increasing an decreasing grants and the implications on local economic growth. This essay has been presented at the XXX SIEP Congress in Padova, at the 2019 DREAMT/AEM Winter Workshop and at the 75th IIPF Congress in Glasgow. Moreover, the draft has been accepted for publication in the *Journal of Regional Science*. Essay 2 investigates on the impact of earthquake occurrences on municipal electoral outcomes and on possible drivers determining these variations. This essay has been presented at the 2018 DREAMT Summer Workshop, at the 59th SIE Congress in Bologna, at a Brown Bag Seminar at the Università della Svizzera Italiana in Februray 2019, at the 75th IIPF Congress in Glasgow and at the XXXI SIEP Congress in Torino. The paper is under review with an economic journal. Finally, Essay 3 relates extreme temperatures to health outcomes and analyzes the role of social expenditure in mitigating adverse temperature-related effects on health. This analysis has been presented at the 18th Annual Conference on Health Economics, Management and Policy in Athens, and at the 2019 iHEA Congress in Basel. Some additional data on hospital admissions and mortality have been recently requested to the Italian Ministry of Health and the Italian Institute for Statistics to improve the robustness of the analysis of this paper. The analysis of the first two essays has been conducted in collaboration with Giuliano Masiero, while the third essay represents a joint work conducted with Giuliano Masiero and Fabrizio Mazzonna at the Università della Svizzera Italiana.

Essay 1

Earthquakes, grants and public expenditure: how municipalities respond to natural disasters

1.1 Introduction

Natural disasters have several implications on affected economies and society. Infrastructures get damaged and need to be repaired, people get injured or die, economic activities are unable to operate and inequalities may worsen (Bui, Dungey, Nguyen, & Pham, 2014; Kahn, 2005; Strömberg, 2007). Whether it is because of legal rules, solidarity or to raise the consensus of the electorate, public authorities commonly intervene by means of higher spending levels and transfers of financial resources from the central government to disaster areas (Barone & Mocetti, 2014; Noy & Nualsri, 2011).[1] It has been noted that expenditure on post-disaster relief is generally less efficient and effective than expenditure on prevention (Healy & Malhotra, 2009; Skoufias, 2003). However, governments prefer to deal with disaster relief measures since the electorate is more likely to perceive (or misperceive) the benefits and, therefore, to provide political consensus (Cavallo & Noy, 2010). Despite the involvement of local authorities and their role as the main channel of interaction between citizens and regional/central

[1] In Italy - a country frequently struck by earthquakes - the central government allocated almost 100 billion Euro at 2014 prices to fund disaster relief just for the five largest seismic events that occurred between 1968 and 2002 (Di Giacomo, 2014).

governments to face natural disasters, there is lacking evidence on the response of local public expenditure in terms of resources use and timing, and the subsequent impact on recovery (Bevan & Cook, 2015).

This essay investigates the response of local government expenditure to natural disasters exploiting detailed data on expenditure and transfers from the universe of Italian municipalities for a 16-year period (2000-2015), and a large historic data set of seismic events since 1000 AD. To this aim, we estimate expenditure variation following earthquake occurrence using panel data regression models on the universe of municipalities as well as on a matching sample, focusing on immediate and medium-run effects of earthquakes. Further, since disasters are particularly good examples of exogenous shocks to economies, we exploit the variability in transfers received for earthquake damage recovery to identify a possible source of inefficiency in post-disaster interventions, i.e., the overreaction to transfers from upper tiers to lower government levels that can offset the growth of income - the so called *flypaper effect* (see e.g., Gennari & Messina, 2014; Hamilton, 1983). Due to their essential matching-grants nature and their duration, the response to earthquake-specific transfers may be more pronounced as compared to other sources of transfers, implying both an income and a substitution effect (Bailey & Connolly, 1998) and leading to persistent path-dependency of local governments expenditure over time. We apply a matching procedure to disentangle different types of grants and explore differences in the response to earthquake-specific and general grants. Then, we investigate the asymmetric responses to increasing and decreasing grants and between Northern and Southern municipalities in terms of resources allocation and recovery. Finally, we analyze whether earthquake occurrences trigger spillover effects in terms of spending levels and composition in unaffected municipalities that share the border with struck municipalities.

We find that an earthquake increases local government expenditure immediately after the shock by about 2 percent, following an inverse U-shaped trend, which persists for about 11-12 years since the disaster. This increase is mainly driven by transfers of financial resources from the central and regional governments. Further, we find evidence of flypaper effects with asymmetric responses to matching (earthquake-related) and unmatching grants and to increasing and decreasing grants. In addition, we testify differences in the response of Northern and Southern municipalities, suggesting that the less efficient use of earthquake-specific grants by Southern municipalities lead to poor economic outcomes. Finally, we find that local governments not affected by earthquakes that share the border with struck municipalities react to disaster occurrences by increasing spending levels and changing the budget allocation for 3-year and 2-year periods, respectively.

Despite the size of public resources employed in the recovery from losses of natural disasters and the long-lasting effort of public authorities, only a few studies analyze the response of public expenditure to natural disasters and its impact. Melecky and Raddatz (2011) investigate the effect of natural disasters on fiscal sustainability using data on a number of high and middle-income countries for the period 1975-2008, and show that public expenditure grows to allow for recovery. Noy and Nualsri (2011) find that governments of developed countries tend to support more disaster areas by means of transfers of financial resources, while governments in developing countries are less committed or even contract the resources transferred to disaster areas. Other studies focus on the impact of natural disasters on economic growth and show that economic gains are context related (e.g. Barone & Mocetti, 2014; Cavallo, Galiani, Noy, & Pantano, 2013; Skidmore & Toya, 2002). Damages from natural disasters may provide the opportunity to reorganize economic activities in affected areas and, therefore, to foster urban development (Xu & Wang, 2019). However, areas with better pre-disaster socioeconomic conditions are more capable to exploit this opportunity as compared to areas with worse pre-disaster conditions (Bondonio & Greenbaum, 2018). Looking at two Italian regions struck by severe earthquakes in 1976 and 1980, Barone and Mocetti (2014) show that in the medium-run (i.e., the first five years after the disaster) transfers from the central government allow to entirely cover the losses, but remarkable differences are observed between the two regions in terms of ability to recover. Hornbeck and Keniston (2017) find that Boston city reconstruction after the 1872 fire is an example of successful recovery with beneficial effects on land and house values and urban growth, while Horwich (2000) finds that the port of Kobe in Japan, struck by a severe earthquake in 1995, was able to recover from damages within one year, but economic growth slowed down because part of economic activities moved to other port cities.[2]

Our analysis contributes to a deeper knowledge of the effects of post-disaster public spending, which helps policy makers to design more effective and efficient relief measures. Usually, natural disasters affect a limited area of a country and, even if an event is not catastrophic, damages may be remarkable at local level. Hence, observing the consequences of these events from a within-country perspective may improve the precision of the analysis. The large majority of studies mentioned above focus at country level and analyze the economic impact of the largest natural disasters, neglecting smaller but harmful disasters. Clearly, cross-country studies can only exploit a limited number of rare and big events, which may undermine the validity of the results. This approach allows to capture the effects of relatively small events since we exploit data for the universe of Italian municipalities and a unique historic data set of all seismic events. Italy is an ideal setting because the country was struck by several hundreds of earthquakes over the last decades, out of which only 19 were large catastrophic events.[3] Moreover, local governments are responsible for housing services, urban road maintenance, economic development, social protection and education, all aspects that are likely affected by catastrophes.

The rest of the essay is structured as follows. Section 1.2 describes the institutional setting and how public authorities respond to natural disasters. Section 1.3 presents the data and some descriptive evidence on the incidence of earthquakes and changes in public expenditure. Section 1.4 defines the empirical strategy and Section 1.5 presents the main results on expenditure behavior and provide some robustness checks. In Section 1.4.2, we extend the analysis to investigate the role of transfers, and in Section 1.5.3 we explore differences in the response to earthquakes, i.e. asymmetric responses to increasing and decreasing grants and heterogeneous flypaper effects across municipalities. In Section 1.5.4, we further explore differences in the response of Northern and Southern local governments in terms of timing and spending composition, and the effects on economic growth. Finally, in Section 1.6, we analyze the presence of

[2] Note that Horwich (2000) uses information on 19 months after the disaster. This does not exclude that the area could have recovered from economic damages in the long-run, as found by Davis and Weinstein (2002) after city bombings in Japan during World War II.

[3] Our elaboration on data provided by the Center for Research on the Epidemiology of Disasters (CRED) (Guha-Sapir, Below, & Hoyois, 2017).

spillover effects of earthquake shocks on the expenditure and spending composition of neighboring local governments not affected by the disasters. Section 1.7 concludes.

1.2 Institutional and seismic background in Italy

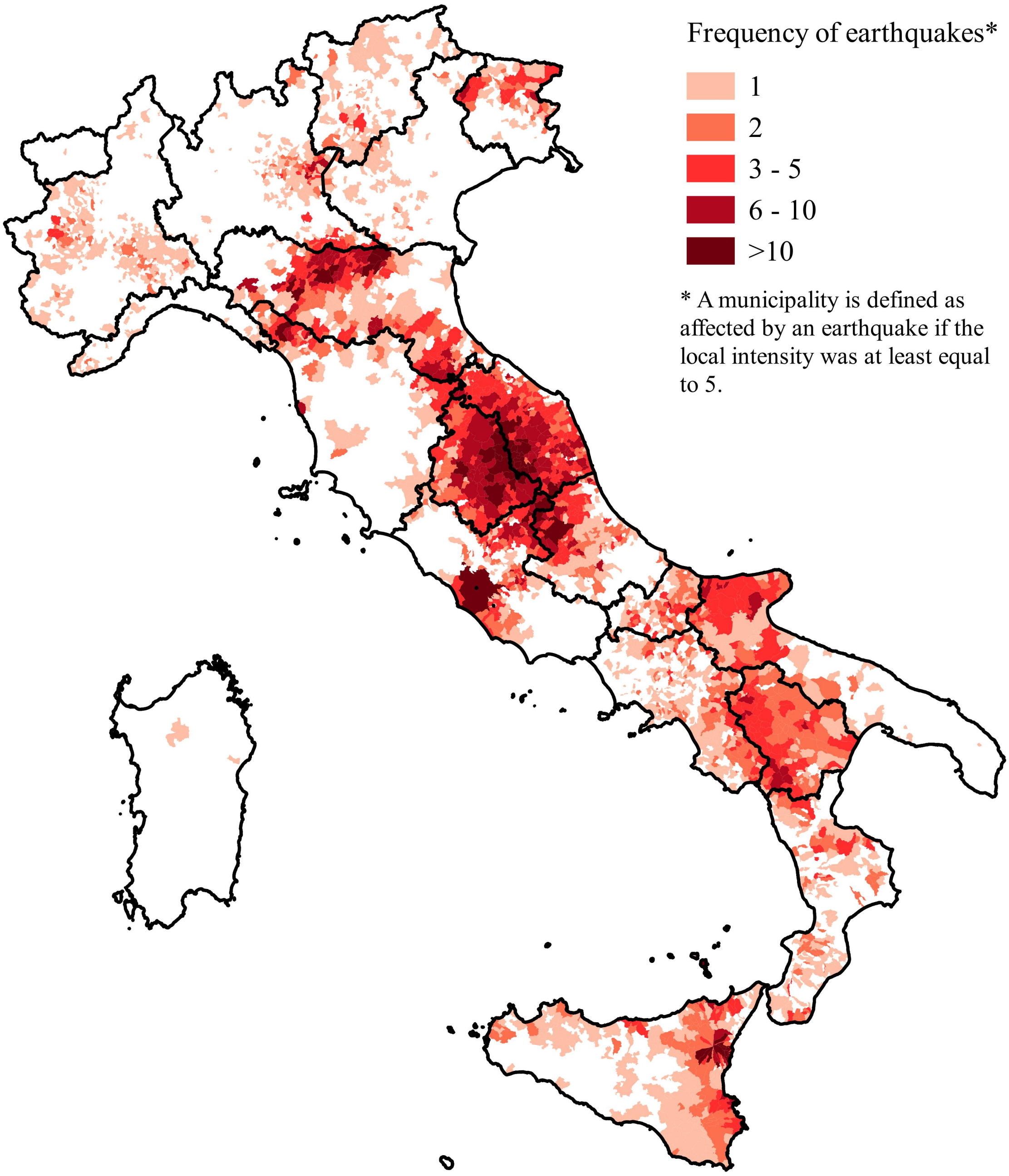
1.2.1 Exposure to earthquake risk

Italy is a country with a high frequency of earthquakes. The country is almost continuously exposed to minor earthquakes and several large events occurred both recently and in the past. However, it is necessary to distinguish the physical strength of an earthquake from the damages it causes. A very strong earthquake that occurs in a not populated area without infrastructures may not cause any damage, while a mild earthquake that strikes a town with weak infrastructures may cause human losses and large damages. The 2017 earthquake of Ischia was a relatively weak earthquake (moment magnitude 4), but very destructive because of poor building standards present in the area. This distinction is of relevance also because Italy is rich in cultural heritage, which is difficult to protect against natural disasters.

Figure 1.1 illustrates the frequency of earthquakes with intensity equal or bigger than 5 at municipality level for the period 1985-2015. Intensity 5 is the lowest level at which damages occur (see Section 1.3.2 on earthquake measurement for details). The map highlights that earthquakes occur across the entire country. One-third of municipalities were struck at least once by a seismic event over the considered period and almost half of them in the period 2000-2015. The areas most frequently affected are the regions Emilia-Romagna in the North, Umbria, Marche, and the municipality Rome in the Center, Abruzzo, Basilicata, Northern Puglia and Eastern Sicily in the South.

The exposure to earthquake risk leads to the classification of municipalities into seismic zones. In 2004, the Italian Institute for Geophysics and Volcanology (INGV), a unit of the Civil Protection with the task to increase the knowledge on the Earth system and its phenomena and to monitor seismic and volcanic events, analyzed the probability to face large earthquakes based on the movement speed of the ground and defined, accordingly, four seismic zones. A more detailed classification with sub-categories was

Figure 1.1: Frequency of earthquakes by municipality (1985-2015)



Notes - The map represents the frequency of earthquakes with intensity ⩾5 by municipality for a 31-year period (1985-2015). The darker the color, the higher the frequency. White areas represent municipalities that did not face any earthquake with intensity ⩾5 over the period.
Source: Our elaboration on data from the DBMI15 database of INGV (Locati et al., 2016). The shape map of the 2016 administrative borders is provided by ISTAT.

realized in 2015. This classification is of interest for the central government because it allows to address policies to the most exposed areas. One of these policies defines building standards that must be fulfilled in high-risk seismic zones. Moreover, the central government allocates funds for infrastructure maintenance to prevent disaster damages based on the classification.

1.2.2 Administrative organization and response to natural disasters

Italy is a decentralized country where the public administration consists of four levels: the central government, the region, the province, and the municipality. The main task of regions is the provision of services in the health care sector. Provinces are responsible for the maintenance of non-urban roads, environmental protection and secondary education. Municipal governments are required to offer a number of services, among which the most relevant are local transports, urban road maintenance, waste disposal, housing, social protection, and primary education.

Since the early '90s, the administrative organization has changed. The Law 142/1990 started a decentralization process of powers from the central government towards local authorities with the attempt to increase the autonomy of local governments. This implied a change in the composition of funding sources. Since 1992, an increasing share of local government revenues derived from the withholding of tax revenues, mainly from property taxes and surcharges on income taxes, and from the revenues generated by local service provision. However, decisions on local tax rates are constrained by national regulation that limits the extent to which local governments can leverage on taxation. The central government reallocate resources among local governments with the purpose to grant equal access to essential services across the country. In 2002, a fund for equalization was established. The resources are distributed to local governments, both directly and through regional governments, so that governments with insufficient own resources are able to provide the necessary services to the population.[4]

[4]The benchmark adopted by the central government is the average revenue of municipalities of a given demographic class. Decree Law 267/2000 (*Testo unico delle leggi sull'ordinamento degli enti locali*) classified municipalities into 12 demographic classes based on the size of the resident population and defined regulation accordingly, because population size determines differences in needs.

To grant equal access to basic services across the country, the central government funds up to 70 percent of the expenditure reported in the balance sheet of the year before.[5] The other services need to be funded with own resources.

In 2015, local governments spent 83 billion Euro, which is 10 percent of total public expenditure in Italy. Transfers of financial resources from the central and regional governments and from other public institutions account for 14 percent of current revenues. These transfers are mainly unconditional. Current transfers represent on average 70 percent of total transfers and they are generally non-earmarked transfers, while the remaining share represents capital transfers, which are generally distributed for specific projects, such as the construction of infrastructures. The remaining 86 percent of local government revenues is composed of own resources. Almost half of own resources are produced by local taxation (Italian Institute for Statistics, 2017a).

The response of public authorities to natural disasters consists of two phases. Immediate aid is provided to meet short-run needs, such as the provision of food and medicals, the preparation of emergency camps, and the inspection and evaluation of damages to infrastructures. Later on, effort is put in the recovery from losses and in the prevention of future disasters. Generally, funds for recovery from damages are matching grants, i.e., they meet spending requirements for specific projects proposed by local public authorities.

Although central authorities are not obliged to intervene in the case of natural disasters, usually they offer immediate support through the Civil Protection Department.[6] Moreover, the law empowers the central government to claim the state of emergency and define its duration and the involved area (Art. 5 of Law 225/1992). This claim has two main implications. First, the central government can recur to decrees to face the situation notwithstanding the current regulation. In this way, public authorities can intervene immediately without the need to recur to legislative procedures, which could impede a prompt and proper response to the catastrophe. The

[5] Since 2009, services provided by local governments are divided into basic services and other services. Basic services are general administration, local police, education, local transport, social protection and local services. Local services are housing, Civil Protection, waste disposal, water services, and services for environmental protection.

[6] The Civil Protection Department, which is administered by the Presidency of the Council of Ministers, guides the prevention, response, forecast and risk monitoring activities related to both natural and man-made disasters through central and local units across the country.

second implication is that the state of emergency allows to transfer financial resources from the fund of the Civil Protection to the affected areas. However, this procedure can have a drawback in terms of timing. The central government can claim the state of emergency only upon request from regional governments through the Civil Protection. Commonly, regional governments decide whether to ask for the state of emergency based on the size of damages. They delegate the collection of information from the citizens to local governments, a procedure that could delay effective intervention.[7]

For medium and long-run support to disaster areas, the central government needs to follow ordinary legislative procedures. Based on the size of damages resulting from inspections, financial resources for the reconstruction of capital and the recovery of economic activities are allocated by means of decree laws. A final tool at government disposal is the yearly financial law, which allows to allocate additional resources to the areas affected by catastrophic events.

1.3 Data and descriptive evidence

1.3.1 Data

In this study we use three main data sets: (1) local government balance sheet data, (2) data on earthquake occurrence, and (3) data on municipality characteristics. Data on local government expenditure are available for 7997 Italian municipalities observed for 16 years (2000-2015).[8] The panel data set is obtained from the Italian Ministry of the Interior and contains detailed information on expenditure as well as revenues of local governments for each year.[9] Our measure of expenditure (revenues) is the sum of current and capital expenditures (revenues) registered in the competence and residual

[7]In 2002 and 2003, further regulation was introduced in order to reduce the time of response and the exposure to seismic risk. In case of extreme events that threaten lives of individuals, the government can assign special powers to a delegate even before claiming the state of emergency (Art. 3 of Law 245/2002). Also, an additional fund, managed directly by the premiership, was established to transfer resources to regional and local governments for both prevention and disaster relief (Art. 32-bis of Decree Law 269/2003).

[8]A small number of municipalities merged over this period. Therefore, to construct a homogeneous panel over the entire period, we aggregate the data of merged municipalities in the years before the merger. We replicate the 2016 municipality structure because some data are available only for that level of aggregation.

[9]Actually, we have data for the period 1990-2015 but differences in the statistics before 1998 and the lack of data on household income in 1998 and 1999 advise not to use those data before 2000.

accounts in each year.[10]

We gathered data on earthquakes from two databases available from INGV that collects information on earthquake occurrence between 1000 and 2014.[11] The first database is the parametric catalog of earthquakes CPTI15 (Rovida, Locati, Camassi, Lolli, & Gasperini, 2016) that includes detailed information on each earthquake (e.g., magnitude, maximum intensity, coordinates of the epicenter). The second database is the macro-seismic database DBMI15 (Locati et al., 2016), which reports local earthquake intensity measures. The selection criteria for the inclusion of an earthquake in the databases are either a maximum intensity equal to or greater than 5 on the Mercalli scale, or a moment magnitude equal to or greater than 4.[12] Although data on earthquakes for 2015 are not available, their impact is likely negligible since INGV stated that fewer earthquakes occurred than in 2014 and only 18 shocks had a magnitude equal to or above 4, no one bigger than 5.

The third data set includes socioeconomic, sociodemographic, and environmental characteristics of Italian municipalities between 2000 and 2015. In particular, the data set contains data on income levels, sourced from the Department of Finance of the Ministry of Economics and Finance, data on population size, age structure and environmental characteristics sourced from the Italian Institute for Statistics (ISTAT), and political characteristics sourced from the Italian Ministry of Interior. Moreover, we use data on minimum and maximum housing prices (per square meter) provided by the Real Estate Market Observatory of the Italian Revenue Agency. These data are collected twice a year and are complete since the second semester of 2003. All monetary values are deflated using the consumer price index to obtain real values at 2010 prices.[13]

The total number of observations (municipality×year) is 127,952. Balance sheet data and political variables are not complete for 8,136 observations. Therefore, our

[10]The competence account registers expenditures and revenues related to cash flows, while the residual account registers transactions for which the cash flow has not occurred yet.

[11]`https://emidius.mi.ingv.it/CPTI15-DBMI15/`.

[12]The intensity is measured on the Mercalli scale and quantifies the observed effects of an earthquake on a scale from 1 to 12. The moment magnitude is a logarithmic scale that measures the energy released by an earthquake. A unit increase in the scale corresponds to $10^{1.5}$ times higher released energy. While the magnitude is measurable with instruments, the intensity is an evaluation performed by experts based on the observable effects on humans, infrastructures and objects.

[13]For the years 2000 and 2001 currency values expressed in Italian Lira were converted to Euro using the fixed exchange rate of 1,936.27.

final data set is an unbalanced panel composed of 119,816 observations.

1.3.2 Measurement of earthquake occurrence

Two measures of earthquake occurrence can be used to identify municipalities affected by earthquakes (treated municipalities): the *magnitude* and the *intensity*. The *magnitude* is an objective measure of the strength of an earthquake and its ability to serve as a proxy for damages to human and physical capital may be questioned. Since the *magnitude* is a space-invariant measure, some assumptions on the propagation of the effect in terms of distance and direction are required to assign earthquake events to municipalities. Generally, the propagation of earthquake waves depends on the depth of the epicenter and on the characteristics of the soil. Instead, *intensity* is the result of the evaluation of the observable impact performed by experts, who usually inspect disaster areas immediately after the shock. One cannot exclude that this evaluation is to some extent affected by subjective judgment driven by emotional involvement (e.g., attachment to the disaster area or to people who live there) or even corruption (e.g., the overestimation of the impact of an earthquake could allow to attract more financial resources from upper-level government). However, *intensity* is assessed for each municipality affected by an earthquake and allows easily to identify towns affected by damages due to the shock. In our analysis, we prefer the *intensity*-based measure of earthquake occurrence because this is a qualitative measure of the local impact of an earthquake and varies among municipalities. The use of fixed effects in our econometric models should address any claim of systematic bias in the measurement of earthquake occurrence due to subjective judgment correlated with the geographical/institutional setting. More than that, we perform robustness checks of our results based on the described *magnitude*-based measure of earthquake occurrence under different assumptions of propagation. We provide a more detailed description of this approach later on in Section 1.5.1.

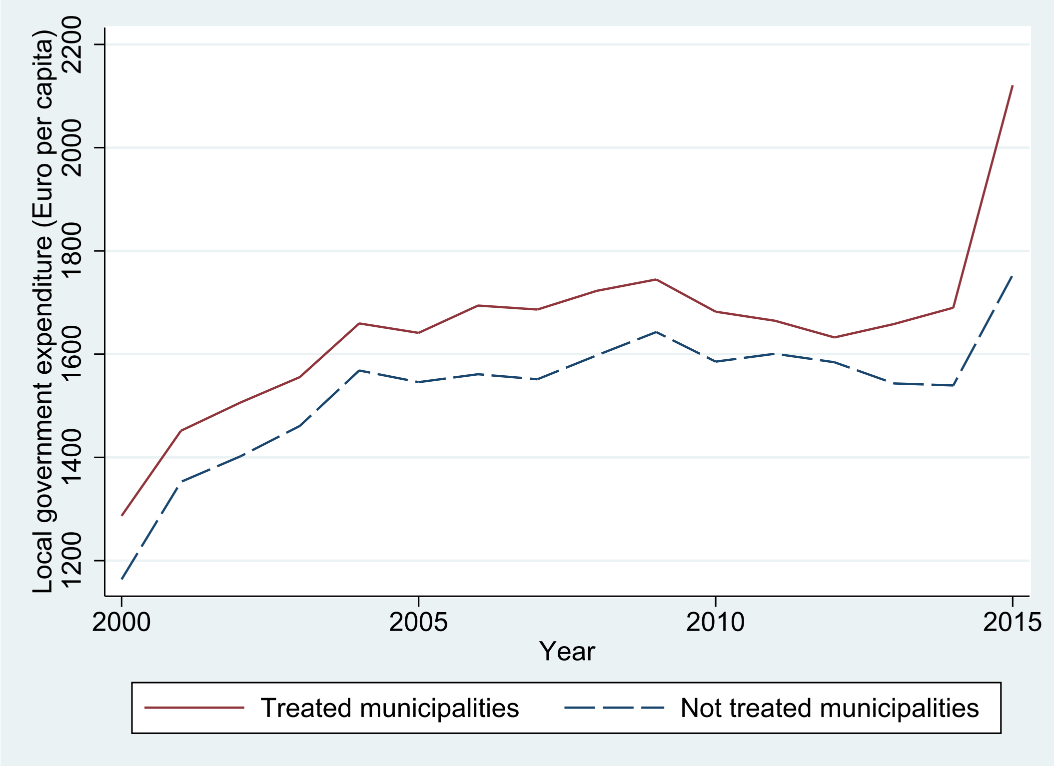
We assign treatment if a municipality is struck by at least one earthquake with *intensity* $\geqslant$5 in a given year. We choose this threshold because 5 is the lowest *intensity* level at which damages usually occur, and because it is the minimum *intensity* level for which we have complete data. Then, we define a set of treatment dummies $EQ_{i,t-j} = 1$, where i denotes the municipality and t the year, if the local maximum intensity of earthquakes occurred in the year $t-j$ (with $j \geqslant 0$) is $\geqslant 5$. This set of variables allows to capture the impact of an earthquake at different points in time before the current year t. Our treatment variables show that 2658 municipalities are struck by an earthquake at least once over the period 1985-2015, and 1129 out of these municipalities are affected at least once over the period 2000-2015.

1.3.3 Descriptive evidence

As preliminary suggestive evidence we compare the per capita local government expenditure of municipalities struck by at least one earthquake over the period 1985-2015 with the expenditure of municipalities that did not face any earthquake during the same period. Figure 1.2 shows that, on average, municipalities affected by earthquakes spend more than other municipalities, with a mean difference for the period 2000-2015 of 106 Euro per individual at 2010 prices. In 2015, local governments increased expenditure by 10 percent on average because the central government loosed the constraints on capital expenditures, which were limited as a consequence of the economic crises in order to attempt to reduce public debt. Clearly, we cannot exclude that this difference is due to factors other than earthquake occurrence, such as institutional differences or historical spending behavior. Indeed, local government expenditure varies both across and within Italian regions, which may be due to factors such as geographical and institutional characteristics and economic development (see Figure A.1 in the Appendix).

To identify the impact of earthquakes on local government expenditure, it would be desirable to observe the same municipality under the two scenarios of treatment (earthquake occurrence) and no treatment. Clearly, this is not possible but may not represent a problem if earthquakes are randomly assigned to municipalities. The assumption of random assignment is challenged by earthquake occurrence over time since some areas are more exposed than others. However, a matching procedure that enhances the comparability of municipalities may grant sufficient strength to the analysis. Therefore, we sharpen the evidence of Figure 1.2 and reduce the unobserved variability, by comparing municipalities that are similar in the period before the occurrence of

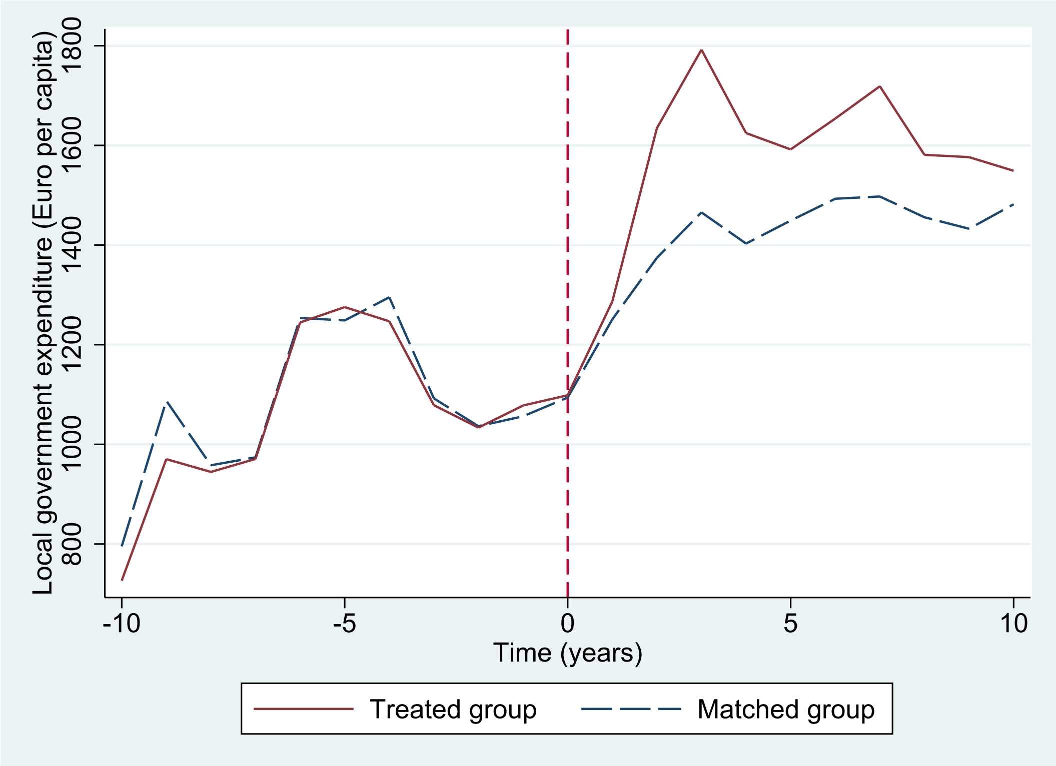
Figure 1.2: Per capita local government expenditure over time (2000-2015)



Notes - The graph compares the average per capita local government expenditure for the period 2000-2015 of 2658 municipalities struck by at least one earthquake with intensity ⩾5 over the period 1985-2015 (red solid line) with 5339 municipalities not struck by an earthquake over the same period (blue dashed line). Expenditure is discounted at 2010 prices.
Source: Our elaboration on balance sheet data of Italian local governments for the period 2000-2015 provided by the Italian Ministry of Interior and data from the DBMI15 database of INGV (Locati et al., 2016).

an earthquake. To do this we construct a counterfactual group of municipalities that allow us to analyze post-treatment variations of spending levels and to claim a causal relationship with earthquakes. Figure 1.3 illustrates the average spending trend of 347 treated municipalities, before and after the occurrence of a shock, with 347 matched municipalities. We identify matched municipalities with coarsened exact matching on average financial, sociodemographic and socioeconomic pre-treatment characteristics, the propensity to face an earthquake and historical earthquake experience (see the Appendix Section A.1 for further information on the matching procedure and Table A.1 for the balancing properties). Note that, before treatment occurs, average per capita local government expenditure is almost identical in the two groups. Starting from the first year after the treatment period (period zero), expenditure sharply diverges. Treated municipalities seem to spend much more than the counterfactual group. Spending trends start to converge again from the seventh year after the disaster, though not completely.

Figure 1.3: Expenditure variation after the occurrence of an earthquake



Notes - The graph compares the average per capita local government expenditure before and after the occurrence of an earthquake, which occurs at time zero, with expenditure of matched municipalities (without an earthquake) in the same year. Treatment is assigned if an earthquake with intensity $\geqslant 5$ occurred over the period 2000-2015. The red solid line represents 347 treated municipalities, while the blue dashed line represents 347 matched municipalities identified with coarsened exact matching performed on average pre-treatment characteristics of municipalities (institutional, sociodemographic, and environmental). Both groups include only municipalities with complete expenditure data for the period 2000-2015. Positive (negative) values on the x-axis indicate years after (before) the treatment. Expenditure is discounted at 2010 prices.
Source: Our elaboration on balance sheet data of Italian local governments for the period 2000-2015 provided by the Italian Ministry of Interior and data from the DBMI15 database of INGV (Locati et al., 2016).

Table 1.1 provides some descriptive statistics on the characteristics of 1129 municipalities struck by an earthquake over the period 2000-2015 and 5339 unaffected municipalities. We observe that in the year before the occurrence of an earthquake, municipalities do not significantly differ in terms of per capita expenditure and revenues, while the revenue composition tends to differ in treated municipalities. Treated municipalities collect less local taxes than the control group, which could be due to the lower household income and the higher share of low-income population.[14] The

[14]We define the share of low-income population as the share of individuals earning a yearly income less than or equal to 10,000 Euro. Note that our income data is structured in eight income classes and for each class we have information on the total amount of income and the number of individuals. According to our definition, the low-income individuals are those of the two lowest income classes representing about 39 percent of the total number of individuals.

lower amount of local tax revenues is partially offset by increased transfers of financial resources from the central and regional governments. The aggregate revenues from local taxation and transfers account for about 60 percent of total revenues.

After an earthquake, both local government expenditure and revenues significantly increase by 198 and 185 Euro per capita, respectively. The immediate increase of revenues allows to limit losses. Additional revenues are composed for more than 60 percent of transfers from the central and regional governments. Revenues from local taxation, instead, do not vary significantly on average. As for the population size and age structure, treated municipalities are almost twice as populated as other municipalities and, before the shock, they have a slightly higher fraction of the youngest and oldest age cohorts. Population size does not significantly vary after the shock, but the age structure changes since the percentage of young people tend to shrink, while the elderly share increases. This could suggest that elderly people are less mobile because of physical limitations, or stronger emotional attachment to their town.

This preliminary evidence suggests that the comparison of expenditure levels between municipalities affected and not affected by earthquakes should carefully address differences in terms of characteristics that could confound expenditure variations. The following empirical strategy controls for those observable characteristics as well as other unobservable time-invariant characteristics.

1.4 Empirical strategy

1.4.1 Earthquakes and spending levels

To assess the impact of earthquakes on local government expenditure, we employ a flexible estimation strategy most closely aligned with the literature on event-study estimation (e.g. Gallagher, 2014) and regress per capita expenditure against earthquake measures and control for characteristics of municipalities and local institutions that may affect spending levels as well as for time-invariant heterogeneity.[15] We specify the

[15]The literature has suggested several features of local governments that are likely to affect the expenditure. See for instance Gennari and Messina (2014) and Lundqvist (2015).

Table 1.1: Descriptive statistics: Municipality characteristics

	(1)	(2)	(3)
	Control group	*Treated group*	
		Before	After
Expenditure p/c	1509.7	1332.1**	1664.1***
	(1647.6)	(861.9)	(1517.1)
Revenues p/c	1624.7	1674.4	1833.3**
	(1686.7)	(1041.0)	(1583.5)
Transfers p/c	550.9	623.5*	706.2*
	(881.1)	(706.5)	(903.3)
Tax revenues p/c	420.4	340.9***	344.1
	(305.3)	(196.7)	(184.9)
Average income	16504.4	14966.0***	15296.9
	(3799.4)	(3728.9)	(3609.5)
% low-income population	38.79	47.68***	45.44***
	(13.26)	(14.51)	(13.65)
Population	6260.8	11714.2***	10479.5
	(26275.1)	(88876.1)	(79286.5)
% young (0-14 years)	13.19	13.40*	12.94***
	(2.865)	(3.169)	(3.007)
% old ($\geqslant$65 years)	21.99	22.65**	23.41**
	(6.150)	(6.755)	(6.412)
Partial mountain jurisdiction	10.11%	9.83%	
Mountain jurisdiction	53.59%	54.03%	
Coastal jurisdiction	10.68%	6.55%	
Observations	84521	920	1165
Municipalities	5339	1129	

Notes - The table presents mean characteristics of municipalities struck by earthquakes (treated group) with intensity $\geqslant$5 over the period 1985-2015 and mean characteristics of unaffected municipalities (control group). Column 1 presents means for the period 2000-2015, Columns 2 and 3 present means for the year before and the year after an earthquake occurs, respectively. If a municipality is affected by multiple earthquakes within three consecutive years, we aggregate the events and define the before-period as the year before the first shock and the after-period as the year after the last shock. This excludes the overlapping of observations on expenditure for the year after the first event and the year before the following event for the same municipality. Stars in column 2 indicate significance levels of t-tests on mean differences between column 1 and 2. Stars in column 3 indicate significance levels of t-tests on mean differences between column 2 and 3. For the last three variables, we show sample frequencies because they are time-invariant. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard deviations are in parentheses. Monetary values are discounted at 2010 prices.

following model:

$$y_{it} = \mathbf{T}'_{it}\boldsymbol{\alpha} + \mathbf{x}'_{it}\boldsymbol{\beta} + \theta_t + \gamma_i + \varepsilon_{it} \tag{1.1}$$

where y_{it} is the natural logarithm of per capita expenditure of municipality i in year t. $\mathbf{T}'_{it}$ is a vector of treatment variables, i.e., earthquake indicators, and $\mathbf{x}'_{it}$ is a vector of time-varying controls, including the intercept term. Controls ($\mathbf{x}'_{it}$) include income, population age structure, geographic and political characteristics, and funding sources from the central and regional governments. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are the vectors of parameters to be estimated. θ_t are time fixed effects, γ_i is a municipality-specific time-invariant element, and ε_{it} is the idiosyncratic error term.

In our baseline specification $\mathbf{T}'_{it}\boldsymbol{\alpha}$ is defined as:

$$\mathbf{T}'_{it}\boldsymbol{\alpha} = \sum_{j=0}^{1} \alpha_j EQ_{i,t-j} + EQ_{i,t-d} \times (\alpha_{d1} Dist_{it} + \alpha_{d2} Dist^2_{it} + \alpha_{d3} Dist^3_{it}) \tag{1.2}$$

where $EQ_{i,t-j}$ and $EQ_{i,t-d}$ are the dummy treatment variables described in Section 1.3.2. More precisely, the two terms in the summation, EQ_{it} and $EQ_{i,t-1}$, capture the effect of an earthquake occurred in the current year and one year before, respectively. The shocks occurred earlier (more than one year before) are captured by $EQ_{i,t-d}$, where d is the temporal distance from the most recent earthquake before $t-1$ ($1 < d \leqslant 15$). We define $Dist_{it} = d$ if $EQ_{i,t-d}$ is equal to one, and zero otherwise. Therefore, the distance polynomial of third degree (within brackets) is a non-linear time-trend capturing medium-run marginal effects of earthquakes on expenditure. We consider a non-linear time-trend to capture a possible inverse U-shaped effect and a tail of earthquakes on expenditure.[16] Indeed, our descriptive statistics suggest that expenditure initially grows and then tends to converge to pre-treatment levels. We impose $Dist_{it} \leqslant 15$ since beyond this period we generally observe a convergence of expenditure to pre-treatment levels, as suggested by the descriptive statistics in Section 1.3.3.[17]

[16] We use a third-order polynomial time-trend because, according to preliminary findings, it is the most suitable specification to capture the effect of an earthquake on local government expenditure. Indeed, in what follows we use also a model specification including yearly lags of earthquake occurrence measures (see Section 1.5.2).

[17] Preliminary findings suggest that spending levels tend to converge to pre-disaster levels between the 10^{th} and the 15^{th} year after an earthquake. Moreover, the impact of an earthquake is fully observed for a maximum of 15 periods in our panel.

The covariates that compose the vector $\mathbf{x}'_{it}$ are a set of time-varying financial, political, socioeconomic, and sociodemographic variables, and a set of time-invariant environmental characteristics. Financial variables include the natural logarithm of per capita transfers from the central and regional governments, and the natural logarithm of per capita revenues from local taxation. Political variables include the vote-share concentration of the local government Council, the number of years before municipal elections, a dummy variable equal to one if the incumbent government is center-right oriented, and a dummy variable equal to one if the incumbent mayor reached his term limit. Socioeconomic variables include the natural logarithm of average yearly per capita income and the share of low-income population, and sociodemographic variables include the share of the youngest (0-14 years) and oldest ($\geqslant$65 years) age cohorts. Environmental characteristics are captured by dummy variables equal to one indicating whether a municipality is a partially mountainous jurisdiction, a mountainous jurisdiction, or a coastal jurisdiction.

To estimate the parameters of our model we use three methods: pooled OLS, random effects, and fixed effects regressions. Pooled OLS provides consistent parameters but treats observations as mutually independent and does not account for serial dependence of observations. Hence, the main limitation of the pooled OLS model is that possible unobserved heterogeneity among municipalities is neglected ($\gamma_i = 0$). However, both OLS and random effects regressions include a region-specific time-invariant effect.[18] The random effects model treats unobserved heterogeneity of municipalities as a random shock and requires the assumption that γ_i is *iid*. The fixed effects model relaxes this assumption by allowing γ_i to be correlated with the other exogenous variables, but it does not allow to include environmental time-invariant characteristics and region fixed effects.[19] The random effects model is more efficient, but if the assumption on the independence of the time-invariant error is violated, the estimates are biased. In that case, the fixed effects model should be preferred because it estimates

[18]Note that region-specific time-invariant effects account for heterogeneity between ordinary and autonomous regions with special statute (i.e. the regions Valle D'Aosta, Friuli Venezia Giulia, Sicily and Sardinia, and the provinces of Bolzano and Trento), such as differences in the funding mechanism of public expenditure. Moreover, conditional on region-specific time-invariant effects, our regression results are not sensitive to the inclusion/exclusion of autonomous regions with special statute.

[19]Two municipalities of the region Marche became part of Emilia-Romagna in 2010. However, this change is not significant.

consistent parameters. Since several unobserved factors could lead to differences in spending levels (e.g., geographic characteristic, touristic attractiveness, economic development), we expect the fixed effects model to be more appropriate. We formally test this assumption using the Hausman test.

In addition, we specify a first-order autoregressive model and include the lag of the dependent variable as a regressor in Equation (1.1). This specification allows to capture the persistence of local government expenditure that may be driven by historic and institutional factors. We estimate this model with municipality fixed effects. Since serial correlation and heteroskedasticity may affect the estimation of the standard errors, we use robust standard errors clustered by municipality in all specifications.

An issue that needs to be discussed is the possible endogeneity of upper-level government transfers. In Equation (1.1), we assume that transfers are exogenous, and hence transfers lead to a variation of local government expenditure because more resources are available, as literature in this field suggests (e.g. Gennari & Messina, 2014; Revelli, 2006). However, variations of transfers from upper-level governments may not be completely exogenous to expenditure variations if they are influenced by higher spending requirements (Lundqvist, 2015) or by the ability of politicians to attract financial resources from upper-level governments (Galletta, 2017). In this case, OLS and GLS estimates could be biased because the assumption on the independence of the error term ($\mathrm{E}[\varepsilon_{it}|\mathbf{X}] = 0$) is violated. The within-estimator of the fixed effects model partially accommodates this problem since it accounts for time-invariant factors that lead to the endogeneity of transfers. We further address this issue by a two-stage instrumental variable (IV) approach discussed in Section 1.5.1.

Furthermore, we need to address two other possible sources of bias. First, if other regressors, such as income, are possibly influenced by a disaster, then the estimated coefficients of earthquake occurrence may be biased. To test the extent to which this issue may affect our results, we estimate Equation (1.1) with and without controls ($\mathbf{x}'_{it}$). Second, due to the way in which earthquakes propagate, spatial correlation may bias our estimates if neighboring local governments affected by a disaster adjust their spending levels, which may generate some spillover effects. To consider the spatial correlation of earthquakes and account for possible collinearity between the intensity of earthquakes in neighboring municipalities, we include two spatial-lag measures of earthquake events in our regressions. These variables, $EQ_{-i,t}$ and $EQ_{-i,t-1}$, are based on the spatial matrix of bordering municipalities and are equal to one if an earthquake occurred in some neighboring municipality, respectively in the current and the previous period.[20]

We test the robustness of our identification strategy by defining other criteria for the assignment of treatment. We use different earthquake-intensity thresholds and magnitude-based measures to define treated municipalities. Note, however, that raising the intensity threshold implies a reduction in the number of treated municipalities. Over the period 2000-2015, municipalities struck by an earthquake with intensity $\geqslant$6 are 213, and only 46 with intensity $\geqslant$7. Such a low number of treated municipalities could have some drawbacks in the econometric estimation. If we raise the intensity cut-off and sharpen our sample of affected municipalities we expect to observe a larger impact of earthquakes on expenditure. To further confirm our evidence, we repeat the analysis using the sharper sample of matched municipalities defined in Section 1.3.3, which is likely less exposed to unobserved heterogeneity but also more prone to dim the effect due to proximity between treated and matched municipalities. Finally, we test the sensitivity of our results by excluding/including municipalities struck by a disaster according to the timing and frequency of earthquake occurrences (see Section 1.5.1 for details).

1.4.2 Asymmetric and heterogeneous responses to grants

Descriptive evidence in Section 1.3.3 suggests that central and regional governments largely contribute to local disaster relief through the transfer of financial resources to municipalities. To better understand how earthquakes, local government expenditure and transfers are related to each other, we run a preliminary analysis using two models, where the dependent variable is either local government expenditure (as in the previous

[20] Boustan, Kahn, Rhode, and Yanguas (2017) use a different approach to account for spatial correlation. They use a single disaster index for both affected and neighboring unaffected US counties that combines information on disasters occurred in a US county with distance-weighted information on shocks occurred in neighboring counties. Since we are interested in estimating the impact of a local earthquake over time, this strategy would complicate the interpretation of our results.

Equation (1.1)) or transfers. To see the impact of earthquakes in different years, we use a linear vector of all earthquake occurrence dummies in the last 12 years, $\mathbf{T}'\boldsymbol{\alpha} = \sum_{j=0}^{11} \alpha_j EQ_{t-j}$, instead of the polynomial specification of Equation (1.2). Therefore, we estimate the yearly ATT of an earthquake on both expenditure and transfers. We limit the analysis to the 11$^{\text{th}}$ year after the disaster since previous results suggest that after that period the effect of one single earthquake is negligible.[21]

One interesting aspect on the effect of grants is the comparison between earthquake-related grants (mostly matching grants) and other types of grants (mostly unconditional grants). The literature on flypaper effects generally suggests that matching grants have greater influence on expenditure than unconditional grants, since the former combine an income and a substitution effect (Gramlich, 1977).[22] To provide empirical evidence on the flypaper effect in Italy, Gennari and Messina (2014) focus on unconditional grants and, therefore, try to exclude outlier observations due to shocks to avoid any confounding factor related to matching grants. We can contrast this approach by exploiting the large and unique dataset of earthquake occurrences to separate (earthquake-specific) matching grants from unconditional grants. This allows us to disentangle heterogeneous flypaper effects and asymmetric responses to different types of grants. Since data on earthquake-specific grants are limited and incomplete, we use the control group of not treated municipalities identified by the matching procedure above to predict the average growth rate of (unconditional) transfers if earthquakes would not have occurred.[23,24]

We can now use predicted grants of different types to expand the linear flypaper effect model (Gennari & Messina, 2014) as follows:

$$Y_{it} = \alpha_1 MG_{it} + \alpha_2 MA_{it} + \alpha_3 UG_{it} + \alpha_4 UA_{it} + \mathbf{X}'_{it}\boldsymbol{\beta} + \theta_t + \gamma_i + \varepsilon_{it} \tag{1.3}$$

[21]We also perform the analysis with $j = 15$, but coefficients for $j > 11$ are not significant.

[22]This is because public goods relative prices tend to fall, which shifts resources away from private goods.

[23]Balance sheet data does not allow to identify transfers received for disaster relief. The Department of the Civil Protection provides reports on the allocation of earthquake relief funds, but these documents cover only the period 2012-2015 and detailed information on the resources received by each local government is not always available.

[24]Barone and Mocetti (2014) compare the effects of two large earthquakes in Italy by means of a synthetic control approach based on regional data.

where Y_{it} is the level of per capita expenditure of municipality i in year t, MG_{it} is the level of (earthquake-specific) matching grants and UG_{it} is the level of unconditional grants. $\mathbf{X}'_{it}$ is the vector of control variables as in Section 1.4. θ_t and γ_i are time and municipality fixed effects, and ε_{it} is an *iid* error term.

The variables MA_{it} and UA_{it} measure the decrease of matching and unconditional grants relative to the previous year $(t-1)$, respectively, and are specified as $MA_{it} = MD_{it}(MG_{it} - MG_{i,t-1})$ and $UA_{it} = UD_{it}(UG_{it} - UG_{i,t-1})$,with MD_{it} and UD_{it} being dummy variables equal to one if the respective grants are decreasing, and zero otherwise. Therefore, MA_{it} and UA_{it} capture the asymmetric response of expenditure to variations in the two types of grants. In accordance with Gennari and Messina (2014), not significant estimates of the parameters α_2 and α_4 imply that local governments react similarly to increases and decreases in transfers. Conversely, significant estimates of α_2 and α_4 imply that $\alpha_1 + \alpha_2$ measures the expenditure response to decreasing matching grants, and $\alpha_3 + \alpha_4$ is the response to decreasing unconditional grants. Negative and significant parameters α_2 and α_4 suggest that local government expenditure is more sensitive to increases than to decreases in transfers, while positive and significant estimates suggest the opposite. In the literature on flypaper effect, the former type of response is known as the "fiscal replacement" effect (Gramlich, 1987), while the latter type of response is the so-called "fiscal restraint" effect (Gamkhar & Oates, 1996).

The final part of our empirical strategy hypothesizes that the response of local governments to earthquake shocks differs across the country, between Northern and Southern municipalities. To this aim, we modify the above Equation (1.3) to include the interaction terms between grants (both unconditional and earthquake-specific grants) and a dummy variable equal to one if a municipality is located in Southern regions, namely Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria and Sicily.[25] The two asymmetry variables are now dropped.[26] For simplicity, we will use *North* and *Northern* to refer to all other regions. A further distinction between North and Center

[25]This classification is provided by ISTAT, except for Sicily which is classified as *Island* together with Sardinia. However, Sicily is commonly identified as a Southern region because of its geographical location and cultural and environmental aspects.

[26]Note that the two asymmetry variables are not significantly different between municipalities in the North and in the South (results not reported here).

has been considered but did not provide significant differences.

1.5 Results

1.5.1 The impact on spending levels

The effect of earthquake shocks on local government spending from the estimation of Equation (1.1) using pooled OLS, random effects, fixed effects, and autoregressive fixed-effects regressions is summarized in Table 1.2.[27] Since the dependent variable, i.e., the per capita local government expenditure, is log-transformed, percentage changes in expenditure after the occurrence of an earthquake are obtained by $100 \times (e^{\hat{\alpha}_j} - 1)$. The coefficients of earthquake occurrence in the current and the previous year (EQ_t and EQ_{t-1}) can be interpreted as average treatment effects on treated municipalities (ATT). The coefficients of all treatment variables are highly significant, slightly less for the immediate effect EQ_t. The OLS results are basically in line with panel data models although repeated observations over time and possible correlation between the treatment variables and unobserved characteristics of municipalities are not taken into account. Only the coefficient of the immediate effect, EQ_t, is likely overestimated.

The estimates from the random and fixed effects models are very similar. However, we can easily reject the null hypothesis of the Hausman test.[28] Thus, the fixed effects model is preferred. The fixed effects specification controls for time-invariant municipality-specific characteristics such as geographical seismic zones.[29] All the coefficients are slightly lower in the autoregressive specification (column 4), which suggests that earthquake measures partially capture the effect of persistent spending.

In the fixed effects specifications, the immediate impact of an earthquake on local government expenditure is between 1.92 percent and 1.95 percent, which roughly corresponds to 27-28 Euro per capita. After one year, the effect of the shock is three

[27] Note that the lag of the dependent variable in the autoregressive model is grouped with the financial time-variant controls.

[28] The Hausman test returns the statistic $\chi^2(29) = 10,861.41$, and the critical value in a 99.9 percent confidence interval is $\chi^2_{0.001}(29) = 58.30$.

[29] Note, however, that the inclusion of seismic zones into OLS and random effects models does not affect the results.

Table 1.2: Impact of earthquakes on local government expenditure

	(1) OLS	(2) RE	(3) FE	(4) FE (AR1)	(5) IV_FE
EQ_t	0.0278**	0.0179*	0.0193*	0.0190**	0.0139
	(0.0107)	(0.00828)	(0.00860)	(0.00736)	(0.00935)
EQ_{t-1}	0.0650***	0.0632***	0.0660***	0.0602***	0.0553***
	(0.0110)	(0.00945)	(0.00976)	(0.00808)	(0.00949)
EQ_{t-d} × Dist	0.0241***	0.0285***	0.0305***	0.0166***	0.0186***
	(0.00402)	(0.00375)	(0.00398)	(0.00254)	(0.00387)
EQ_{t-d} × Dist^2	-0.00283***	-0.00409***	-0.00456***	-0.00261***	-0.00253***
	(0.000636)	(0.000593)	(0.000617)	(0.000405)	(0.000610)
EQ_{t-d} × Dist^3	0.0000797**	0.000142***	0.000163***	0.0000966***	0.0000782**
	(0.0000264)	(0.0000245)	(0.0000252)	(0.0000170)	(0.0000253)
Observations	119816	119816	119816	119102	112153
Overall R-squared	0.685	0.648	0.383	0.760	0.433
Within R-squared		0.594	0.599	0.663	0.445
Between R-squared		0.687	0.279	0.825	0.422
Region fixed effects	Yes	Yes	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Financial time-variant controls	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes
Environmental controls	Yes	Yes	No	No	No
Hausman test					666.9***
Endogeneity test					40.61***

Notes - The table presents regression results for the log of per capita local government expenditure. Model 1 is a pooled OLS regression, model 2 a random effects regression, models 3 and 4 are fixed effects regressions, and model 5 is a two-stage fixed effects regression where log transfers are instrumented with the second lag of log average transfers received by neighboring municipalities. EQ_t and EQ_{t-1} are dummy variables equal to one if there has been an earthquake in the current year and in the previous year, respectively, and zero otherwise. EQ_{t-d} is a dummy variable equal to one measuring the occurrence of the latest earthquake within the last 15 years, and zero otherwise. $1 < d \leqslant 15$ measures the temporal distance from the latest earthquake. All models control for financial time-variant (logs of per capita transfers from the central and regional governments and revenues from local taxation), political (center-right government, vote concentration, term limit, years before elections), socioeconomic (average income and percent of low-income population) and sociodemographic factors (population density, percent of young and percent of old population), and year fixed effects. Models 1 and 2 further control for environmental characteristics (mountain, partial mountain and coastal jurisdiction) and region fixed effects, which are time-invariant, and model 4 for the lag of the dependent variable. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices.

times larger with a shift of local government expenditure between 6.20 percent and 6.82 percent (100-112 Euro per capita). This is an expected result for a developed country according to Noy and Nualsri (2011). Since local governments may not respond immediately to the shock and the budget needs some time to be adjusted, we observe that the impact is higher one year after the event. The local government may rather decide to respond immediately by changing the spending composition and reallocate the resources destined to services that cannot be offered anymore due to unavailable infrastructures or loss of human capital. Other spending categories (e.g. local services, social protection) may now require more resources to tackle the consequences of the seismic event. After one year the expenditure tends to increase because of investments in disaster relief, e.g. cleaning, reconstruction and reimbursement of damages to citizens. Moreover, the delay in the increase of expenditure may be due to the timing of external aid from upper-level governments and from charity.

Differences in spending levels between treated and unaffected municipalities are not limited to the short-run. The first-, second- and third-order interaction terms between earthquake occurrence and time passed since the latest shock suggest that the effect on spending levels tends to increase in the years after the event, but then expenditure slowly converges to pre-disaster levels (negative coefficient of second-order interaction and positive coefficient of the third-order interaction). The estimates show that expenditure continues to grow until four-five years after the disaster and then regresses to pre-disaster levels after 11-12 years.[30]

To correct the estimates for possible endogeneity of transfers from central and regional governments, we use an IV approach and estimate the model in column 3 using 2SLS and the second lag of transfers received by neighboring jurisdictions as an exogenous instrument.[31] The estimates for the parameters are reported in column 5. Diagnostic tests confirm that transfers are endogenous and that the IV specification provides consistent estimates compared to the fixed effects specification. The coefficients of all earthquake-occurrence variables are lower in absolute values and EQ_t loses significance. This is most likely determined by the fact that transfers from central and regional governments increase when an earthquake occurs and, given that the first-stage regression of the IV approach accounts also for earthquake variables, exogenous transfers in the second-stage regression capture part of the effect of an earthquake on expenditure. Nevertheless, the coefficients still show that the effect of an earthquake on expenditure lasts for 11-12 years.

To account for the potential bias induced by the inclusion of time-varying controls possibly affected by earthquake shocks, such as income, we re-estimated Equation (1.1) excluding the full set of covariates (see columns 1 and 2 of Table A.2 in the Appendix). The estimated coefficients differ only slightly, and are very similar to

[30] We compute the growing period by looking at the maximum of the estimated function defined by the two interaction terms ($d = (-2\hat{\alpha}_{d2} - \sqrt{4\hat{\alpha}_{d2}^2 - 12\hat{\alpha}_{d1}\hat{\alpha}_{d3}})/6\hat{\alpha}_{d3}$, with $\hat{\alpha}_{d1}$, $\hat{\alpha}_{d2}$ and $\hat{\alpha}_{d3}$ being the estimates of the parameters α_{d1}, α_{d2} and α_{d3} in Equation (1.2), respectively) and calculate the convergence period by computing the zeros of the same function ($d = (-\hat{\alpha}_{d2} - \sqrt{\hat{\alpha}_{d2}^2 - 4\hat{\alpha}_{d1}\hat{\alpha}_{d3}})/2\hat{\alpha}_{d3}$).

[31] Differences are negligible indeed if we repeat the estimation using the first or the second temporal lag of transfers instead of the spatial-temporal lag.

the baseline results both in terms of magnitude and levels of significance. The only exception is the coefficient of the immediate impact of an earthquake (EQ_t) that is smaller and not significant, though still positive.[32]

Finally, the size of the estimated coefficients of EQ_t and EQ_{t-1} decreases only slightly when spillover effects are included in columns 3 and 4 of Table A.2. The immediate impact of natural disasters occurred in neighboring municipalities is not significant, but we observe a significant impact after one year. The latter spillover effect is about 28 percent of the effect of earthquakes occurred within the municipality borders.

Robustness checks and sensitivity analysis

The robustness of our main results is ensured by two alternative approaches to identify the effect of earthquakes on local government expenditure. The first approach is based on the matching sample described in Section 1.3.3 (see also the Appendix Section A.1 for information on the matching procedure), while the second approach tests the sensitivity of our estimates on the full sample to the inclusion/exclusion of municipalities according to the timing and frequency of earthquake occurrences. Finally, we consider several different criteria for the assignment of treatment.

When we run regressions using the sample of matched municipalities (see Table A.3 in the Appendix) we obtain similar results, but the coefficients of the treatment variables and standard errors are slightly larger. This is because the matching sample includes less heterogeneous municipalities and we exploit a limited number of struck units (347 of 1129 municipalities struck between 2000 and 2015).

Then, we exclude from the full sample municipalities that are struck more than once by a disaster between 2000 and 2015 (see Table A.4, columns 1 and 2, in the Appendix), or municipalities that are struck in the 12 years before 2000 (columns 3 and 4), or municipalities struck by a disaster after 2009 (columns 5 and 6).[33] Again, the

[32]Two-tailed hypothesis tests for coefficients differences between models with and without the full set of covariates do not show any statistically significant difference in the autoregressive fixed effects specification. Conversely, statistically relevant differences are only observed for the coefficients of the first-, second- and third-order interaction terms between earthquake occurrence and time in the fixed effects model.

[33]The latter exclusion allows at least six years of lag for each municipality struck by a disaster, which corresponds to half of the estimated impact-period of an earthquake on expenditure. Using

results are in line with our baseline findings. However, as expected, when we exclude municipalities struck by a disaster in the 12 years before 2000, the estimated coefficients and standard errors are generally larger because the sample of struck municipalities is composed of only 819 units. Moreover, our estimates may now suffer from a selection bias if the excluded municipalities are those more frequently struck by earthquakes and, therefore, more resilient. The estimates of the remaining sensitivity analysis are very close to our baseline results.

We run a third robustness check using higher minimum intensity levels (6 and 7 instead of 5) to assign treatment (see Table A.5, columns 1 and 2, in the Appendix). The results are in line with our baseline results, although the effects are much larger due to the focus on stronger earthquakes. Also, spending levels reach pre-treatment levels 15 years after the shock, three years later than previous estimates suggest.

Finally, we define earthquake occurrence measures based on the magnitude of the earthquake. We select earthquakes with moment magnitude $\geqslant 4$ because this is the minimum magnitude for which the INGV includes earthquakes in the database. The magnitude is generally more objective than the intensity, but we need to assume that the energy released by an earthquake propagates homogeneously from the epicenter in all directions since it is measured at the epicenter only.[34] Therefore, we considered municipalities within some distance from the closest epicenter. In particular, we use 10 km, 20 km, and 30 km distance thresholds between the epicenter and the centroid of each municipality. As shown in Table A.5, columns 3-5, in the Appendix, our baseline results are confirmed. The estimates show that the greater the distance from the epicenter, the lower is the impact on local government expenditure (moving from column 3 to column 5). In particular, the model using the 20-km range for the assignment of treatment (column 4) provides similar estimates to those obtained in Table 1.2. This implies that municipalities struck with intensity $\geqslant 5$ are located, on average, within 20 km from an epicenter with magnitude $\geqslant 4$.

a more complete set of lagged effects improves our year-fixed effects specification since we limit the risk that measured lag effects are due to specific economy-wide effects in different time periods.

[34]In 2017, an earthquake struck the isle of Ischia in the Campania region with a relatively low magnitude of 4, but caused relevant damages.

1.5.2 The role of grants

The role played by grants from upper-level governments in raising expenditure following an earthquake is summarized by the results reported in Table 1.3. Column 1 shows fixed effects estimates on the natural logarithm of per capita local government expenditure, and column 2 on the natural logarithm of per capita transfers. The coefficients of treatment variables are significant until the 10^{th} year after the disaster for local government expenditure, similarly to the results obtained in Table 1.2, and until the 9^{th} year for transfers. Moreover, transfers of financial resources grow initially faster than local government expenditure after an earthquake, and absolute per capita variations (in Euro) show that transfers increase more than expenditure between the 2^{st} and the 7^{th} year after an event (see columns 3 and 4 of Table 1.3).[35] This evidence is illustrated in Figure 1.4 with 95 percent confidence intervals. While the increase in per capita expenditure is roughly stable between the 2^{nd} and the 6^{th} year after an earthquake, transfers from central and regional governments follow a different trend. Central and regional governments tend to respond immediately to the higher spending requirements of treated municipalities. Then, from the eight year after the event, additional transfers fall below the increase in expenditure. Overall, the increase in transfers overcomes the increase in expenditure.

Over the overall period (11 years), treated municipalities spend 952 Euro per individual more than not affected municipalities, while per capita transfers are 1201 Euro higher. Hence, transfers of financial resources from central and regional governments seem to exceed expenditure by 247 Euro per individual. If we consider that the average population of a treated municipality between 2000 and 2015 is about 10,000 individuals and 1129 municipalities are struck by an earthquake, the difference between transfers and expenditure amounts to almost 2.8 billion Euro. Generally, policy makers at central and regional levels allocate grants to municipalities affected by earthquakes mainly in the form of matching transfers. Although local governments are supposed to make use of these resources over time, some amount remains on hold and does not

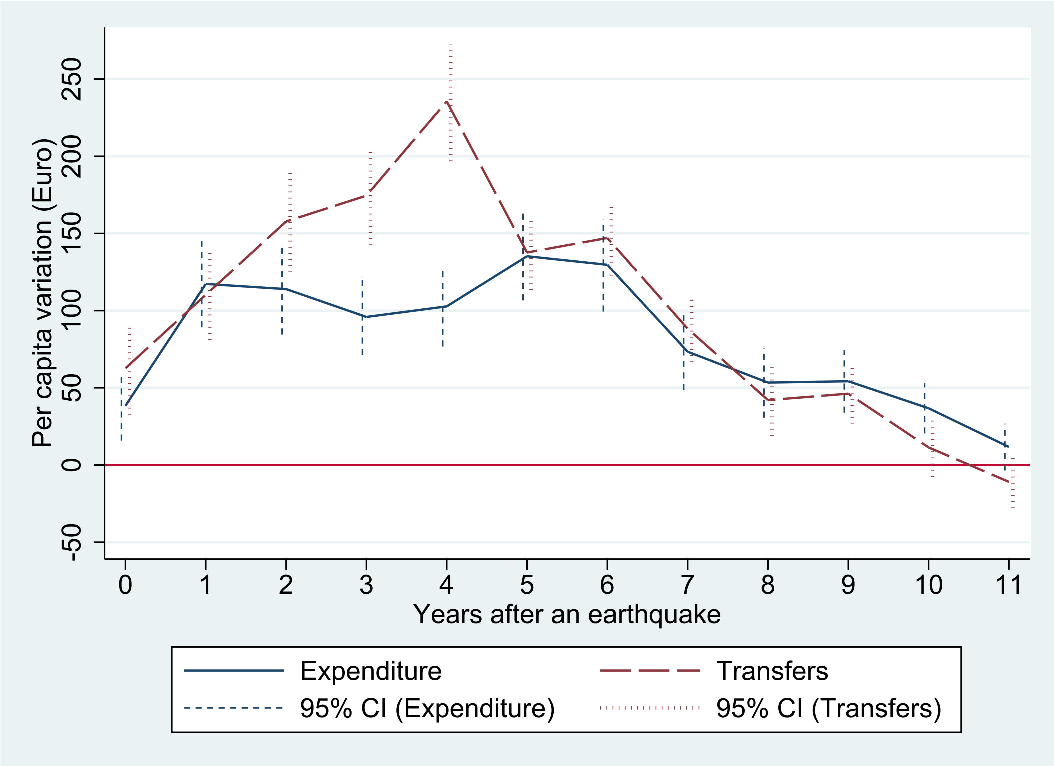
[35] We transform the estimates of the treatment variables in columns 1 and 2 into real per capita variations using $\hat{ATT}_{t-j} = (1 - e^{-\hat{\alpha}_j})\bar{y}_{t-j}$, with y identifying either per capita expenditure or per capita transfers at 2010 prices, $\bar{y}_{t-j} = E[y_{it}|EQ_{i,t-j} = 1]$, and $\hat{\alpha}_j$ being the estimated coefficients of EQ_{t-j}.

Table 1.3: Impact of earthquakes on local government expenditure and transfers by year

	(1)	(2)	(3)	(4)
	Log		*Euro per capita*	
	Exp.	Transf.	Exp.	Transf.
EQ_t	0.0280***	0.0901***	38.82	62.69
	(0.00835)	(0.0225)		
EQ_{t-1}	0.0746***	0.162***	117.2	110.2
	(0.00941)	(0.0232)		
EQ_{t-2}	0.0664***	0.206***	114.0	157.7
	(0.00899)	(0.0238)		
EQ_{t-3}	0.0616***	0.221***	95.80	174.5
	(0.00831)	(0.0227)		
EQ_{t-4}	0.0616***	0.248***	102.6	235.4
	(0.00814)	(0.0231)		
EQ_{t-5}	0.0771***	0.196***	135.5	137.6
	(0.00854)	(0.0190)		
EQ_{t-6}	0.0688***	0.210***	129.5	147.1
	(0.00843)	(0.0193)		
EQ_{t-7}	0.0415***	0.134***	73.31	88.21
	(0.00727)	(0.0176)		
EQ_{t-8}	0.0312***	0.0653***	53.29	42.00
	(0.00686)	(0.0185)		
EQ_{t-9}	0.0332***	0.0772***	54.16	46.19
	(0.00644)	(0.0173)		
EQ_{t-10}	0.0251***	0.0192	36.61	11.37
	(0.00576)	(0.0162)		
EQ_{t-11}	0.00788	-0.0187	11.57	-10.93
	(0.00529)	(0.0145)		
Observations	119816	119837		
Overall R-squared	0.384	0.154		
Within R-squared	0.599	0.436		
Between R-squared	0.281	0.0323		
Municipality fixed effects	Yes	Yes		
Year fixed effects	Yes	Yes		
Financial time-variant controls	Yes	No		
Political controls	Yes	Yes		
Socioeconomic controls	Yes	Yes		
Sociodemographic controls	Yes	Yes		

Notes - The table presents fixed effects regression results for the log of per capita local government expenditure (column 1) and the log of per capita transfers from central and regional governments (column 2). Columns 3 and 4 transform regression results in real per capita values. EQ_{t-j}, with $0 \leqslant j \leqslant 11$, is a dummy variable equal to one if the latest earthquake occurred j years before the current year, and zero otherwise. Model 1 controls for financial time-variant factors (logs of per capita transfers from the central and regional governments and revenues from local taxation), and both models control for political (center-right government, vote concentration, term limit, years before elections), socioeconomic (average income and percent of low-income population) and sociodemographic factors (population density, percent of young and percent of old population), and year fixed effects. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices.

Figure 1.4: Variation of local government expenditure and transfers after an earthquake



Notes - The graph represents the estimates of the impact of an earthquake with intensity $\geqslant 5$ on per capita local government expenditure (blue solid line) and per capita transfers of financial resources from central and regional governments (red dashed line) for a 12-year period after the occurrence of an earthquake. Vertical blue dashed and red dotted segments are 95 percent confidence intervals for the estimates of expenditure and transfers respectively. Local government expenditure is adjusted for time-variant financial, political, socioeconomic and sociodemographic factors, and municipality and time fixed effects. Transfers are adjusted for time-variant socioeconomic and sociodemographic factors, and municipality and time fixed effects. Monetary values are discounted at 2010 prices.
Source: Our elaboration on socioeconomic and sociodemographic data of ISTAT, local government balance sheet data provided by the Italian Home Office, and data on earthquakes of the DBMI15 database of INGV (Locati et al., 2016).

translate into higher expenditure for several years. Actually, an effective monitoring system on how resources are spent is still not in place, and transfers may also partially compensate lower revenues from local taxation, since the central government can allow to postpone the payment of taxes for people residing in disaster areas.

1.5.3 Flypaper effect and asymmetric response

The effects of earthquake-related grants (matching grants) and unconditional grants on local government spending are compared in Table 1.4. This table reports the results from fixed effects regressions using Equation (1.3). In column 1 the two asymmetry variables are initially excluded from the estimation. Note that both earthquake-specific and unconditional grants stimulate expenditure more than income does. The expenditure response to one additional Euro of unmatching grants is almost 13 times larger than the response to income.[36] Our estimated coefficient is slightly different from the coefficient estimated by Gennari and Messina (2014). This is because we use a fixed effects specification and data for a different period, and aggregate central and regional government transfers and current and capital transfers. However, our results are similar to the results obtained by Gamkhar and Oates (1996). Although the impact of matching grants is more than 5 times the effect of income, the multiplier is smaller than the multiplier of unconditional grants (about half). This is apparently surprising since the theory suggests that specific transfers should have at least the same effect on expenditure as unconditional transfers (Bailey & Connolly, 1998). However, as we will see later in Section 1.5.4, this is an average effect that does not account for heterogeneity in the response across the country, likely due to remarkable variation of efficiency in the use of earthquake-specific transfers.

In column 2, we extend the model to include the two asymmetry variables that capture different effects between increasing and decreasing transfers. The negative and significant coefficient of the asymmetry variable relative to unconditional grants suggests that there is a replacement effect when transfers decrease, i.e., expenditure is sticky to decreasing unconditional grants, a result in line with the findings of Gennari and Messina (2014). Similarly, expenditure is less responsive to decreasing than to increasing earthquake-specific grants, although this asymmetric response is more pronounced than the response to unconditional transfers. The sum of the estimated parameters of earthquake-specific grants ($\hat{\alpha}_1$) and their asymmetry variable ($\hat{\alpha}_2$) is close to zero and suggests that a reduction in the transfers for earthquake recovery has negligible effects on spending levels.

In column 3, we report the results from the estimation of a 2SLS fixed effects regression instrumenting general transfers and the relative asymmetry variable with the second lag of general transfers and the second lag of general transfers of neighboring municipalities (two-years spatial lag).[37] Diagnostic tests confirm that general

[36]The coefficient of unmatching grants does not change if we estimate Equation (1.3) using only the sub-sample of municipalities not affected by earthquakes.

[37]To enhance the comparability of our results with those obtained by Gennari and Messina (2014), we repeat the estimation using the first and the second temporal lag of transfers, but differences are insignificant.

Table 1.4: Flypaper effect and asymmetric response to variations in transfers

	(1) FE	(2) FE	(3) IV
Earthquake-specific grants	0.280***	0.294***	0.254**
	(0.0790)	(0.0794)	(0.0830)
Asymmetry (Eq.-specific grants)		-0.245***	-0.219***
		(0.0436)	(0.0471)
General grants	0.657***	0.746***	1.648**
	(0.0499)	(0.0445)	(0.588)
Asymmetry (General grants)		-0.336***	-0.0210
		(0.0286)	(0.673)
Income	0.0521***	0.0426***	0.0421***
	(0.00769)	(0.00689)	(0.00984)
Observations	119816	111825	103681
Overall R-squared	0.262	0.300	0.523
Within R-squared	0.248	0.241	0.0188
Between R-squared	0.268	0.320	0.648
Municipality fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Financial time-variant controls	Yes	Yes	Yes
Political controls	Yes	Yes	Yes
Sociodemographic controls	Yes	Yes	Yes
Hausman test			2020.3***
Endogeneity test			21.23***

Notes - The table presents regression results for per capita local government expenditure. Models 1 and 2 are OLS regressions and model 3 is a two-stage least square regression where general grants and the relative asymmetry variable are instrumented with the second lag of general grants and the second lag of general grants of neighboring municipalities (two-years spatial lag). *Matching grants* are earthquake-specific per capita transfers from central and regional governments allocated for recovery after the occurrence of an earthquake. *Unconditional grants* are general grants obtained as the difference between total grants and earthquake-specific grants. The two asymmetry variables measure decreases of each type of transfers between period $t-1$ and t. All models control for financial-time variant characteristics (per capita revenues from local taxation), political (center-right government, vote concentration, term limit, years before elections), socioeconomic (average income and percent of low-income population) and sociodemographic factors (population density, percent of young and percent of old population), municipality and year fixed effects. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices.

transfers are endogenous and that the instrumental variable approach yields consistent estimates. We can see that the effect of general grants on spending levels is more remarkable than in column 1 and 2, and the coefficient of the asymmetric response to decreasing grants loses significance. These coefficients are very close to the estimates of Gennari and Messina (2014). Conversely, the estimated parameters of earthquake-specific grants and their asymmetry variable are very close to the coefficients reported in column 2. Overall, these results allow to conclude that there is evidence of flypaper effect for both types of grants. However, we find inconclusive evidence of an asymmetric response to increasing vs. decreasing unconditional transfers (fiscal replacement), similarly to most previous studies but differently, for instance, from Levaggi and Zanola (2003), who testify a fiscal restraint type of asymmetry on regional health care expenditure in Italy. Conversely, the fiscal replacement effect is remarkable for earthquake-specific matching grants, suggesting that public officials may exploit the occurrence of earthquakes to maintain higher spending levels. Moreover, local governments are apparently unable to fully exploit upper-level government transfers to increase expenditure when struck by an earthquake. This suggests a delay in the response to increasing grants, leading to an inefficient use of resources for disaster relief. We further address this aspect in the next Section 1.5.4.

1.5.4 The North-South divide

Timing of the response

Local governments may differ in the response to earthquake recovery measures. Several aspects, such as culture, history and institutional quality, may affect this response. Barone and Mocetti (2014) argue that these differences influence economic outcomes after an earthquake. They compare two big earthquakes in Italy and show that the lower institutional quality in the South worsened after the shock and led to a lower economic growth (for a discussion on the regional divide in Italy, see for instance Felice (2018) and González (2011)). Following this evidence and inspired by the above findings on asymmetric and heterogeneous flypaper effects, we analyze how the response of local governments to earthquake shocks differs between Northern an Southern municipalities. The results from the estimation of the extended Equation (1.3) to include the interaction terms between grants and location are reported in Table 1.5.

As for unconditional grants, we do not observe a significantly different effect between Northern and Southern municipalities (in column 1, the coefficient of the interaction term between the South dummy and unconditional grants is not significant). Conversely, earthquake-specific grants show a significantly different effect between

Table 1.5: Impact of transfers on local government expenditure by macro regions

	(1) Full sample	(2) North and Center	(3) South
Earthquake-specific grants	1.432**	0.679***	0.132**
	(0.487)	(0.132)	(0.0409)
South × Earthquake-specific grants	-1.205*		
	(0.492)		
Earthquake-specific grants $(t-1)$		1.103*	0.156***
		(0.506)	(0.0372)
Earthquake-specific grants $(t-2)$		1.393	0.306***
		(0.768)	(0.0435)
General grants	0.646***	0.757***	0.786***
	(0.0572)	(0.0505)	(0.0392)
South × General grants	0.0714		
	(0.0614)		
Income	0.0521***	0.0450***	0.0727***
	(0.00761)	(0.00974)	(0.0208)
Observations	119816	74587	29253
Overall R-squared	0.270	0.393	0.483
Within R-squared	0.258	0.219	0.408
Between R-squared	0.275	0.456	0.525
Municipality fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Financial time-variant controls	Yes	Yes	Yes
Political controls	Yes	Yes	Yes
Sociodemographic controls	Yes	Yes	Yes

Notes - The table presents fixed effects regression results for per capita local government expenditure. Model 1 uses the full sample of observations, model 2 uses the sub-sample of municipalities located in the regions in the Northern and Central regions, and model 3 uses the sub-sample of municipalities located in the Southern regions (Abruzzo, Campania, Puglia, Basilicata, Calabria and Sicily). *Matching grants* are earthquake-specific per capita transfers from central and regional governments, allocated for recovery after the occurrence of an earthquake. *Unconditional grants* are general transfers calculated as the difference between total grants and earthquake-specific grants. The two asymmetry variables measure decreases of each type of transfers between period $t-1$ and t. *South* is a dummy variable equal to one for municipality located in the Southern regions of Italy. All models control for financial-time variant characteristics (per capita revenues from local taxation), political (center-right government, vote concentration, term limit, years before elections), socioeconomic (average income and percent of low-income population) and sociodemographic factors (population density, percent of young and percent of old population), and year fixed effects. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices.

Northern and Southern municipalities. In the North, one additional Euro of transfers for earthquake recovery raises expenditure by 1.43 Euro, while in the South the effect is significantly lower (0.23 Euro, i.e., the sum of the coefficient of earthquake-specific grants and the interaction term). Therefore, municipalities in the North seem to have a larger reaction to transfers for earthquake recovery, while expenditure in the South is much more sticky. Note that Northern municipalities are generally less dependent on transfers, since personal income levels are higher, and their spending levels are lower, which may suggest a lower inertia to changes in transfers. As suggested by Vegh and Vuletin (2015), an increase in transfers has a larger effect on spending levels where the ratio between transfers and income is lower because transfers increase the municipality's income portfolio diversification and, thus, willingness to spend. Indeed, the flypaper effect is larger in the North than in the South since the correlation between earthquake-specific grants and personal income is lower in the former region (0.036 and 0.143, respectively).

The possible delay in the utilization of earthquake-related funds is worth of further analysis. The model in columns 2 and 3 includes the first and second lag of earthquake-specific grants and runs separate regressions for Northern and Southern municipalities. In the North, the inclusion of past matching grants in the regression reduces the estimated coefficient of current-period grants below one, while the coefficient of the first lag is significant and equal to 1.1, and the coefficient of the second lag is not significant. This suggests that Northern local governments have at most one-year delay in the reaction to additional resources from upper-level governments. Instead, in the South, the immediate response to matching grants is lower (0.132 vs. 0.679), and both the first and the second lag of grants are significant. Moreover, both lag coefficients are below one and lower than the estimated coefficients for the North, suggesting that a larger amount of financial resources received by local governments is not spent in the short-run. This may indicate that municipalities in the South are affected by poorer institutional quality, which in turn may cause only partial or delayed recovery from earthquake damages and hinder local economic growth in the future. As suggested by Mauro (1995), the slower use of earthquake-related resources by municipalities in the South may be the consequence of higher levels of corruption.

Spending composition and growth

To further explore possible inefficiencies in local government response to earthquake shocks, we analyze how disaster relief resources are allocated to different spending categories. In Table 1.6, we compare variations in the spending composition between municipalities in the North and in the South in the five years before and after the occurrence of an earthquake.[38,39] Before the shock, municipalities in the South spend on average 25.9 percent of the total budget on *local services*, which exceeds by 6.6 percent the budget allocated by municipalities in the North. Not surprisingly, after the shock, the expenditure share of *local services* grows in both macro regions since it includes expenditure on public infrastructures, water supply and waste disposal. More precisely, municipalities in the North allocate 2.32 percent and 0.96 percent significantly more resources to *local services* and *administration*, respectively, while the budget share for the other spending categories significantly decreases, except for *transport services*. Instead, the share allocated to *local services* by Southern municipalities increases by 5.1 percent, which goes to the detriment of the budget share allocated to the other spending categories (a significant decrease for *transport services* and *other services*). Therefore, the main difference in the spending composition between Northern and Southern municipalities lies in the remarkable increase of funds for local services in the South, and a relatively more equal allocation of resources across spending categories in the North. While the response of local governments to earthquake shocks in Northern municipalities encompasses all areas of government action, Southern municipalities put their effort mainly in the enhancement of *local services*.

The heterogeneous response to earthquake shocks observed between the North and the South in terms of timing in the use of resources and their allocation points at the most efficient recovery from earthquake shocks. Therefore, we relate the availability and allocation of earthquake-specific resources to economic growth and compare treated and matched unaffected municipalities in the North and in the South.[40] We

[38] The spending category *Other* includes local police, justice, culture, sports and economic development which aggregated account on average for less than 10 percent of the total budget.

[39] Table 1.6 in the Appendix reports variations before and after the shock and between municipalities in the North and in the South and significance levels of t-tests on mean differences.

[40] In this part of the analysis we exclude municipalities from the region Abruzzo because the 2009 earthquake that affected this region is an outlying shock with strong damages and large financial windfall for reconstruction from upper-tier governments.

Table 1.6: Variation (in percent) of spending composition after an earthquake

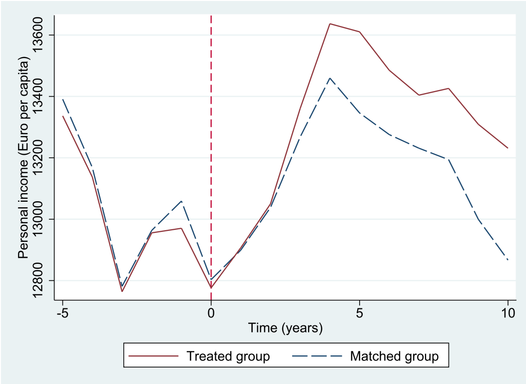
	(1)	(2)	(3)	(4)	(5)
	Before		After		
	North	South	Δ North	Δ South	Δ North - Δ South
Local services	19.34	25.94	2.32***	5.10***	-2.78***
General administration	30.93	32.36	0.96*	-0.80	1.76**
Education	11.02	7.90	-0.84***	-0.32	-0.52
Social protection	11.82	6.72	-1.65***	-0.22	-1.42***
Transport services	13.44	12.25	0.38	-0.65*	1.03**
Other services	13.05	14.75	-0.94**	-3.04***	2.10***
Observations	911	951	3587	2572	

The table reports budget shares (columns 1 and 2) allocated to the main local government spending categories in the five years before a shock (with intensity $\geqslant 5$) and average variations (in percent) within five years after the occurrence of the shock (columns 3 and 4). Southern municipalities include the regions of Abruzzo, Campania, Puglia, Basilicata, Calabria and Sicily. Stars in columns 3 and 4 indicate significance levels of t-tests on differences in means before and after the shock. Column 5 reports mean differences between variations in the North and the South, and stars indicate significance levels of t-tests on mean differences. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$.

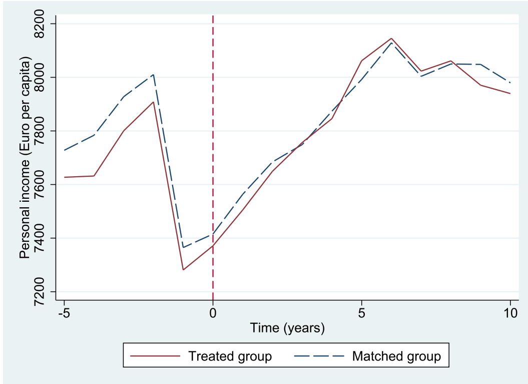
use personal income and mean housing prices as proxies for local economic growth since data on gross domestic product (GDP) are not available at municipality level.[41] The trends of these variables are illustrated in Figure 1.5. Note that, in the North, personal income grows faster in struck municipalities than in unaffected municipalities in the first decade after an earthquake (Figure 1.5a). Conversely, in the South, the two groups of municipalities have identical income trends (Figure 1.5b). Similarly, housing prices (per square meter) in the South do not change significantly between struck and unaffected municipalities (Figure 1.5d). Instead, in the North, housing prices start to grow faster after two years in struck municipalities as compared to unaffected municipalities (Figure 1.5c). This evidence is even more pronounced if we limit the focus to earthquakes with intensity equal or greater than 6. It appears that the result is related to different responses to earthquake shocks between municipalities in the two macro-regions. Transfers from central and regional governments in the North (Figure 1.6a) grow after the occurrence of an earthquake, but converge to pre-earthquake levels after five years. Conversely, in the South, struck municipalities remain persistently more dependent on upper-tier government transfers for at least 10 years (see Figure 1.6b). Also, the budget share for local services in the South increases more in the treated group than in the counterfactual group after an earthquake (Figure 1.6d), but the gap between the two groups appears less prominent than in the North (Figure

[41]See, for instance, Cheung, Wetherell, and Whitaker (2018) and Naoi, Seko, and Sumita (2009) for an examination of the effects of earthquakes in terms of house and land values.

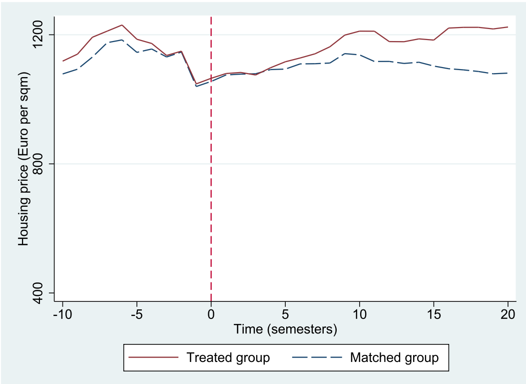
Figure 1.5: Economic outcomes after the occurrence of an earthquake



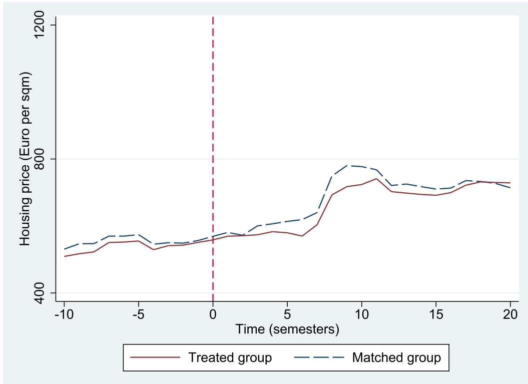
(a) Personal income (North)



(b) Personal income (South)



(c) Housing prices (North)



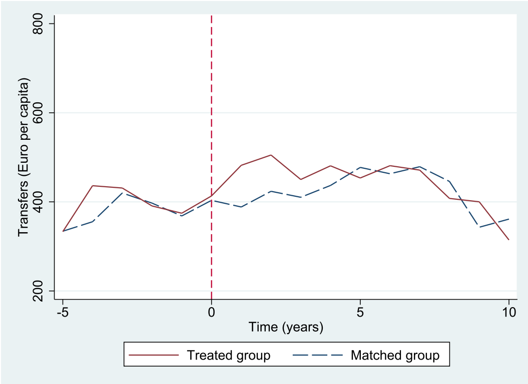
(d) Housing prices (South)

Notes - The graphs illustrate personal income (Figure (a) for Northern municipalities and Figure (b) for Southern municipalities) and mean housing prices per square meter (Figure (c) for Northern municipalities and Figure (d) for Southern municipalities) before and after the occurrence of an earthquake with intensity $\geqslant 5$, which occurs at time zero. The top figures compare municipalities struck by an earthquake over the period 2000-2015 (treated group - red solid line) with matched unaffected municipalities (blue dashed line) identified with coarsened exact matching performed on average pre-treatment characteristics of municipalities (institutional, socioeconomic, financial, sociodemographic). The bottom figures compare municipalities struck by an earthquake over the period 2003-2015 with matched unaffected municipalities identified with coarsened exact matching performed on average pre-treatment housing prices. Both groups include only municipalities with complete data for the respective period. Positive (negative) values on the x-axis indicate years (or semesters for housing prices) after (before) the treatment. Monetary values are discounted at 2010 prices.
Source: Our elaboration on income data provided by the Italian Ministry of Economics and Finance, data on housing pries provided by the Real Estate Market Observatory of the Italian Revenue Agency, and data on earthquakes of the DBMI15 database of INGV (Locati et al., 2016).

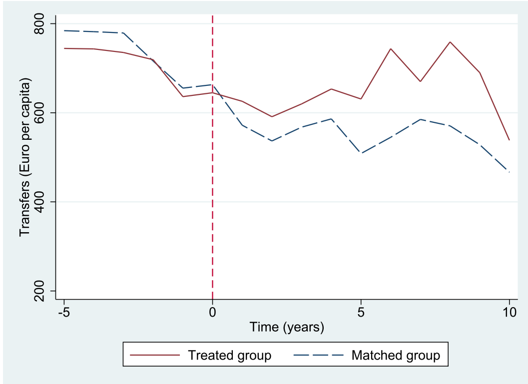
1.6c).

This evidence obtained from the large dataset of all Italian municipalities and earthquake events between 2000 and 2015, seems to confirm the heterogeneous effects between North and South found by Barone and Mocetti (2014) in their deep investigation of two Italian earthquakes. Even if a larger amount of resources for recovery is allocated to disaster areas in the South, these jurisdictions seem unable to exploit the financial windfall to recover from damages and improve economic growth.

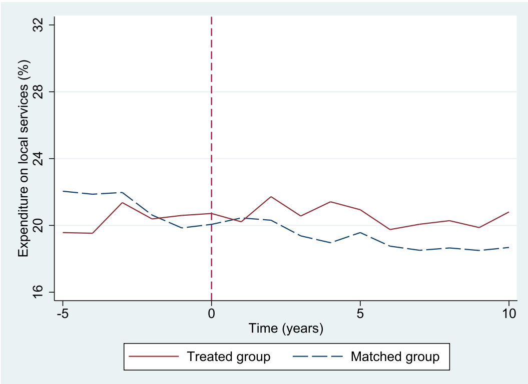
Figure 1.6: Variation of municipal financial characteristics after an earthquake



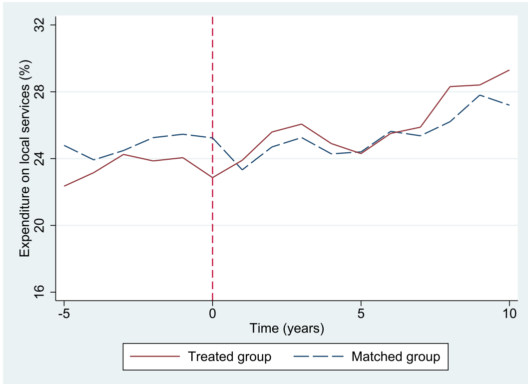
(a) Transfers (North)



(b) Transfers (South)



(c) Budget share for local services (North)



(d) Budget share for local services (South)

Notes - The graphs illustrate per capita transfers from central and regional governments (Figure (a) for Northern municipalities and Figure (b) for Southern municipalities) and the budget share allocated to local services (Figure (c) for Northern municipalities and Figure (d) for Southern municipalities) before and after the occurrence of an earthquake with intensity $\geqslant 5$, which occurs at time zero. Each graph compares municipalities struck by an earthquake over the period 2000-2015 (treated group - red solid line) with matched unaffected municipalities (blue dashed line) identified with coarsened exact matching performed on average pre-treatment characteristics of municipalities (institutional, socioeconomic, financial,sociodemographic). Both groups include only municipalities with complete data for the period 2000-2015. Positive (negative) values on the x-axis indicate years after (before) the treatment. Monetary values are discounted at 2010 prices.
Source: Our elaboration on local government balance sheet data provided by the Italian Home Office, and data on earthquakes of the DBMI15 database of INGV (Locati et al., 2016).

Conversely, local governments in the North appear more efficient in exploiting transfers from upper-level governments to expand expenditure and recover from damages. This translates into new infrastructure and the replacement of obsolete technologies destroyed or damaged by the earthquake, which allows to foster local economic development and to accelerate growth. Likely, the allocation of resources among spending categories in the North speeds up recovery and fosters local economic growth. The higher increase in the expenditure share for *local services* in the South could suggest that resources are not used efficiently or favor corruption. Indeed, although *local services* represents the spending category mostly affected by earthquakes (urban road maintenance and the maintenance/construction of public buildings), the construction industry is also well exposed to corruption scandals.

The interpretation of our results finds some support in theories that explain the backwardness of the South of Italy in the last century. The lower institutional quality compared to the North is a pre-existing characteristic of the area that affects efficiency in the response to earthquakes. The South is historically characterized by rent-seeking behavior, reluctance to change, lack of entrepreneurship and a weak socio-institutional structure that hinders public intervention to reduce the North-South gap (Capello, 2016). Whether it is because of the low efficiency of public institutions or the lack of private initiative, these characteristics make it difficult to exploit the opportunity offered by earthquakes and earthquake-specific grants to reconstruct and reorganize local growth and development. Hence, the slow recovery is likely the result of upper-tier government intervention rather than local economic resilience (Xiao, 2011).

1.6 Spillover effects

The effects of earthquake shocks on local government expenditure and spending composition may not be limited to the area directly affected by the disasters. Elected officials in municipalities close to an area affected by a shock may change their spending decisions because they mimic the decisions taken by their neighboring elected officials (Besley & Case, 1995) or because they perceive the threat of facing an earthquake in future, as it happens in jurisdictions close to local governments that are dismissed for criminal behavior because of a higher perception of the risk of punishment (Galletta, 2017).

To analyze if earthquake occurrences trigger spillover effects of spending levels, we adopt a strategy similar to Galletta (2017) and re-estimate Equation 1.1 within the sample of municipalities that share the border with municipalities struck by an earthquake with intensity $\geqslant 5$ at least once during the study period. We use the following linear vector of spatially lagged earthquake occurrence dummies instead of the polynomial expressed in Equation 1.2:

$$\mathbf{T}'_{it}\boldsymbol{\alpha} = \sum_{j=0}^{3} \alpha_j EQ_{i-1,t-j} \tag{1.4}$$

with $EQ_{i-1,t-j}$ being a dummy variable equal to 1 if a neighboring municipality $i-1$ was struck by an earthquake j years before the current year, with $0 \leqslant j \leqslant 3$, and 0 otherwise.[42] This approach allows to identify causal spillover effects triggered by earthquake occurrences because the timing of seismic shocks is random and we do not need to account for systematic differences between unaffected neighboring local governments and other unaffected local governments that may lead to different spending choices after shock occurrences.

Then, we investigate spillover effects of spending composition and repeat the above described estimation strategy using the expenditure share on local services as the dependent variable. We focus only on this spending component since it funds the provision of the most relevant type of services in the aftermath of earthquake shocks as described in Section 1.5.4. Indeed, increasing expenditure for local services allows to invest into prevention by improving local infrastructures.

The effect of earthquake shocks occurring in neighboring municipalities on the natural logarithm of unaffected local governments per capita expenditure (columns 1 and 2) and on the budget share allocated to local services (columns 3 and 4) from the estimation of Equation 1.1 using fixed effects and autoregressive fixed effects models are summarized in Table 1.7. While, in the year in which an earthquake strikes ($EQ_{i-1,t}$), neighboring jurisdiction do not show evidence of significant variations in spending levels, per capita local government expenditure significantly grows by 1.78%-1.99% (27.18-30.38 Euro) in the year after earthquake occurrence ($EQ_{i-1,t-1}$). In the second ($EQ_{i-1,t-2}$) and third year since the disaster ($EQ_{i-1,t-3}$), unaffected local governments maintain significantly higher spending levels as compared to periods before the shock, but the effect tends to converge to pre-disaster levels. These results suggest that unaffected local governments close to disaster areas tend to mimic their neighbors

[42] We analyze the effect of an earthquake over a 4 year period because preliminary analysis showed that, after the third year since the occurrence of an earthquake, spending levels in unaffected municipalities that share the border with struck municipalities converge to pre-shock levels.

Table 1.7: Impact of earthquake shocks on neighboring municipalities.

	(1)	(2)	(3)	(4)
	Expenditure		% Local services	
	FE	FE (AR1)	FE	FE (AR1)
$\text{EQ}_{i-1,t}$	0.00752	0.00684	0.305	0.385*
	(0.00523)	(0.00455)	(0.209)	(0.192)
$\text{EQ}_{i-1,t-1}$	0.0197***	0.0176***	0.556**	0.432*
	(0.00551)	(0.00463)	(0.207)	(0.179)
$\text{EQ}_{i-1,t-2}$	0.0176**	0.00976*	0.613**	0.406*
	(0.00569)	(0.00487)	(0.207)	(0.178)
$\text{EQ}_{i-1,t-3}$	0.0156**	0.0104*	0.101	-0.142
	(0.00511)	(0.00453)	(0.196)	(0.173)
Observations	27717	27537	27716	27533
Overall R-squared	0.484	0.793	0.0382	0.352
Within R-squared	0.593	0.666	0.0535	0.193
Between R-squared	0.433	0.911	0.0422	0.501
Municipality fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Financial time-variant controls	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes
Sociodemographic controls	Yes	Yes	Yes	Yes

Notes - The table presents regression results for the log of per capita local government expenditure (columns 1 and 2) and the share of local government expenditure on local services (columns 3 and 4) for unaffected municipalities that share the border with municipalities struck by an earthquake with intensity $\geqslant 5$. Columns 1 and 3 are fixed effects regressions, and columns 2 and 4 are autoregressive fixed effects regressions. $EQ_{i-1,t-j}$, with $0 \leqslant j \leqslant 3$, is a dummy variable equal to one if the latest earthquake in a neighboring municipality $(i-1)$ occurred j years before the current year, and zero otherwise. All models control for financial time-variant (logs of per capita transfers from the central and regional governments and revenues from local taxation), political (center-right government, vote concentration, term limit, years before elections), socioeconomic (average income and percent of low-income population) and sociodemographic factors (population density, percent of young and percent of old population), and year fixed effects. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices. The share of local government expenditure on local services is multiplied by 100.

until the third year after the shock, but the growth in spending levels is much more limited as compared to local governments directly affected by a seismic shock.

The regression results of budget share allocated to local services show that higher spending levels are used in favor of this expenditure component. The results from the autoregressive fixed effects model (column 4) suggest that the expenditure share for local services increases immediately after the shock by 0.39%, and persists at significantly higher levels until the second year after the disaster occurrence. Then, it converges to pre-earthquake levels. In the fixed effects model (column 3), the expenditure share variation is not significant in the year in which neighboring local governments are struck by an earthquake, but coefficients of variables identifying shocks occurred in the previous years are similar to those in the autogregessive model. These findings suggest that incumbent politicians in local governments close to disaster areas take similar expenditure allocation decisions as their peers in struck municipalities.

The results provide evidence of earthquake-driven spillover effects of spending levels and composition in municipalities that are sufficiently close to the disaster area. Elected officials in local governments that are not affected by an earthquake but share an earthquake occurrence risk similar to their struck neighbors, may perceive the threat of facing a destructive seismic shock when they observe the devastating consequences of an earthquake occurred in a neighboring jurisdiction, and increase investments in prevention to mitigate the risk of facing damages. This explanation reflects individuals' behavior that react to punishment for criminal behavior in neighboring households or jurisdictions because observing law enforcement raises the fear of being caught in the near future (Galletta, 2017; Rincke & Traxler, 2011; Sah, 1991). Though this evidence applies to a different type of shocks, we argue that it provides an explanation for spillover effects of spending decisions when earthquakes strike in nearby local governments. Indeed, this behavior of incumbent politicians allows to send a signal of reassurance to voters who compare local government performance with the performance of neighboring jurisdictions in order to evaluate their elected officials' competences (Besley & Case, 1995).

1.7 Concluding remarks

Local governments differ in the response to economic and social damages caused by natural disasters (earthquakes), in terms of spending behavior and the use of grants from upper tiers. Earthquake-related grants (matching grants) may also differ from other types of grants (mostly unconditional) in terms of stimulatory power, and expenditure may differ in the response to increasing and decreasing grants, leading to asymmetric and heterogeneous reactions (different *flypaper effects*). Since natural disasters are particularly good examples of exogenous shocks to economies, the exogenous nature of earthquakes allows us to better identify any flypaper effect. Moreover, we investigate whether earthquake shocks influence spending decisions in unaffected local governments close to the disaster area. We explore these aspects using municipality data and all earthquake shocks from a country largely exposed to seismic events - Italy - between 2000 and 2015.

We find evidence of increasing expenditure for about 11-12 years after a shock, before regressing to pre-earthquake levels. Over the whole period, affected municipalities spend 962 Euro per individual more than not affected municipalities, and transfers from central and regional governments exceed expenditure by about 250 Euro per individual. The average impact of both earthquake-specific and unconditional grants on expenditure is much larger than the response to income, suggesting the presence of a flypaper effect. However, we find evidence of an asymmetric response to decreasing grants (i.e., a fiscal replacement effect) only for earthquake-specific grants, suggesting that public officials tend to maintain higher spending levels after the occurrence of an earthquake.

The impact of matching grants is remarkably heterogeneous across the country. In the North, municipalities are more sensitive to variations in transfers (one additional Euro raises expenditure by 1.43 Euro), while Southern municipalities react to the drop of grants showing inertia in expenditure levels (0.23 Euro response). Likely, the lower dependency on upper-tier government transfers by the North allows for a larger effect on municipality income portfolio diversification and, therefore, spending levels as compared to the South (Vegh & Vuletin, 2015).

Although earthquake shocks provide the opportunity to reorganize economic activities and foster urban development (Xu & Wang, 2019), this opportunity is channeled through the efficient use of resources. Our evidence suggests a more efficient recovery in Northern municipalities which allows both personal income and housing prices to grow faster than if no earthquake would have occurred, as suggested by Barone and Mocetti (2014). These findings are consistent with Bondonio and Greenbaum (2018) showing that more socioeconomically disadvantaged areas (the South) are less able to exploit opportunities to recover. Indeed, while the response of Northern municipalities encompasses all areas of government action, Southern municipalities put their effort mainly in the enhancement of local services. Therefore, evidence from Northern municipalities points at a possible explanation in accordance with the recent finding by Allers and Vermeulen (2016), showing that additional grants are capitalized into house values rather than in rent taking by bureaucrats or politicians. Conversely, the extraction of rent from uninformed voters by self-interested politicians (Brollo, Nannicini, Perotti, & Tabellini, 2013; Persson & Tabellini, 2000) could represent a more valid explanation for Southern regions. Here, the spending category mostly affected by earthquake damages (local services) attracts the largest part of additional grants, fostering exposure to corruption scandals within the construction industry (Galletta, 2017).

Finally, we find that earthquake occurrences cause spillover effects of local governments spending levels and composition in unaffected municipalities that share the border with struck municipalities, but the magnitude and the duration of the spending variations is remarkably lower than in struck municipalities. This reaction is driven by the higher perception of the threat of facing an earthquake in the near future (Galletta, 2017; Rincke & Traxler, 2011; Sah, 1991).

While the use of a matching procedure that accounts for the ex-ante probability of facing an earthquake allows to reach a high level of internal validity of our results, it is difficult to generalize them to different contexts for two reasons. First, the information on the ex-ante probability of facing an earthquake in future (seismic zones) is available to the public, and this may lead to a selection effect as individuals and firms may decide to relocate to low-risk zones or to take preventive actions in order to mitigate their exposure to disaster occurrence risk (Boustan et al., 2017). Second, the Italian institutional setting differs from the setting of other countries, and this makes it hard to generalize results on the magnitude and duration of local government spending variations and on the stimulatory power of earthquake-specific grants in the aftermath of seismic shocks. Nonetheless, the response to earthquake shocks provided by Italian institutions in terms of public expenditure variation is in line with the behavior of other developed countries (Noy & Nualsri, 2011). Therefore, we might expect that local governments in other developed countries behave in a similar manner as in Italy.

We conclude that the role of upper-level governments is crucial in disaster relief but the quality of the response of local governments affects economic outcomes. There is scope for an improved monitoring system on how local governments employ disaster relief resources in order to recover quickly and efficiently. Future research should investigate more in detail factors affecting efficient recovery to identifying best-practices and provide guidance for policy makers.

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Essay 2

Natural disasters and electoral support

2.1 Introduction

Natural disasters are good examples of climate shocks that may affect vote decisions since affected voters can update preferences and expectations on policies and politician performance (Ashworth, Bueno de Mesquita, & Friedenberg, 2018). Indeed, politicians are pushed into the center of the storm because they need to provide a response to unexpected damages and needs. Voters can use information on politicians' response to assess incumbent politicians' competences and evaluate whether they deserve maintaining their position and punish or reward them at the following elections. Several studies address the question of voter behavior at elections when disasters occur (e.g. Gallego, 2018; Klomp, 2019). However, findings are mixed and evidence on the alignment between variations in electoral support in local-level elections and incumbent mayor performance is lacking.

In this essay, we investigate how the occurrence of natural disasters (earthquakes) affects electoral outcomes. To this aim, we use data from 11,966 municipal elections in Italy where incumbent mayors run for reelection between 1993 and 2015, and exploit a rich dataset of all earthquake events occurred within the same period. In particular, we analyze how the reelection probability and vote share of incumbent mayors differ between struck and unaffected municipalities in local elections. Our empirical strategy to identify the causal impact of earthquake occurrence on electoral outcomes is based on propensity score matching (PSM) combined with regression adjustment. We use probit regressions of incumbent mayor reelection probability and OLS regressions of vote share weighted by the reciprocal of normalized propensity scores. Moreover, we employ a difference-in-difference strategy, combined with PSM, to estimate the impact of earthquake shocks on vote share. We find that the occurrence of destructive earthquakes raises the support for the incumbent mayor by increasing both the reelection probability and the share of votes gained. The results are robust to the use of alternative matching procedures and placebo tests. Then we analyze possible channels through which earthquake occurrence changes vote decisions. In particular, we focus on politician performance and visibility on the main Italian press agency (*ANSA*). While data for the measurement of performance (local government financial indicators) are available from institutional sources, we collected data on political visibility using a search strategy on the Factiva database to obtain the frequency of news mentioning incumbent mayors and competing candidates. We find that both incumbent mayor performance and visibility on the media increase after the occurrence of an earthquake, which explains improved electoral outcomes for incumbent mayors. Although voters tend to reward the good performance of the incumbent, the mediatic exposure of incumbent mayors relative to their competitors biases voters' choice towards the incumbent.

Previous studies tend to suggest that the occurrence of natural disasters reduces the support for the incumbent politician if his/her response is perceived as inadequate (Eriksson, 2016; Lay, 2009) or if he/she takes actions which go to the detriment of voters welfare (Akarca & Tansel, 2016). Conversely, an appropriate response, generally measured by the size of financial transfers from the central government, raises the support for the incumbent government (e.g. Healy & Malhotra, 2009), although incumbents may use these tools to attract votes in an opportunistic manner (Bechtel & Hainmueller, 2011). Belloc, Drago, and Galbiati (2016) show that between 1000 and 1300, political and religious leaders (bishops) in autocratic Italian cities exploited the occurrence of earthquakes to maintain their power leveraging on fear and the religious sphere of individuals. However, whether voters are able to identify the politicians who are responsible for a positive (negative) response to disasters and reward (punish) them at elections is an under-investigated question and provides mixed evidence. Gasper and Reeves (2011) analyze the impact of extreme rainfalls in the US on electoral outcomes at county and federal level and find that voters are able to identify politicians who are responsible for a good (or bad) response to disaster occurrence, and reward (or punish) them accordingly. Conversely, Achen and Bartels (2017) argue that voters express their frustration at elections when disasters strike, and blame incumbents as long as there is some reason to believe that they are accountable for disaster occurrence.

The investigation of other channels driving vote decisions when natural disasters occur is still lacking. Studies investigating the incumbent government response generally focus on spending levels but neglect the performance in recovery from damages (e.g. Bechtel & Hainmueller, 2011; Healy & Malhotra, 2009). Also, a large strand of the literature analyzes the role of media in biasing vote decisions, showing that the influence of media can shift votes towards a specific party or shape the evaluation of politicians' competences (e.g. DellaVigna & Kaplan, 2007; Hetherington, 1996). To our knowledge, there are no studies that relate variations in political visibility following a disaster and electoral outcomes. Our contribution to this literature is twofold. First, we use a unique and very detailed data set on earthquake occurrences to capture the impact of these shocks on municipal electoral outcomes, an institutional level that has been neglected in previous studies.[1] Second, we extend the understanding of channels driving vote decisions and take into account factors that have been neglected in past studies.

The remainder of this essay is structured as follows. Section 2.2 provides an overview of electoral rules in local elections in Italy. Section 2.3 presents a simple framework of voters' response to earthquake occurrence. Section 2.4 describes the data and presents some preliminary evidence on the relationship between votes and earthquake occurrences. Section 2.5 presents our identification strategy, while Section 2.6 discusses the main results of the analysis. Finally, in Section 2.7 we provide

[1] Exceptions are Nikolova and Marinov (2017) who focus on corruption determined by flood-driven relief funds and incumbent reelection, and Bodet, Thomas, and Tessier (2016) who analyze the effect of a flood on electoral outcomes in one town and for one electoral period.

evidence on possible channels driving our results. Section 2.8 concludes.

2.2 Institutional setting

2.2.1 Municipal elections in Italy

Italy is a parliamentary republic with a multiparty system organized in 20 regions, 110 provinces and almost 8000 municipalities.[2] Substantial power is delegated by the central government to sub-national governments and each institutional level has a government with executive power and a council with legislative power. Local (municipal) governments have the task to provide a number of services to the resident population. The main services are primary education, waste disposal, urban road maintenance, public residential buildings and social protection.[3] The mayor is the head of the Executive Committee (*Giunta Comunale*), which holds executive power, and the Municipal Council (*Consiglio Comunale*) exercises legislative power.

In this study, we focus on municipal elections. At local level, the mayor and the Council members are elected directly by the electorate, while the Executive Committee is proposed by the mayor and approved by the Council. Local government elections are ruled by two electoral systems (majoritarian and proportional) which are assigned based on the population size of the most recent population census. Municipalities with less than 15,000 inhabitants adopt a single-ballot majoritarian system and each mayor candidate can be supported by a single party/list. Municipalities with more than 15,000 inhabitants adopt a two-ballot proportional electoral system and each mayor candidate is supported by a coalition of parties. The second ballot takes place if no candidate wins the absolute majority in the first ballot. Therefore, voters express their preference for one of the two candidates who obtained the largest shares of votes in the first ballot.[4]

Until 2000, each term lasted 4 years. Afterwards, the term was extended to 5 years and a term limit was introduced for mayors.[5] In municipalities with less than 3,000

[2] These numbers refer to 2015. Since 1993, provinces increased from 103 to 110 and municipalities have followed a consolidation process from 8100 to 7997 jurisdictions.

[3] See Decree Law 267/2000 (*Testo unico delle leggi sull'ordinamento degli enti locali*).

[4] See Law 81/1993 for further details on municipal elections in Italy.

[5] Law 120/1999, Art. 7.

inhabitants a mayor is allowed to rule for not more than three consecutive mandates, while in municipalities with more than 3,000 inhabitants only two consecutive mandates are allowed. Elections do not take place at the same time in each municipality. Anticipation is possible if a mayor loses the support of the Council or resigns, or the central government replaces the elected officials because of connections with the mafia. Between 1993 and 2015, the *regular* election years are 1995, 1999 and every 5 years afterwards. Less than 50% of municipalities have governments that reach the end of their mandates in every electoral cycle.

2.2.2 Response to earthquake shocks

Between 1993 and 2015, 397 municipalities were struck at least once by a destructive earthquake (i.e. an earthquake with Mercalli scale intensity greater than 5). In addition, 1524 municipalities registered an intensity equal to 5 and many other jurisdictions below that threshold. Following the shocks, the central government intervenes through the Civil Protection, a department administered by the Presidency of the Council of Ministers with the task to manage prevention, response and forecast of natural and man-made disasters, and through delegates who can act notwithstanding the regulation in order to face the state of emergency. Large amounts of financial resources are transferred to local governments from both central and regional governments.[6]

The response of local governments to the occurrence of an earthquake is generally immediate. Evidence suggests that local governments in struck municipalities increase expenditure by about 100 Euro per capita for 11 years after the shock (see Essay 1). This expenditure variation is allowed by a higher availability of transfers from the central and regional governments. Moreover, local governments adjust the spending composition to face the consequences of the disaster. Local governments increase the share of resources for housing, Civil Protection, waste disposal, water services and services for environmental protection, and reduce the expenditure share of minor services such as justice, culture and sports.

[6] See for example Barone and Mocetti (2014), Di Giacomo (2014) and Essay 1 for a discussion on public transfers and expenditure in the aftermath of earthquake shocks in Italy.

2.3 A simple framework of voters' response to natural disasters

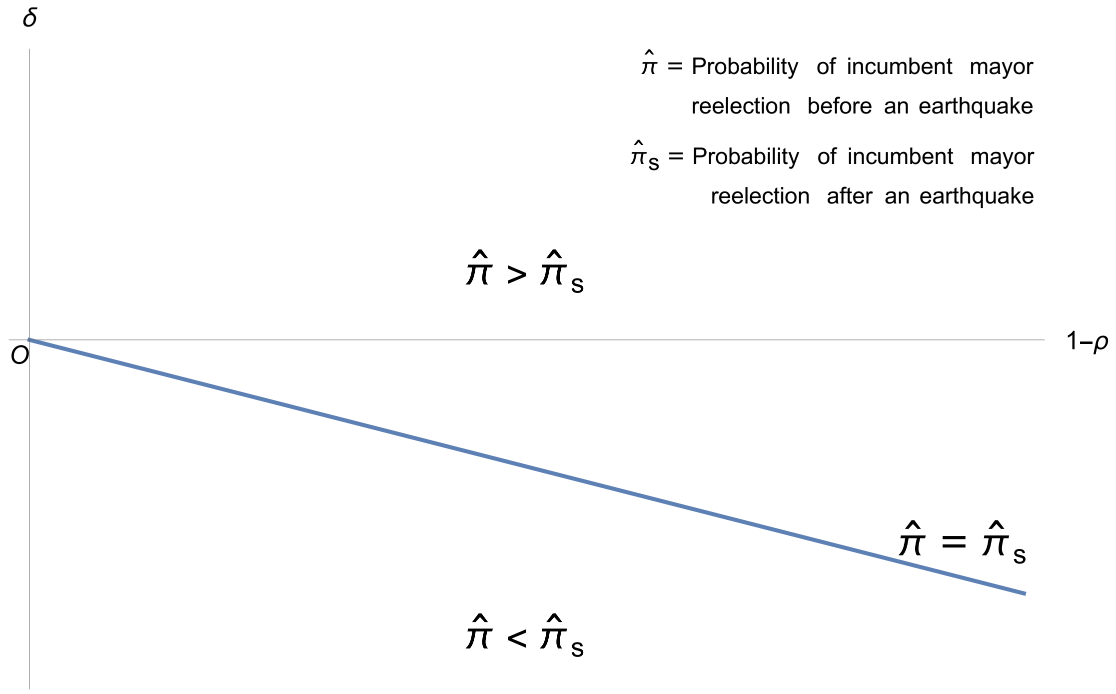
To understand how natural disaster shocks may affect voters' decisions between incumbent and competitor politicians in municipal elections in Italy we sketch a simple theoretical framework. We consider a voter with a utility function strictly concave and increasing with the level of wealth (w). We assume uncertainty regarding the effect of policy measures proposed by political rivals. If the incumbent (I) wins, the individual expects some continuity of previous policy measures, which translates into a certain level of wealth w. Instead, the individual is uncertain about the effect of competitor's (C) policy measures, and expects wealth $w - \varepsilon$ (with $\varepsilon > 0$) with probability $\pi \in [0, 1]$ and $w + \varepsilon$ with probability $1 - \pi$. Consequently, the individual will vote for the incumbent if $EU_I[w] \geqslant EU_C[w, \varepsilon, \pi]$. Under homogeneous policy measures, a probability threshold $\pi = \hat{\pi}$ can be defined such that the voter is indifferent between the incumbent and the competitor (see Appendix B.1 for details).

Now, assume that an earthquake occurs and voters face a loss of wealth $L > 0$. Expectations regarding the incumbent and the competitor ability to recover from the loss is $\rho \in [0, 1]$. This reduces the expected utility from both the incumbent and the competitor provided that $\rho < 1$. However, the incumbent can send a signal (δ), such as recovery from disaster damages, at zero cost that affects voter's expectations regarding his/her ability to restore initial wealth.[7] Therefore, voter's expectations on incumbent ability to restore wealth is $\rho_I = \rho + \delta$, which is higher than ρ if the signal is positive ($\delta > 0$). The new indifference threshold that makes the voter indifferent between the incumbent and the competitor when an earthquake occurs ($\hat{\pi}_s$) is a decreasing function of L and δ and is formally derived in the Appendix (Equation B.6).

From the comparison between the previous probability threshold and the new threshold (after the earthquake), we can see that $\hat{\pi}_s < \hat{\pi}$, implying that the incumbent increases the chance of reelection. This is illustrated in Figure 2.1, where the line represents the equivalence between the likelihood of being reelected before and after the

[7] For instance, incumbent governments may benefit from sudden media exposure and emergency transfers from central governments that allow to increase expenditure.

Figure 2.1: Gain in voter support after the occurrence of an earthquake



Notes - The figure illustrates the gain in voter support by an incumbent mayor after an earthquake depending on expectations about political candidates' inability to recover from earthquake losses $(1-\rho)$ and the signal sent by the incumbent mayor (δ). The blue thick line represents the set of combinations $(1-\rho,\, \delta)$ for which the incumbent mayor has the same reelection probability $(\hat{\pi} = \hat{\pi}_s)$, before and after an earthquake. Above the line, the incumbent has a higher chance of being reelected, while below the line he loses voters support.

earthquake, i.e. $\hat{\pi} = \hat{\pi}_s$. Above the line, the likelihood of supporting the incumbent when an earthquake occurs increases with the probability of no recovery (1-ρ) and the signal of reassurance (δ) sent to the voter. However, if a negative signal is sent to the voter ($\delta < 0$), then a threshold $\hat{\delta}$ exists below which $\hat{\pi}_s < \hat{\pi}$ and the incumbent loses support (below the line).

2.4 Data and descriptive evidence

2.4.1 Sample and variables

To analyze the impact of earthquake occurrence on electoral outcomes, we merge a number of data sources with information aggregated at municipality level. Data on municipal electoral outcomes are provided by the Italian Ministry of Interior and are available on the online historical election archive (*Archivio storico delle elezioni*). These data include information on election dates, candidates, lists/coalitions, vote participation and preferences for elections taking place between 1993 and 2015.[8] Since these data lack some information on municipal elections, we supplement the information with a second data set (*Anagrafe degli amministratori locali*) which includes yearly information on gender, age and education for all elected officials. Between 1993 and 2015, 41,361 municipal elections (about 5 per municipality) took place.

The municipal election data set includes 16,266 observations relative to incumbent mayors running for reelection. Using these data, we define two electoral outcome measures. The first is a dummy variable equal to one if an incumbent mayor is reelected. The second is the share of votes received by the incumbent computed as the proportion of preferences relative to the total number of valid votes. The reelection dummy is a dichotomous measure that allows to assess the success of the incumbent in the electoral run, but it does not suggest if and how much the incumbent gains or loses support during his mandate. Instead, the vote share, especially if related to the votes received in the previous election, measures how much support an incumbent gains or loses, but looking at the vote share variation does not allow to make inference on electoral success.

Using the sources above, we also compute the number of candidates participating in the electoral run and the political orientation of the incumbent government (center-left, center-right, independent or *Movimento 5 Stelle*).[9] In municipalities with more than 15,000 inhabitants, we classify governments according to the political orientation of the parties forming the winning coalition.

We use several other data sources to complete our data set. Data on earthquake occurrence are provided by the Italian Institute for Geophysics and Volcanology (INGV) and these data are discussed in detail in the next section. We use population data for the period 1993-2015 provided by the Italian Institute for Statistics (ISTAT) to define sociodemographic indicators (percentage variation of population and variation in the share of elderly people), and population census data for the years 1991, 2001 and 2011 to classify municipalities by electoral system (proportional or majoritarian). Local government balance sheet data are provided by the Italian Ministry of Interior.

[8] Data on more recent electoral outcomes are available, but we cannot use them because we lack data on earthquake occurrences.

[9] About 60% of the lists supporting mayors are reported as *civic lists*, i.e. lists which do not have an explicit political orientation and generally are independent from national parties.

Total expenditure and revenue data are available for the period 1993-2015, and detailed data (spending categories and revenue sources) for the period 1998-2015. All monetary values are deflated using the consumer price index to obtain real values at 2010 prices.

We exclude elections taking place in autonomous regions (Valle D'Aosta, Friuli Venezia Giulia, Sicily and Sardinia) and provinces (Bolzano and Trento) because the institutional setting is not comparable to the setting in regions with ordinary statute (including the electoral system), and drop observations with incomplete data. Thus, our final sample is composed of 11,966 observations.

2.4.2 Measurement of earthquake occurrence

We use data on earthquake occurrences from the Italian Macroseismic Database DBMI15 (Locati et al., 2016) provided by INGV aggregated by municipality and electoral period. The INGV institute is managed by the Civil Protection and has the purpose to increase the knowledge of natural phenomena in terms of occurrence and relevance, with a particular focus on seismic and volcanic events. The DBMI15 database includes detailed information on earthquakes occurred in Italy between 1000 AD and 2014.[10] We are interested in the Mercalli scale intensity (I), which measures observable effects caused by an earthquake on humans, animals, buildings and objects. This is plausibly the best measure of exposure to earthquake risk.[11]

Following Belloc et al. (2016), we classify earthquakes into destructive earthquakes ($I > 5$) and weak earthquakes ($2 < I \leqslant 5$). Belloc et al. (2016) exploit both types of shocks since religious authorities in medieval times leveraged on the intense sentiment of fear to keep their power. However, voters in modern economies are unlikely to reward or punish incumbent governments without any visible consequence. Therefore, in our baseline analysis we use destructive earthquakes to distinguish between struck and unaffected municipalities.[12] We define a dummy variable (EQ_i) equal to one if

[10] Data for 2015 are not available. Note, however, that in 2015 only a few earthquakes occurred and none of them was destructive.

[11] The alternative Richter scale measures the energy released by an earthquake. Although this is probably a more objective measure of earthquake strength, it is also less suitable to capture damages, and, therefore, observable effects, in the area.

[12] We extend the analysis to non-destructive earthquakes ($I = 5$) in Section 2.6.3.

at least one destructive earthquake occurred in the municipality area (i) between two consecutive electoral periods ($t-1$ and t), and zero otherwise.

Between 1993 and 2015, there are 397 struck municipalities with 406 occurrences of destructive earthquakes between two electoral cycles (see Figure 2.2 for an illustration of earthquake occurrence across Italian municipalities). Our final sample includes 170 municipalities struck once by a destructive earthquake.[13] 57% of these municipalities are located in 4 regions: Emilia Romagna, Umbria, Marche and Abruzzo.

2.4.3 Preliminary evidence on electoral outcomes

Before analyzing electoral outcomes, it is worth to observe that mayors decision to run for reelection is not significantly related to earthquake occurrence, since it does not differ between municipalities struck by an earthquake between two electoral cycles and unaffected municipalities. The first line of Table 2.1 shows that the average probability of observing a mayor who decides to run for reelection is almost identical and not significantly different between the two groups of municipalities.[14] This suggests that the unconditional probability of reelection is not confounded by running decisions of incumbent mayors.

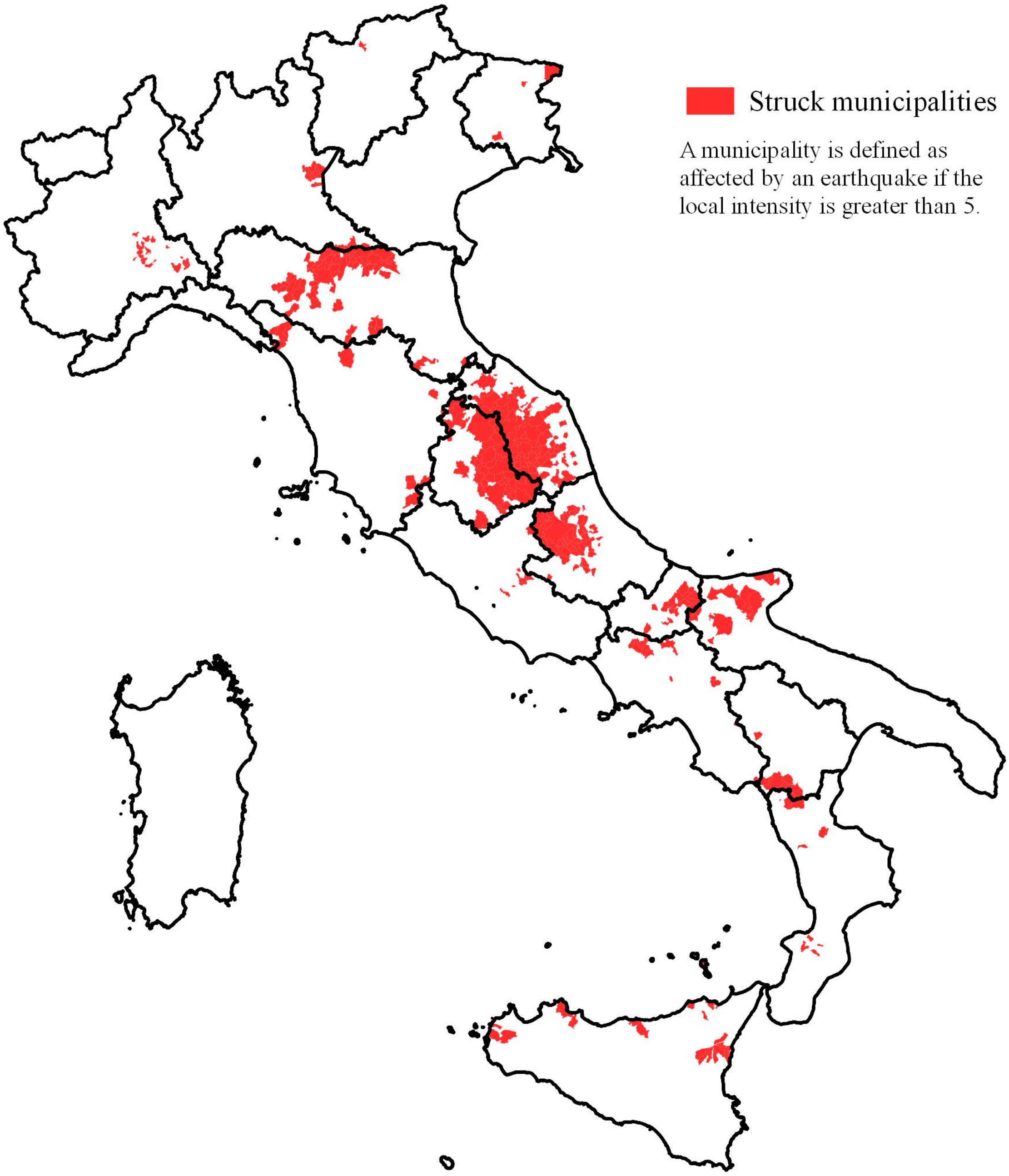
The remainder of Table 2.1 reports mean characteristics of municipalities struck between two electoral cycles (column 2) and unaffected municipalities (column 1). The reelection probability when an earthquake occurs is on average 7% higher, and the vote share grows by an additional 3.3% compared to unaffected municipalities between two electoral cycles. Results of t-tests on mean differences (reported with stars in column 2) show that differences are statistically significant for both variables.

Vote participation is not significantly affected by the occurrence of earthquakes, which suggests that shocks do not affect the willingness to express preferences for political representatives. Also, the number of candidates participating in elections is not significantly different when an earthquake occurs and decreases slightly less between two electoral cycles in municipalities struck by an earthquake. This suggests

[13] In the full sample, we observe 216 earthquake occurrences after which an incumbent mayor seeks for reelection. We drop 13 shocks because they occur in regions and provinces with special statute and 33 shocks because of missing data.

[14] To test mean differences, we use data from 29,901 municipal elections where an incumbent mayor has the possibility to decide whether or not to seek for reelection.

Figure 2.2: A map of earthquake occurrence in Italy (1993-2015)



Notes - The map represents municipalities struck by a destructive earthquake (with intensity >5) between 1993 and 2015. Red areas represent struck municipalities.
Source: Our elaboration on data from the DBMI15 database of INGV (Locati et al., 2016). The shape map of the administrative borders is provided by ISTAT.

Table 2.1: Descriptive statistics

	(1) No earthquake	(2) Earthquake
Runs for reelection (=1)	0.487	0.486
Reelected (= 1)	0.783	0.853**
Δ Vote share of the incumbent	1.869	5.169**
Vote participation (%)	76.47	76.86
Δ candidates	-0.114	-0.0118
Inumbent education years	14.40	14.25
Incumbent is man (=1)	0.926	0.918
Incumbent age	46.59	45.26**
Proportional electoral system (=1)	0.0827	0.100
Obs.	11796	170

Notes - The table reports mean characteristics of unaffected municipalities (column 1) and municipalities struck by a destructive earthquake (with intensity >5) between two electoral cycles (column 2). The reported statistics are related to municipal elections where a mayor runs for reelection (except for *Runs for reelection* which exploits the universe of municipal elections). Stars in column 2 indicate significance levels that result from one-side t-tests on mean differences between the two groups of municipalities. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

that earthquakes do not affect the decision to run for election by alternative candidates and, therefore, the electoral competition is apparently unchanged. Also characteristics of incumbent mayors are not significantly different between the two groups of municipalities, except for age, which is more than one year lower in struck municipalities on average. Finally, the two groups are composed of a non-significantly different share of municipalities with a proportional electoral system.

2.5 Methodology

2.5.1 Identification strategy

Although earthquake occurrence is random over time, the assignment of a municipality to the group of struck municipalities may not be random because of the heterogeneous exposure to earthquake risk due to the characteristics of the ground. This issue is amplified if we believe that risk preferences shape vote decisions and voters living in areas with high seismic risk have different risk preferences as compared to voters in low-risk areas. Moreover, we observe earthquake occurrence only in 170 of the 11,966 observations (1.4%). Therefore, comparing struck municipalities with the universe of unaffected municipalities may further confound the analysis due to heterogeneity among municipalities and among electoral cycles. To address these concerns, we build our identification strategy on a propensity score matching (PSM) method. This method allows us to reduce the unobserved heterogeneity between struck (*treatment group*) and unaffected municipalities (*control group*), and to identify the causal impact of earthquake occurrence on electoral outcomes (e.g. Caliendo & Kopeinig, 2008; J. J. Heckman, Ichimura, & Todd, 1997; Imbens, 2004; Rosenbaum & Rubin, 1983). The PSM approach addresses the sample selection bias to obtain a comparable counterfactual group of unaffected municipalities since the matching procedure identifies a sub-sample of unaffected municipalities that is identical to the treatment group, on average, and therefore achieves pseudo-randomization.

The average treatment effect of earthquake occurrence on electoral outcomes on the treated municipalities (ATT) is:

$$\tau_{ATT} = E[Y_1 - Y_0 \mid EQ = 1] = E[Y_1 \mid EQ = 1] - E[Y_0 \mid EQ = 1], \tag{2.1}$$

where Y_1 and Y_0 are measures of electoral outcomes (incumbent reelection or vote share) when an earthquake strikes and if it would not have occurred, respectively, and EQ assigns municipalities to the treatment group. The limitation of observational data is that we do not observe $E[Y_0 \mid EQ = 1]$. If we assume $E[Y_0 \mid EQ = 1] = E[Y_0 \mid EQ = 0]$, then:

$$\tau_{ATT} = E[Y_1 \mid EQ = 1] - E[Y_0 \mid EQ = 0]. \tag{2.2}$$

If the assignment to treatment is random, Equation 2.2 provides a consistent estimate of τ_{ATT}. Otherwise, as in our case, the consistent estimation of τ_{ATT} builds on the assumptions of unconfoundedness and common support. The first assumption requires that outcomes in control municipalities are independent of assignment to treatment conditional on observable characteristics of municipalities ($Y_0 \perp EQ \mid \mathbf{X}$). The second assumption requires that, conditional on observable characteristics, earthquake occurrence is not perfectly predictable ($P(EQ = 1 \mid \mathbf{X}) < 1$).[15]

[15]Note that the assumptions of unconfoundedness and common support presented here are valid only for the estimation of the ATT and are weaker than the assumptions that allow to consistently estimate the average treatment effect (ATE) (Caliendo & Kopeinig, 2008).

Since conditioning on a large set of covariates makes it difficult to identify suitable matches, Rosenbaum and Rubin (1983) suggest to use balancing scores. This scores can be defined as:

$$P(X) = P(EQ = 1 \mid \mathbf{X}) \tag{2.3}$$

with $\mathbf{X}$ being observable characteristics of municipalities predicting earthquake occurrence. $P(\mathbf{X})$ measures the probability that a municipality is assigned to the treatment group. If the assumption of unconfoundedness holds conditional on $\mathbf{X}$, it holds also conditional on $P(\mathbf{X})$ (Imbens, 2004). Therefore, we can reformulate the identifying assumption as:

$$E[Y_0 \mid EQ = 1, P(\mathbf{X})] = E[Y_0 \mid EQ = 0, P(\mathbf{X})] \tag{2.4}$$

and define the following matching estimator:

$$\tau_{ATT}^{PSM} = E[Y_1 \mid EQ = 1, P(\mathbf{X})] - E[Y_0 \mid EQ = 0, P(\mathbf{X})]. \tag{2.5}$$

Since we observe the vote share of an incumbent mayor both before (when he/she is elected for the first time) and after the occurrence of an earthquake (when he/she seeks for reelection), we also combine our matching approach with a difference-in-difference (DD) strategy to sharpen our identification strategy (J. Heckman, Ichimura, Smith, & Todd, 1998). This approach has the advantage that the assumption of unconfoundedness is relaxed because it is possible to account for unobserved factors. The identifying assumption is:

$$E[Y_{0,t} - Y_{0,t-1} \mid EQ = 1, P(\mathbf{X})] = E[Y_{0,t} - Y_{0,t-1} \mid EQ = 0, P(\mathbf{X})] \tag{2.6}$$

with $Y_{0,t}$ being the electoral outcome after the occurrence of treatment if treatment has not occurred, and $Y_{0,t-1}$ being the electoral outcome before treatment. Thus, the DD-PSM estimator can be written as:

$$\tau_{ATT}^{DD-PSM} = E[Y_{1,t} - Y_{0,t-1} \mid EQ = 1, P(\mathbf{X})] - E[Y_{0,t} - Y_{0,t-1} \mid EQ = 0, P(\mathbf{X})]. \tag{2.7}$$

In the following analysis, we will use the matching estimator in Equation 2.5 for both electoral outcomes, incumbent reelection and vote share, and the matching estimator in Equation 2.7 only for vote share.

2.5.2 Matching method

To estimate the propensity scores as described in Equation 2.3, we regress earthquake occurrence against a set of time-varying variables observed in the electoral period before earthquake occurrence and time-invariant variables using the following probit regression model:

$$PS_i = Pr[EQ_i = 1 \mid \mathbf{X}_i] = \Phi(\alpha + \mathbf{X}_i'\boldsymbol{\gamma}) \tag{2.8}$$

Time-varying variables include the election year and per capita local government expenditure, while time-invariant variables are the four seismic zones, defined by the Italian Institute of Geophysics and Volcanology (INGV), which classify municipalities according to the probability of facing earthquakes in the future (zone 1 = highest probability and zone 4 = lowest probability), and geo-institutional characteristics (mountain jurisdiction, coastal jurisdiction and geographic location).[16]

Various matching algorithms can be adopted to identify a comparison group for treated municipalities. In this paper, we use the radius matching (Dehejia & Wahba, 2002). This approach is described by the following expression:

$$PS_j^C \mid ||PS_i^{EQ} - PS_j^C|| < R \tag{2.9}$$

where PS_i^{EQ} and PS_j^C are the propensity scores of the treated municipality i and the comparison municipality j, respectively, and R is a radius (or caliper). In words, each treated municipality is matched with the unaffected municipalities with propensity scores falling within the specified radius R. Compared to other algorithms, such as nearest neighbor or kernel matching, the advantage of this procedure is that it allows to match treated municipalities with additional or less units when good or bad matches are available, respectively. Since our donor pool is large, we prefer this method because

[16]We also included political factors (e.g. incumbent vote share and political orientation, and electoral system) and some characteristics of incumbent mayors (e.g. age, education and gender) on the right-hand side of Equation 2.8, but the coefficients are not significant and increase the variance of the propensity scores. Moreover, political factors do not determine earthquake occurrence and do not significantly differ between treated and control municipalities even without matching, except for incumbent mayor age (see Section 2.4.3). However, after matching, we check the balancing properties of political and incumbent mayor characteristics.

it allows for oversampling but avoids the risk of including bad matches into the control group. The radius we use is $R = 0.001$.[17]

While the treatment group is composed of the 170 struck municipalities identified in Section 2.4.2, the donor pool is composed of the remaining *municipality* $\times$ *election* observations with some exceptions. We exclude observations of treated municipalities in electoral periods when no earthquake occurs to avoid that treated municipalities are matched with themselves. Moreover, we exclude municipalities struck by destructive earthquakes in periods without observations on electoral outcomes (i.e. when an incumbent mayor does not run for reelection) and municipalities struck by weak earthquakes (intensity equal to 5) because their inclusion may confound or dim our results due to temporal and spatial spillover effects, respectively. Hence, the donor pool is composed of 10,679 observations.

2.5.3 Estimation of the ATT

To estimate τ_{ATT}^{PSM} in Equation 2.5, we follow Hirano and Imbens (2001) and combine propensity score weighting and regression adjustment. The advantage of this approach is that propensity score weighting ensures that regressors are not correlated with earthquake occurrence and we can adjust the PSM estimator for outstanding bias if the matching is not exact. When the dependent variable is incumbent mayor reelection, we use the following probit regression model weighted by the reciprocal of the normalized propensity scores:[18]

$$p_i = Pr[Y_i = 1|EQ_i, \mathbf{X}_i] = \Phi(\alpha + \tau_{ATT}^{PSM} EQ_i + \mathbf{X}_i'\boldsymbol{\gamma}_1 + \mathbf{Z}_i'\boldsymbol{\gamma}_2) \tag{2.10}$$

where EQ_i is the treatment dummy variable, α is the intercept term, $\mathbf{X}_i'$ is the vector of variables used to predict propensity scores and $\mathbf{Z}_i'$ is a set of political characteristics (characteristics of incumbent mayor, political orientation of local government and electoral system). τ_{ATT}^{PSM} and the $\boldsymbol{\gamma}$s are the parameters to be estimated. Instead, when the dependent variable is incumbent vote share, we use the following OLS regression

[17] Note that preliminary findings using higher (e.g. $R = 0.01$) or lower calipers (e.g. $R = 0.0005$) provided results that are comparable to those presented in the remainder of the paper.

[18] Since weights do not necessarily add up to one, we normalize them to unity. Thus, each treated observation has a weight equal to one and the sum of weights of matched observations equals one.

model weighted by the reciprocal of the normalized propensity scores:

$$Y_i = \alpha + \tau_{ATT}^{PSM} EQ_i + \mathbf{X}_i'\boldsymbol{\gamma}_1 + \mathbf{Z}_i'\boldsymbol{\gamma}_2 + \varepsilon_i \tag{2.11}$$

where ε_i is an *iid* error term. The inclusion of regressors ($\mathbf{X}_i'$ and $\mathbf{Z}_i'$) allows us to adjust the estimates of the ATT for outstanding bias if the matching is inexact and to correlate political characteristics with electoral outcomes since PSM does not account for that. The drawback of this approach is that a parametric estimation of τ_{ATT}^{PSM} requires assumptions on the functional form, but this issue is offset by the fact that combining different approaches to estimate the ATT (matching and regressions adjustment) allows us to obtain a consistent estimate even if either the earthquake probability model (Equation 2.8) or the electoral outcome model (Equations 2.10 and 2.11) is not correctly specified (Imbens, 2004). We use robust standard errors to account for possible heteroskedasticity.

Then, we estimate the DD-PSM estimator using the following equation weighted by the reciprocal of the normalized propensity scores:

$$Y_{it} = \tau_{ATT}^{DD-PSM} EQ_i \times post_t + \delta\, post_t + \alpha_i + \mathbf{Z}_{it}'\boldsymbol{\gamma}_2 + \varepsilon_{it} \tag{2.12}$$

with $post_t$ being a dummy variable equal to 1 in the period after earthquake occurrence. Time-invariant differences between the treatment and control groups are absorbed by municipality fixed effects (α_i) and time-specific shocks common to both groups are absorbed by time-specific effects (δ). Moreover, municipality fixed effects adjust estimates for outstanding bias if the matching is not exact and absorb time-invariant political characteristics (i.e. $\mathbf{Z}_{it}'$ is composed of time-varying variables) and fixed unobserved characteristics.[19]

Before estimating Equations 2.10, 2.11 and 2.12, we verify that the treatment and matched control samples are balanced on covariates conditional on propensity scores, which ensures the independence between assignment to treatment and observed covariates. Moreover, we impose common support and drop observations that cannot

[19] Note that the $\mathbf{X}_i'$ are absorbed by municipality fixed effects because these variables are time-invariant. Moreover, we do not include time-varying variables used to predict propensity scores (e.g. local government expenditure) because they may be determined by earthquake occurrence and, thus, their inclusion risks to bias our estimates.

be matched to similar unaffected municipalities (Becker & Ichino, 2002).

To ensure that our estimates are independent from the selection of the radius matching algorithm, we repeat the matching using alternative algorithms. As the sample size grows, the matching estimator should yield the same estimates independently from the adopted matching algorithm because the estimates reach asymptotically the true value of τ_{ATT}^{PSM} (Smith, 2000). However, if the estimates vary with the adopted matching procedure, then it is necessary to disentangle the sources of the differences (Bryson, 2002). Then, we perform a set of placebo tests and assign treatment to alternative control groups where the treatment is expected to have no effect. If we find that the placebo treatment has a significant effect, then the assumption of unconfoundedness is not valid. Conversely, insignificant estimates of the ATT do not imply the validity of the unconfoundedness assumption, but the finding would increase the plausibility of validity (Imbens, 2004). Finally, we compare our results with the effects caused by other more predictable, and hence preventable, types of natural disasters (rainfall shocks) since we expect that the occurrence of these shocks may lead to negative effects on incumbent mayor reelection probability and vote share due to a lack of effort in preventive actions.

2.6 Results

2.6.1 PSM results

Using the procedure described in Section 2.5.2, we first performed a radius propensity score matching. In Table 2.2, we report probit regression results of earthquake occurrence probability using Equation 2.8. Except for per capital local government expenditure, all variables show significant coefficients. The three seismic-zone coefficients indicate that the probability of facing an earthquake is the lowest in the lowest risk zone 4 (the baseline). Moreover, seismic zones 1 and 2 show similar coefficients in magnitude and larger than the coefficient of zone 3. Mountain municipalities have a higher chance of facing an earthquake and coastal jurisdictions are less exposed to seismic risk because earthquakes mainly occur along the Appennine mountain range, i.e. in the hinterland of the country. Moreover, municipalities in the Center of Italy

Table 2.2: Probit regression model of earthquake occurrence probability

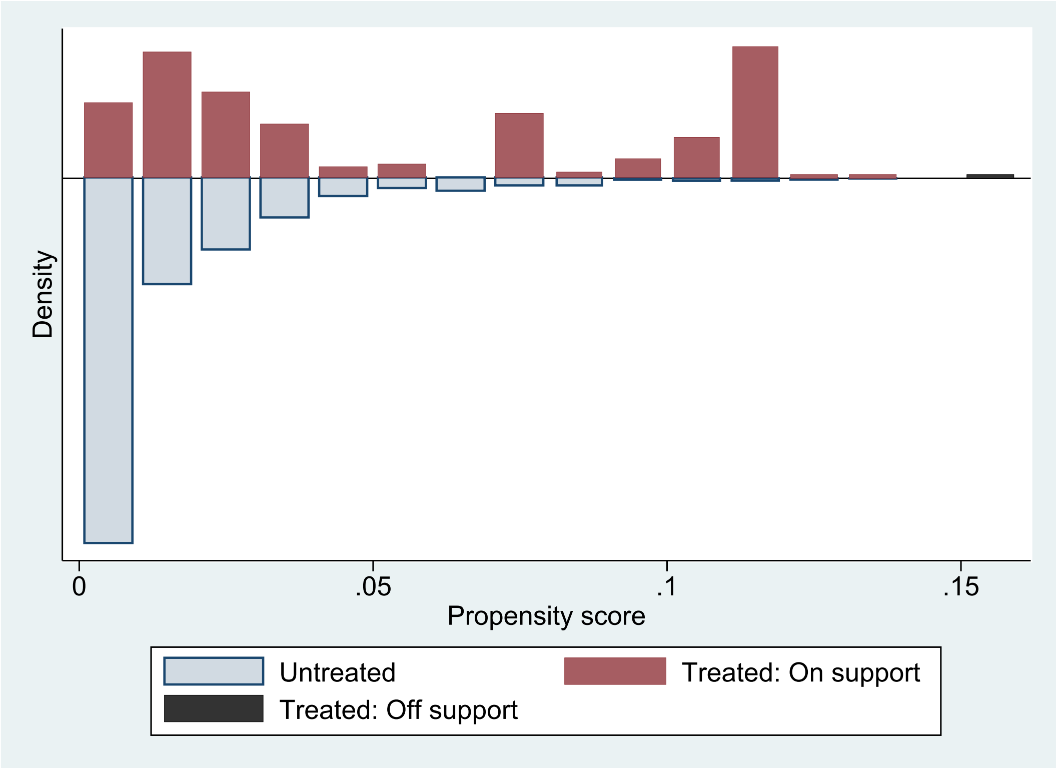
	(1)
Dependent variable	Earthquake
Election year$_{t-1}$	-0.0261***
	(0.00595)
Seismic zone 1	1.270***
	(0.194)
Seismic zone 2	1.287***
	(0.166)
Seismic zone 3	0.882***
	(0.152)
Mountain municipality	0.187**
	(0.0701)
Coastal municipality	-0.951**
	(0.329)
Center (=1)	0.288**
	(0.105)
South (=1)	-0.277*
	(0.117)
Per captia local government expenditure $_{t-1}$	0.0213
	(0.0114)
Obs.	10858
No. of treated	170
Pseudo R-sq.	0.163
Log-likelihood	-732.7

Notes - The table reports probit regression results of earthquake occurrence probability. The dependent variable is a dummy variable equal to 1 if a destructive earthquake occurred between two electoral cycles (between $t-1$ and t). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors are in parentheses.

have a higher probability of facing an earthquake than municipalities in the North, while the opposite happens for municipalities in the South.

Using the estimates in Table 2.2, we predict propensity scores and perform the matching. The radius matching algorithm is able to match 169 municipalities with 9,709 observations from the donor pool. One observation in the treatment group is off support because no comparable municipality can be identified. Figure 2.3 illustrates distributions of balanced propensity scores for treated municipalities (red/dark bars)

Figure 2.3: Balanced propensity scores



Notes - The figure represents the distribution of propensity scores obtained from a radius matching algorithm with caliper 0.001. Red/dark bars represent the distribution for treated municipalities (on support), and blue/light bars represent matched unaffected municipalities. The black bar represents the single treated municipality off support.
Source: Our elaboration on data provided by the Italian Ministry of the Interior.

and matched control municipalities (blue/light bars). The overlapping of the two distributions highlights that the common support assumption holds.

The balancing properties of covariates used to predict propensity scores before (U) and after matching (M) are reported in Panel A of Table 2.3. The matching procedure is effective in reducing bias between the treatment and the control group. Indeed, variables showing significant mean differences between treated and unaffected municipalities before the matching do not show significant differences after the matching.

Since the matching procedure does not account for political characteristics that determine electoral outcomes, we verify that the PSM does not introduce imbalance in these characteristics. Balancing properties for political characteristics (incumbent mayor vote share before earthquake occurrence and incumbent characteristics, political orientation of the local government, and electoral system) are reported in Panel B of Table 2.3. The means of all variables, except for incumbent mayor age, are not significantly different before the matching. After matching, all of the variables have

Table 2.3: Balancing properties

Variable	U/M	Treated	Control	% bias	t	p> |t|
Panel A: Predictors of earthquake occurrence						
Election year$_{t-1}$	U	2003.4	2005.6	-38.4	-4.87	0.000
	M	2003.4	2003.1	5.0	0.47	0.642
Seismic zone 1	U	.15294	.08963	19.4	2.85	0.004
	M	.15385	.12553	8.7	0.75	0.454
Seismic zone 2	U	.61765	.2457	80.9	11.15	0.000
	M	.61538	.59298	4.9	0.42	0.675
Seismic zone 3	U	.2	.21828	-4.5	-0.57	0.567
	M	.20118	.24911	-11.8	-1.05	0.293
Mountain municipality	U	.61176	.38716	46.0	5.96	0.000
	M	.60947	.59616	2.7	0.25	0.803
Coastal municipality	U	.00588	.06933	-33.8	-3.25	0.001
	M	.00592	.00828	-1.3	-0.26	0.797
Center (=1)	U	.46471	.11948	81.9	13.62	0.000
	M	.46154	.49534	-8.0	-0.62	0.535
South (=1)	U	.27647	.26609	2.3	0.30	0.761
	M	.27811	.23484	9.7	0.91	0.364
Per captia local government expenditure $_{t-1}$	U	1.8244	1.5285	19.6	2.27	0.023
	M	1.7681	1.5905	11.8	1.37	0.172
Panel B: Political characteristics						
Incumbent vote share$_{t-1}$	U	55.438	56.483	-7.5	-0.84	0.400
	M	55.415	55.341	0.5	0.05	0.958
Incumbent is man (=1)	U	.91765	.92496	-2.7	-0.36	0.720
	M	.92308	.94693	-8.8	-0.89	0.375
Incumbent age	U	45.259	46.727	-16.1	-1.99	0.046
	M	45.367	45.656	-3.2	-0.31	0.759
Inumbent education years	U	14.253	14.369	-3.2	-0.42	0.672
	M	14.231	14.603	-10.3	-0.97	0.334
Center-right local government	U	.10588	.12622	-6.3	-0.79	0.428
	M	.10651	.11352	-2.2	-0.21	0.837
Civic-list local government	U	.00588	.00281	4.7	0.75	0.456
	M	.00592	.00141	6.8	0.68	0.494
Proportional electoral system (=1)	U	.1	.08243	6.1	0.83	0.409
	M	.10059	.08364	5.9	0.54	0.591

Notes - Panel A reports balancing properties of covariates used to predict propensity scores using a radius PSM with caliper 0.001. Panel B reports balancing properties for political variables. *U* represents the full (unmatched) sample and *M* the matched sample of municipalities.

means that do not significantly differ between treated and control municipalities. In particular, note that the bias of incumbent mayor vote share slightly decreases after matching.[20] Therefore, the matching procedure does not affect or, if ever, reduces the bias in political characteristics.

2.6.2 Impact of earthquakes on electoral outcomes

Using the samples of treated and matched control observations and the predicted propensity scores, we estimate the ATT of incumbent mayor reelection probability and vote share, as from Equations 2.10, 2.11 and 2.12. The results are summarized in Table 2.4. Columns 1 and 2 report probit regression results of reelection probability (Equation 2.10).

In order to interpret the coefficients as percentage variations in reelection probability, we compute the marginal effects at the mean using the delta method for dummy treatment variables. Regression results of incumbent mayor vote share are reported in columns 3 and 4 for OLS regressions (Equation 2.11), and columns 5 and 6 for the DD strategy (Equation 2.12). Columns 1, 3 and 5 control only for earthquake occurrence, and columns 2 and 4 include the full set of variables used to predict treatment and political characteristics. Column 6 controls only for time-varying political characteristics. All regressions are weighted by the reciprocal of the normalized propensity scores.

All of the coefficients are positive and significant at the 5% level. Models controlling for the outstanding bias of inexact matching and political characteristics (columns 2, 4 and 6) provide coefficients similar in magnitude and significance, except for the DD model of vote share which provides identical results since municipality fixed effects account for most of the bias. Even if the bias is relatively small (0.16% for reelection probability and -0.16% for vote share), this correction further improves the accuracy of our estimates. Moreover, the explanatory power of the models increases with the inclusion of controls. In probit regression models, the pseudo R^2 is almost 6 times larger when covariates are included and the log-likelihood is lower in absolute value.

[20]Even if, for some of the variables, the bias is slightly larger after the matching, note that mean differences between the treatment and the control groups remain insignificant. Moreover, the empirical strategy takes into account outstanding bias for these variables (see Section 2.5.3).

Table 2.4: Regression results of electoral outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Incumbent reelection		Incumbent vote share			
Model	Probit (marginal effects)		OLS	OLS	DD	DD
Earthquake (× Post)	0.0705**	0.0689**	3.195**	3.211**	3.121**	3.121**
	(0.0340)	(0.0336)	(1.504)	(1.432)	(1.304)	(1.304)
Municipality fixed effects	No	No	No	No	Yes	Yes
Time fixed effects	No	No	No	No	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Obs.	9878	9878	9878	9878	19756	19756
(Pseudo) R-sq.	0.00876	0.0515	0.00873	0.109	0.631	0.633
Log-likelihood	-159.5	-152.7				

Notes - The table reports regression results of electoral outcomes weighted by the reciprocal of normalized propensity scores. Columns 1 and 2 report the marginal effects computed at the mean from probit regression results of incumbent mayor reelection probability. Columns 3 and 4 report OLS regression results of incumbent mayor vote share, and columns 5 and 6 report results using a difference-in-difference strategy. *Earthquake* is a dummy variable equal to 1 if a municipality was struck by an earthquake since the previous electoral period. In columns 5 and 6, *Earthquake* × *Post* is a dummy variable equal to 1 for struck municipalities in the electoral period after earthquake occurrence. Columns 2, 4 and 6 control for political variables (election year and electoral system), characteristic of the incumbent (education years, age and gender) and geo-institutional characteristics (seismic zones, mountain or coastal jurisdiction, and geographic location). Columns 5 and 6 further control for municipality and time fixed effects (post-earthquake electoral cycle). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors are in parentheses.

Similarly, the explained variance is more than 12 times larger when covariates are included in the vote share model. Clearly, the DD models have the largest explanatory power with about 63% of explained variance in both models with and without control variables since they account for municipality-specific time-invariant heterogeneity.

The results show that the occurrence of a destructive earthquake raises a mayor's probability of being reelected by 6.89%-7.05%. Moreover, the mayor's vote share increases by 3.12%-3.21%. Thus, earthquake occurrence raises both the incumbent mayor's chance of being reelected and his/her strength in the municipal council, *ceteris paribus*. This result is in contrast with Achen and Bartels (2017) who argue that incumbent politicians are punished at elections when disasters occur, but is in line with other studies showing that incumbent politicians gain support if the response to disasters meets voters expectations and needs (e.g. Gasper & Reeves, 2011; Healy & Malhotra, 2009). However, the results presented here do not allow to draw conclusions on the effectiveness of the response provided by incumbent mayors, an aspect that will be further investigated later in Section 2.7. Moreover, note that our results are somehow in line with Belloc et al. (2016) who find that earthquake occurrence in the Middle Ages provided support to religious authorities in place and delayed political transition. Clearly, fear of God is not a credible channel that could explain our results in modern societies where voters are generally aware that earthquakes are natural phenomena.

The results just discussed provide valid estimates of τ_{ATT} conditional on the assumptions of unconfoundedness and common support. However, while we showed that the assumption of common support is satisfied (see Section 2.6.1), the validity of unconfoundedness is worth of further investigation.[21] We provide some robustness checks in the following section.

[21] Note that repeating the analysis with the inclusion of the observation from the treatment group that is off support provides results that are almost identical to those presented in this section.

2.6.3 Robustness checks

Alternative matching algorithms

To test whether our results shown in Table 2.4 depend on the choice of the matching algorithm, we perform both nearest-neighbor and kernel matching. Then, for each procedure, we estimate Equations 2.10, 2.11 and 2.12 using the new control groups and propensity score weights.

We carry out kernel matching with bandwidth 0.01 and nearest-neighbor (NN) matching with 10 neighbors. With kernel matching, we are able to match 169 treated municipalities, and with NN matching all of the 170 treated municipalities. In the case of kernel matching, the control group is composed of 10,679 observations, while for NN matching the control group is composed of 1,037 observations.[22] As in our baseline approach, we impose common support and balancing properties are satisfying (see Tables B.1 and B.2 in the Appendix for kernel and NN matching, respectively).

The estimates of the ATT based on the kernel matching procedure show negligible differences relative to our baseline estimates for all of the models (see Table B.3, columns 1-3). When we base our estimates on NN matching, the resulting coefficients are slightly lower in magnitude and less significant. This is due to the fact that NN matching attaches the same weight to all matched control municipalities but the control group may include bad matches since no caliper is set to filter them out. Still, the results point into the same direction of our baseline results, but the radius and the kernel matching procedures are more precise in selecting and weighting control municipalities.

Placebo tests

We perform a set of placebo tests to assess whether our estimates are sensitive to unobserved confounding factors. We estimate the effect of the placebo treatment on electoral outcomes using Equation 2.10 for incumbent reelection probability and Equations 2.11 and 2.12 for incumbent vote share, respectively.

[22] The control group obtained from NN matching is not composed of 1,700 observations (170 treated $\times$ 10 neighbors) because matching occurs with replacement and, therefore, treated municipalities can share the neighbors. Weights account for the frequency with which a neighbor is matched with treated municipalities.

We run two tests. First, we assign treatment to election periods of treated municipalities when no earthquake occurs (i.e. before and after earthquake occurrence). This implies that we measure the impact of placebo shocks on electoral support for incumbent mayors who are different from those in charge when earthquakes strike, and in electoral periods taking place at least 5 years before or after earthquake occurrence. We do not find significant estimates for both incumbent reelection and vote share models (see Table B.4, columns 1-3, in the Appendix).[23]

Then, following J. J. Heckman et al. (1997), we assign treatment to an alternative sample of municipalities (not used in our baseline matching procedure) exposed to earthquake occurrence, but where earthquakes did not cause visible damages to humans, animals, buildings and objects, and, hence, treatment was not assigned. These municipalities are those hit with an intensity equal to 5 and represent 636 observations. Since the treatment group for this placebo test is composed of different municipalities, we repeat the matching procedure described in Section 2.5.2 to predict propensity scores and identify a new control group. We are able to match 630 treated municipalities with 8,284 observations from the donor pool. Also in this case, we do not find significant estimates in all of the models (see Table B.4, columns 4-6). This suggests that weak earthquakes are not sufficient to trigger a significant variation in electoral outcomes, which implies that our identification strategy is robust to unobserved confounders.

2.6.4 Other types of natural disasters

To further ensure the validity of the results presented in Section 2.6.2, we investigate the impact of more predictable types of natural disasters on incumbent mayor reelection and vote share. As compared to unpredictable earthquake shocks, we might expect to find the opposite effect because predictable disasters could have been prevented if elected officials would have operated efficiently. To this aim, we exploit extreme rainfall shocks and apply our identification strategy using a set of heavy pre-

[23] We aggregate elections taking place before earthquake occurrence with elections taking place afterwards because, before earthquake occurrence, we do not observe electoral periods in which an incumbent mayor runs for reelection for all of the treated municipalities, and vice versa. However, note that distinguishing between electoral periods before and after earthquake occurrence does not provide evidence of significant heterogeneous effects.

cipitation measures to identify the group of treated municipalities. Extreme rainfall increases the probability of flood and landslide occurrences (Gallego, 2018), and, as compared to earthquakes, these shocks are much more frequent, can be forecasted and are known to have a higher probability to occur in specific seasons, such as Autumn.[24]

Daily rainfall data for the period 1993-2015 are collected from the Global Summary of the Day (GSOD) database provided by the National Climatic Center. Since these data are available by weather station, we measure precipitation in municipality i on day d as follows:

$$Rain_{id} = \sum_k w_{ik} Rain_{kd} / \sum_k w_{ik} \tag{2.13}$$

with $Rain_{kd}$ being the daily precipitation registered in weather station k on day d, and w_{ik} being the inverse of the distance between the centroid of municipality i and weather station k. We consider weather stations that are located within a 40 km radius from a municipality's centroid. For municipalities that are located farther than 40 km from the closest weather station, we assign rainfall registered at the closest station.[25]

We use two measures of heavy precipitation to identify treated and unaffected municipalities. We assign treatment to a municipality if, at least once between two electoral periods, the daily precipitation, measured as mm of rain per m^2, exceeds 70 mm or the 95th percentile of the 1993-2015 municipality-specific rainfall distribution for three consecutive days or more.[26] Since heavy precipitation does not necessarily trigger floods or landslides, we also collected data from 168 municipalities declared as flooded between October 10th and 14th, 2014, in the North of Italy, and exploit this information to assign treatment.[27]. In particular, we assign treatment to the 86 municipalities where we observe an incumbent mayor running for reelection in the following electoral period. Although these data are very limited, they allow us to

[24] Although floods and landslides are frequent shocks occurring in Italy, there is no database collecting information on the location, timing and impact of these disasters. Therefore, heavy precipitation is the most adequate proxy for these types of shocks.

[25] Note, however, that we tried to exclude municipalities located farther than 40 km from the closest weather station from the sample and we obtained similar results to those presented later in this section.

[26] We use these two definitions of heavy precipitation because these are the most commonly adopted measures and there is not an agreement on which type of measure better captures these types of shocks (World Meteorological Organization, 2015).

[27] See the Ministerial Decree of the Italian Ministry of Economics and Finance of October 20th, 2014

verify that the impact of heavy precipitation and floods points into the same direction. Note that, when we use floods to assign treatment, we limit the donor pool to the only elections taking place between 2013 and 2015 in unaffected municipalities located in the same regions of the flooded municipalities in order to reduce systematic heterogeneity among regions and electoral periods affects our results.

According to the above definitions of rainfall and floods, we define two dummy variables equal to 1 if a municipality faced 3 consecutive days with daily precipitation above 70 mm or in the top 5th percentile of the municipality-specific rainfall distribution, and a dummy variable equal to 1 if a municipality was affected by a flood. Using the PSM approach, we are able to match 391 municipalities affected by heavy precipitation above 70 mm for at least three consecutive days, 1,325 municipalities affected by heavy precipitation exceeding the 95th percentile of the local rainfall distribution for at least three consecutive days, and 50 flooded municipalities with 11,573, 10,639 and 430 unaffected municipalities, respectively. Using these samples of treated and matched control observations and the predicted propensity scores, we estimate the ATT of incumbent mayor reelection probability and vote share, as from Equations 2.10, 2.11 and 2.12, using heavy precipitation and floods to identify treated municipalities. The results are summarized in Table 2.5. Panel A reports results using the dummy treatment variable based on rainfall levels. We find that heavy rain has a negative and unsignificant impact on both incumbent mayor reelection probability and vote share. The results are similar when using the dummy treatment variable based on the rainfall distribution (Panel B). Though not significantly, the reelection probability of incumbent mayors in treated municipalities results to be lower as compared to mayors in unaffected municipalities. Conversely, the OLS vote share model in column 2 shows a positive and not significant impact of rainfall shocks on incumbent vote share, but the more precise DD model in column 3 highlights a negative and not significant impact of heavy rain.

Panel C summarizes results using flooded municipalities as the treatment group. As for heavy rainfall, all models show that the electoral support for incumbent mayors in flooded municipalities decreases as compared to unaffected municipalities, but the effect is significant only in the OLS vote share model (column 2). Although this

Table 2.5: Impact of heavy rainfall on electoral outcomes

	(1)	(2)	(3)
Dependent variable	Reelection	Vote share	Vote share (DD)
Panel A: Rain ⩾70mm for 3 days			
Heavy rain (× Post)	-0.0145	-1.375	-1.081
	(0.0206)	(0.987)	(0.884)
Municipality fixed effects	No	No	Yes
Time fixed effects	No	No	Yes
Controls	Yes	Yes	Yes
Obs.	10794	10794	21588
(Pseudo) R-sq.	0.0347	0.108	0.717
Log-likelihood	-352.3		
Panel B: Rain ⩾95th percentile for 3 days			
Heavy rain	-0.00993	0.592	-0.315
	(0.0119)	(0.581)	(0.566)
Municipality fixed effects	No	No	Yes
Time fixed effects	No	No	Yes
Controls	Yes	Yes	Yes
Obs.	10579	10579	21158
(Pseudo) R-sq.	0.0491	0.121	0.599
Log-likelihood	-1233.5		
Panel C: Municipalities flooded in October, 2014			
Flood (× Post)	-0.0114	-6.855**	-4.683
	(0.0626)	(3.250)	(3.357)
Municipality fixed effects	No	No	Yes
Time fixed effects	No	No	Yes
Controls	Yes	Yes	Yes
Obs.	230	230	460
(Pseudo) R-sq.	0.254	0.226	0.697
Log-likelihood	-38.65		

Notes - The table reports regression results of electoral outcomes weighted by the reciprocal of normalized propensity scores using heavy rainfall to assign treatment. In Panel A, treatment is assigned if, at least once between two electoral periods, daily rainfall exceeded 70 mm for three consecutive days or more. In Panel B, treatment is assigned if, at least once between two electoral periods, daily rainfall exceeded the 95th percentile of the 1993-2015 municipality-specific rainfall distribution for three consecutive days or more. In Panel C, the sample is limited to elections taking place between 2013 and 2015 and to regions where at least one municipality was flooded between October 10th and 14th, 2014, and treatment is assigned to the flooded municipalities. Column 1 reports marginal effects computed at the mean from probit regression results of incumbent mayor reelection probability. Column 2 reports OLS regression results of incumbent mayor vote share, and column 3 reports results using a difference-in-difference strategy. In columns 1 and 2, the variables *Heavy rain* and *Flood* are dummy variables equal to 1 if a municipality is affected by a heavy rain shock or a flood, respectively. In column 3, the variables *Heavy rain* × *Post* and *Flood* × *Post* are dummy variables equal to 1 if a municipality is affected by by a heavy rain shock or a flood, respectively, in the electoral period after the occurrence of the shock. All models control for political variables (election year and electoral system), characteristic of the incumbent (education years, age and gender) and geo-institutional characteristics (mountain or coastal jurisdiction, and geographic location). Column 3 further controls for municipality and time fixed effects (post-earthquake electoral cycle). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered by municipality are in parentheses.

identification strategy has strong limitations because it assumes that no other floods occurred over the considered period, it provides support for the identification strategy based on heavy rainfall shocks since the results point into the same direction.

These results suggest that heavy rain does not significantly affect electoral outcomes, but if there is any effect, it is negative. The opposite effect of rainfall shocks on incumbent mayor reelection and vote share as compared to the impact of earthquakes presented in Section 2.6.2 may be explained by the fact that the former type of shocks are easier to prevent thanks to weather forecasting. For this reason, voters may blame incumbent politicians at elections for heavy rainfall because they under-invested in prevention against disasters triggered by heavy precipitation. Symmetrically, the electorate may increase the support for incumbent mayors when an earthquake strikes if the response to disaster damages is evaluated as sufficiently adequate because the occurrence of these shocks are much more difficult to predict. We further address this aspect in Section 2.7.

2.7 Channels driving vote decision

2.7.1 Post-disaster relief and incumbent mayor performance

A channel that may explain the change in electoral outcomes following the occurrence of an earthquake is politicians' ability to recover from earthquake damages through the use of additional public resources. Previous studies argue that public financial windfalls from the central government increase the support for the incumbent party in national elections (Bechtel & Hainmueller, 2011; Healy & Malhotra, 2009), and voters are able to identify how incumbent politicians perform in recovering from disasters (Gasper & Reeves, 2011). This suggests that incumbent mayors may benefit from an effective response to disaster occurrence.

Since performance indicators for local politicians are not available, to investigate this channel we follow Gagliarducci and Nannicini (2013) and exploit balance sheet data to build performance measures. Indeed, pre-electoral expenditure could signal incumbent politicians' ability to expand the availability of public goods (Rogoff, 1990; Rogoff & Sibert, 1988). We investigate how per capita expenditure, transfers from regional and central governments, deficit (the difference between per capita expenditure and revenues), tax revenues, and the ratio between budget allocation to investments (capital expenditure) and goods and services (current expenditure) observed in the year before elections vary following earthquake occurrence.[28] Moreover, we also investigate variations in personal income as a proxy for local economic growth. We express all monetary values in real values at 2010 prices. For each variable, we apply the DD strategy described in Section 2.5.3 (Equation 2.12, excluding controls Z'_{it}) to estimate the impact of earthquake occurrence.

The results are summarized in Table 2.6. Incumbent mayors provide a remarkable response to earthquake occurrence since the expenditure significantly increases by 740 Euro per capita (column 1). This is not unexpected since governments in developed countries generally provide aid to disaster areas (Noy & Nualsri, 2011). The additional resources spent by local governments are allocated to investments, which grow significantly by almost 22% more than expenditure on other services and goods (column 2). The sharp increase in spending levels is driven by the intervention of upper-tier governments that significantly increase transfers to municipalities struck by earthquakes by 1,140 Euro per capita (column 3). Conversely, deficit significantly decreases by 449.2 Euro per capita (column 4). This variation is the result of the partial use of additional transfers for disaster relief since it roughly corresponds to the gap between the increase in expenditure and transfers (403.4 Euro per individual). Finally, tax revenues slightly decrease (column 5) and personal income slightly increases (column 6), although neither of these two variations is significant.

These results suggest that, on average, incumbent mayor performance in recovering from earthquake damages is positively welcomed by the population. Incumbent mayors expand spending levels and foster investments to reconstruct damaged infrastructures (e.g. streets and public buildings), to allow local economic activities to start operating again without laying the burden of reconstruction on voters' fiscal contributions. As shown by Gasper and Reeves (2011), voters appear to be able to assess

[28]Since data for expenditure components, transfers and tax revenues are available only for the period 1998-2015 (see Section 2.4), we exclude observations for 3962 elections, including 99 treated observations, to improve comparability across the results presented here. Note, however, that the baseline estimates of the impact of earthquake occurrence on electoral outcomes presented in Table 2.4 hold also using this sub-sample of observations.

Table 2.6: Incumbent mayor fiscal performance after an earthquake

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Expenditure	Inv./Cur.	Transfers	Deficit	Tax revenues	Personal income
Earthquake × Post	736.9***	0.218***	1140.3***	-449.2***	-31.48	117.6
	(155.3)	(0.0799)	(223.3)	(151.3)	(26.36)	(131.9)
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	12616	12616	12616	12616	12616	11582
R-sq.	0.832	0.637	0.667	0.481	0.860	0.974

Notes - The table reports regression results from a DD strategy applied on a set of incumbent mayor performance indicators. Performance indicators are per capita local government expenditure, the ratio between investments and current expenditure, per capita transfers and deficit (expenditure - revenues), tax revenues and personal income. *Earthquake × Post* is a dummy variable equal to 1 for struck municipalities in the electoral period after earthquake occurrence. All models control for municipality and time fixed effects (post-earthquake electoral cycle). Monetary values are expressed in 2010 prices. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors are in parentheses.

the performance of incumbent mayors who respond to earthquake occurrence limiting voters' wealth losses (no variation in personal income). Moreover, the electorate rewards improved fiscal performance (lower deficit) which is achieved despite disaster occurrence (Brender & Drazen, 2008). Thus, voters do not express their frustration at elections as suggested by Achen and Bartels (2017), but rather express their gratitude to well-performing politicians.

Clearly, incumbents are not accountable for the increase in resources available for recovery, since these resources are decided by upper-tier governments, while local governments are subject to substantial budget constraints. Nevertheless, mayors are accountable for the use of these additional resources and our results suggest that incumbent mayors are rewarded for appropriate responses to natural disasters.

A concern that may arise from the evidence above is that voters may act under bounded rationality since they do not have access to complete information on the fiscal performance of local governments. If this is the case, then voters may reward incumbents just for providing a response which is actually driven by upper-tier government transfers. However, we may also argue that, due to the mediatic exposure of earthquake occurrence (see the next Section 2.7.2), voters are aware that upper-tier governments intervene by means of earthquake-specific transfers and are informed on the response provided by incumbent mayors. Moreover, voters are also likely to observe the response of incumbent mayors who favor expenditure on investments at the expense of other goods and services, and the former spending component is characterized by a higher visibility as compared to the latter (Drazen & Eslava, 2010; Kneebone & McKenzie, 2001).

2.7.2 Political visibility

Natural disasters receive extensive media coverage immediately after the events. Detailed information is provided on their impact in terms of damages, consequences for individuals, the reaction of local administrators and the response of upper-tier governments. Both local politicians and representatives in upper-tier governments are frequently cited and interviewed by the media. Therefore, catastrophic events increase the visibility of local politicians allowing them, either opportunistically or not, to send signals to the electorate, mostly in terms of reassurance and promises of fast recovery. The higher visibility on the media of incumbent politicians as with respect to the potential competitors may provide another possible explanation for the observed relationship between earthquake events and reelections. Therefore, to what extent the higher visibility of incumbent politicians in earthquake areas affects electoral outcomes is worth to be explored.

To this aim, we adapt the search strategy used by Giommoni (2017) and measure political visibility using frequencies of news reporting the name of incumbent mayors geolocalized in the ruling municipality and released while they were in charge. Our search strategy is applied on the *Factiva* database, a research tool that provides access to news from all over the world. We limit the collection of information from the main Italian press agency (*ANSA*), though, along with *ANSA*, several other Italian local and national news providers are accessible. This is because *ANSA* covers information over the entire country and for the longest period (since 2001). Indeed, data from the second most frequent newspaper sources, *Corriere della Sera* and *Il Sole 24 Ore*, are available since 2005 for about 2,500 observations and only 25 of them belong to the treatment group. Since our access is limited to news released after 2001, we exclude electoral cycles before that year or overlapping with it. To control for media exposure of political competitors, we apply a similar search strategy and build a competitor visibility measure using frequencies of news relative to the main challenger (most mentioned competitor).[29] We collected news frequencies for 4,663 elections, but for 1,965 elections we did not find any news mentioning the incumbent or the competing politicians. Therefore, we treat news frequencies for these observations as missing values.[30] Moreover, since news frequencies on incumbent mayors in very large municipalities reach several thousand units and largely exceed both the mean and median news frequencies, we drop 30 observations in the highest percentile of the incumbent news frequency distribution to avoid that outliers confound our results. Hence, the sub-sample of electoral runs that we use to analyze the relationship between elec-

[29]Other measures of competitor's visibility, such as the average news frequencies of all competitors, can be used. However, the share of news issued on the incumbent and the main challenger is on average 96.85% of the total news issued on candidates, suggesting that the remaining candidates have a marginal role in the electoral run.

[30]Note, however, that including elections with news frequency equal to 0 would provide results that are very similar to those presented later in this section.

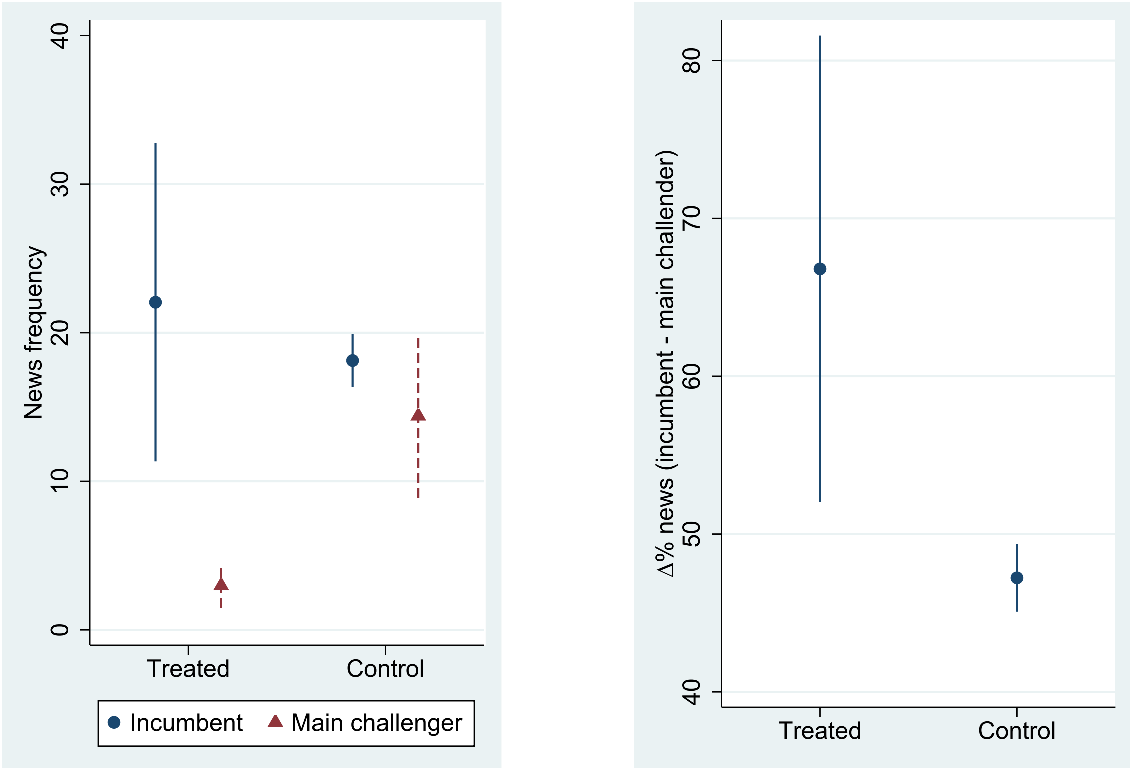
toral outcomes, earthquakes and politician visibility on media is composed of 2,668 observations, 41 of which compose the treatment group.

As a result of our search, we find 18.19 and 14.22 press-agency news on average per municipality on incumbent mayors and main challengers, respectively. The proportion of news on incumbents on total news exceeds the proportion of news on the main challenger by about 67% in municipalities treated by an earthquake, whereas the same difference in control municipalities, weighted by the reciprocal of normalized propensity scores, is significantly lower and equal to 47% (see Figure 2.4b). The different distribution of news in treated municipalities is determined by a sharp and significant increase of news on the incumbent relative to the main challenger (19.07 news on average), while the gap between incumbent and challenging politician visibility in control municipalities is much lower and not significant (3.73 news on average; see Figure 2.4a). These figures suggest that, after the occurrence of an earthquake, the incumbent mayor may benefit not only from a higher visibility on the media, but also from a higher visibility relative to his main challenger, in accordance with the many studies showing that media coverage can influence citizens' opinion about politicians and parties (e.g. Arceneaux, Johnson, & Murphy, 2012; Druckman & Parkin, 2005; Ladd & Lenz, 2009).

To further investigate the channel of political visibility, we include the measure of media exposure and its interaction with earthquake occurrence in our regression models of electoral outcome. In particular, we estimate Equations 2.10 and 2.11 for incumbent mayor reelection and vote share, respectively, and control for the natural logarithm of the frequency of news on the incumbent mayor and for the natural logarithm of the frequency of news on the main competing candidate.[31] The regression results are reported in Table 2.7. Likely, the limited number of observations in the treatment group undermines the consistent estimation of the impact of earthquakes on vote shares, leading to different size and significance of the coefficient of earthquake occurrence (columns 1 and 3) as compared to previous results (Table 2.4). However, higher incumbent news frequency raises both the probability of being reelected (col-

[31] We do not re-estimate the DD model in Equation 2.12 because the measure of media exposure is time-invariant for the sub-sample for which we were able to collect data and, therefore, is collinear with municipality fixed effects.

Figure 2.4: Political visibility



(a) News frequency (b) Share of news

Notes - The figures illustrate mean frequencies of news (Figure 2.4a) and the share relative to total news on politicians with 90% confidence intervals. In Figure 2.4a, blue circles represent news on incumbent mayors and red triangles news on main competing candidates over an electoral cycle. Markers denoted by *Treated* represent municipalities struck by a destructive earthquake (with intensity >5) between two elections and markers denoted by *Control* refer to matched unaffected municipalities identified with radius PSM and weighted by the reciprocal of normalized propensity scores. *Source:* Our elaboration on data collected from the *Factiva* database.

umn 1) and the vote share (column 3). Symmetrically, the higher the media coverage of the main challenger, the lower is the incumbent mayor reelection probability and the vote share.

In columns 2 and 4, we include the interaction term between earthquake occurrence and news frequency of the incumbent. The results show that the estimated coefficient of the interaction term is positive suggesting that incumbent mayors in struck municipalities benefit more from higher media visibility. Although the estimated coefficient is significant only in the vote share model (column 4), the coefficient of earthquake occurrence loses magnitude in all models and significance in the reelection probability model (column 2), which indicates that incumbent mayors in struck municipalities gain electoral support through higher media visibility. Voters are now more responsive to signals of reassurance and quick recovery, which drives preferences towards a re-

Table 2.7: Regression results of electoral outcomes and incumbent mayor visibility on media

	(1)	(2)	(3)	(4)
Dependent variable	Incumbent reelection		Incumbent vote share	
Model	Probit (marginal effects)		OLS	OLS
Earthquake (Eq.)	0.122**	0.00300	1.814	-4.144
	(0.0595)	(0.134)	(1.921)	(3.637)
Eq. $\times$ News on incumbent		0.0804		2.767**
		(0.0642)		(1.291)
News on incumbent	0.0365***	0.0357***	1.266***	1.220***
	(0.00848)	(0.00851)	(0.296)	(0.298)
News on main challenger	-0.0321***	-0.0320***	-2.153***	-2.152***
	(0.00814)	(0.00813)	(0.295)	(0.295)
Controls	Yes	Yes	Yes	Yes
Obs.	2688	2688	2688	2688
(Pseudo) R-sq.	0.0662	0.0666	0.154	0.155
Log-likelihood	-1482.4	-1481.9		

Notes - The table reports regression results of electoral outcomes weighted by the reciprocal of normalized propensity scores. Columns 1 and 2 report the marginal effects computed at the mean from probit regression results of incumbent mayor reelection probability. Columns 3 and 4 report OLS regression results of incumbent mayor vote share. *Earthquake* is a dummy variable equal to 1 if a municipality was struck by an earthquake since the previous electoral period. *News on incumbent* is the natural logarithm of the frequency of news on the incumbent mayor, and *News on main challenger* is the natural logarithm of the frequency of news on the main competing politician. All models control for political variables (election year and electoral system), characteristic of the incumbent (education years, age and gender) and geo-institutional characteristics (seismic zones, mountain or coastal jurisdiction, and geographic location). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors are in parentheses.

warding vote for the incumbent. This result points at the prediction of the theoretical model that a positive signal sent by the incumbent (visibility) when an earthquake occurs increases incumbent chances of winning the electoral competition (see Section 2.3).

While DellaVigna and Kaplan (2007) and Clinton and Enamorado (2014) find that media can bias voters towards a specific party coalition, our evidence suggests that media bias voters towards politicians under the spotlight because of natural disasters, namely incumbent mayors. Although visibility on the media is also a channel through which voters get informed on politician performance, i.e. the response to earthquake occurrence, and some performance indicators (e.g. expenditure following disasters) seem to improve as shown in Section 2.7.1, we cannot exclude that other factors, such as the opportunistic behavior of incumbent mayors who seek media exposure for reelection, also play a relevant role in shaping vote choices after the occurrence of an earthquake.

2.8 Conclusions

The occurrence of climate shocks such as natural disasters requires politicians to provide effective responses to recover from damages, which may disclose information on their competence. It has been suggested that the occurrence of natural disasters and the response provided by national-level governments affect vote decisions (e.g. Eriksson, 2016; Gasper & Reeves, 2011). However, the implications of natural disasters on vote decisions at local level and the investigation of possible channels driving these votes have received little attention in the literature so far.

We exploit a rich and unique dataset of all seismic events occurred between 1993 and 2015 in Italy and data on municipal electoral outcomes from 11,966 municipal electoral cycles where incumbent mayors seek reelection. We compare electoral outcomes in municipalities struck by an earthquake before the election with unaffected municipalities using propensity score matching combined with regression adjustment and a difference-in-difference strategy. We find that the occurrence of an earthquake increases incumbent mayor reelection probability by about 7% and vote share by more than 3%.

Two possible channels may help to explain our result. First, we find that reelection is associated with a better performance of incumbent politicians who increase spending levels and investments to recover from damages, and are able to reduce deficit without apparently affecting the wealth of local population. This may suggests that voters rationally update their expectations on incumbent mayor performance and competence based on signals sent by politicians to the electorate (Ashworth et al., 2018). Second, incumbent politicians appear to benefit from a higher visibility on the media, both in terms of news frequency and relative to their competitors. Although this may allow incumbent mayors to inform the electorate about the implemented measures to foster recovery from earthquake damages, the post-disaster disproportion between news covering incumbent mayors as compared to their competing challengers suggests that voters' decisions may be biased in favor of incumbent politicians (Clinton & Enamorado, 2014; DellaVigna & Kaplan, 2007). Indeed, higher political visibility may just naturally arise from the mediatic relevance of earthquake occurrence. Future research on the role of media in shaping vote decisions in the aftermath of natural disasters would help to better understand the drivers of vote decisions.

The identification strategy used in this essay allows to reach high levels of internal validity since we are using a matching approach that allows to reduce unobserved heterogeneity between treated and control municipalities. In particular, we are able to reduce heterogeneity determined by the different ex-ante probability of facing an earthquake in the near future among municipalities controlling for seismic zones. However, the availability of this information also determines a limitation of this study since it likely causes a selection effect that undermines the external validity of our results. Indeed, risk averse voters may prefer to live in or relocate to municipalities classified as low-seismic-risk zones in order to mitigate the exposure to earthquake risk. In this case, the distribution of voters' risk preferences may not be random and, therefore, our results may not apply to other areas where the selection effect does not occur because information on seismic zones is not available to the public. An argument that favors the external validity of our results is that we are using data for the period 1993-2015, but information on seismic zones in Italy were disclosed in 2004, which implies that our results are the outcome of both pre- and post-disclosure vote choices. However, we cannot exclude that, before 2004, voters chose were to live based on their perception of seismic risk built on the history of seismic shocks across the country.

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Essay 3

Does social expenditure mitigate the impact of environmental shocks on health?

3.1 Introduction

Growing health care expenditure is a phenomenon with which many countries need to deal with because of the large share relative to countries' GDP (about 8% on average in the EU and 17.15% in the US in 2017). To this trend contribute the adverse effects of extreme temperatures on health which are known to affect especially the youngest and oldest population. Given that population is aging fast and climate is changing, diseases caused by extreme temperatures will likely grow. Therefore, less expensive alternative services to health care deserve further investigation to reduce health care utilization and adverse health outcomes when weather shocks occur. Public social expenditure for the provision of services and subsidies targeted to the poor and needing population may be a relevant source to foster the use of social care services which allow to reduce the inefficient health care services utilization by individuals who require institutional care but cannot afford it (Costa-Font, Courbage, & Swartz, 2015) or do not get access because the poor coordination between institutions limits the availability of these services (Bodenheimer, 2008; Hofmarcher, Oxley, & Rusticelli, 2007). Therefore, these alternative services would allow to mitigate weather-related health effects and health care utilization by monitoring the most vulnerable age groups and taking care of them at home or in dedicated institutes (e.g. nursing homes and kindergartens). Indeed, low levels of autonomy and isolation are among the major risk factors when extreme temperature shocks occur, especially among the elderly (Brücker, 2005), and social services aim to provide support to people in poor living conditions. However, whether public expenditure on social services allows to reduce health care service utilization and improve health outcomes is an under-investigated topic.

In this paper, we investigate if public social expenditure mitigates the impact of extreme temperature shocks on health. To this aim, we use monthly data on mortality for the period 2003-2015 and on hospital admissions for cardiovascular and respiratory diseases for the period 2001-2015 from Italian municipalities, and data on average daily temperatures by weather station. In particular, we focus on emergency hospital admissions since heat- and cold-related shocks are expected to have immediate effects on health, and on young children (0-5 years) and the elderly population (over 75 years) since individuals in these age groups are those most vulnerable to weather shocks and among the main consumers of social care. Our empirical strategy follows two steps. First, we identify the effect of temperature shocks on mortality rates and emergency hospital admission rates and for cardiovascular diseases of the elderly using flexible temperature bin OLS regression models that control for population age structure (only in the mortality model), personal income, precipitation, pollution, province-specific time trends, and municipality, $month \times year$ and $province \times month$ fixed effects. We compare the performance of two different measures of temperatures, one based on levels and the other based on deviations from municipality-specific mean temperatures. Then, we investigate the mitigating effect of social expenditure on weather-related mortality and hospital admission surges by comparing the effect of extreme temperatures among groups of municipalities identified by quintiles of the year-specific distribution of per capita local government social expenditure lagged by on year.

Our findings suggest that temperature measures based on deviations from municipality-specific mean temperatures are more effective in capturing the adverse effects of temperature shocks on health outcomes than measures based on temperature levels because the former measure allows to account for heterogeneity in local resilience to climate and offsetting behaviors. Using our preferred temperature measures, we find that extremely hot days increase mortality rates, and both extremely hot and cold days cause surges in emergency hospital admission rates for respiratory diseases in both the youngest and oldest age groups, and in emergency hospital admission rates for cardiovascular diseases of the elderly. Moreover, we find evidence of a mitigating effect of social expenditure on the impact of extremely hot and cold days on both emergency hospital admission and mortality rates, with the effect on the latter outcome being driven by the reduced short-run temporal displacement of death. Moreover, we find that social expenditure tends to mitigate the adverse effects of extreme temperatures on emergency hospital admissions of children and of the elderly, but we do not find this effect for mortality.

Temperature peaks have mainly effects on the cardiovascular and the respiratory systems since they are more stressed during hot periods leading to diseases such as stroke, myocardial infarction, hypothermia and pneumonia (Basu & Samet, 2002). Cold temperatures increase respiratory diseases due to the reduced resistance of the immune system to infections, and cardiovascular diseases, such as ischaemic heart and cerebrovascular diseases, due to the higher risk of thrombosis and other cold-driven cardiovascular reflexes (The Eurowinter Group, 1997). Children, in particular those aged 5 years or less, and elderly are more vulnerable to extreme weather conditions because their body temperature regulation is less responsive as compared to adults, and they are more likely to depend on others for the regulation of environmental temperature levels (Basagaña et al., 2011; Basu & Ostro, 2008; Kenney & Hodgson, 1987; Shea, 2007). However, while literature provides evidence of heat-related surges in hospital admission and mortality rates, the effect of cold temperatures on these health outcomes is still inconclusive (Karlsson & Ziebarth, 2018).

Economic literature analyzed the impact of temperature shocks on a variety of aspects, including health.[1] Deschênes and Moretti (2009) and Deschênes and Greenstone (2011) find that average daily temperatures above 80°F or below 30°F increase mortality rates in the US. Other studies show that long-run exposure to high or cold temperatures makes population resilient against weather conditions and reduces mor-

[1]See Dell, Jones, and Olken (2014) for a review of the studies on and the methodologies to analyze the impact of climatic shocks on economics aspects.

tality rates with the effect of hot temperatures being mitigated mainly by the adoption of air conditioning systems (Barreca, Clay, Deschênes, Greenstone, & Shapiro, 2015; Barreca, Clay, Deschenes, Greenstone, & Shapiro, 2016), although outdoor workers are still exposed to a higher risk of facing heat-related diseases (Dillender, 2019).

Conversely, evidence relating the supply of social services to health outcomes and health care services utilization is spurious. Of relevance is the recent finding by Costa-Font, Jimenez-Martin, and Vilaplana (2018) who exploit a policy on the introduction of social care subsidies in Spain to show that hospital care utilization and costs decrease because replaced by cheaper social care services. Other studies show that social expenditure has both a direct effect on health thanks to an easier access to health care services and prevention (Bradley, Elkins, Herrin, & Elbel, 2011; Olsen & Dahl, 2007; Stuckler, Basu, & McKee, 2010; Vavken, Pagenstert, Grimm, & Dorotka, 2012), and an indirect effect through the positive association between spending and socioeconomic status (Dahl & van der Wel, 2013; Gesthuizen, Huijts, & Kraaykamp, 2012), but results are inconclusive since some studies do not find a significant relationship between social expenditure and health outcomes (Dunn, Burgess, & Ross, 2005; Ko et al., 2013). However, these studies do not address endogeneity of social expenditure and whether it mitigates the use of hospital care and, more in general, health care services.

Our contribution to the literature is threefold. First, we extend the knowledge on the impact of temperature shocks on health outcomes using, for the first time, the universe of deaths and hospital admissions for cardiovascular and respiratory diseases in Italy.[2] Second, we provide a discussion on different measures of exposure to temperatures to assess adverse effects on health. Third, we shed light on the role of social expenditure in mitigating adverse health outcomes and hospital care utilization in Italy. emergency hospital admissions among children and elderly in Italy.

The remainder of the essay is structured as follows. Section 3.2 describes the hospital care system and the role of social expenditure in Italy. Section 3.3 describes the data used in this study and how temperature shocks are measured. Section 3.4 presents the identification strategy and Section 3.5 presents the results of the impact

[2]Previous studies using data from Italy use data from single hospitals or health agencies (e.g. Morabito et al., 2005).

of temperature shocks on health outcomes. Section 3.6 analyzes the mitigating effect of social expenditure on surges in mortality and hospital admissions when temperature shocks occur, and Section 3.7 concludes.

3.2 Institutional setting

3.2.1 Hospital care in Italy

The Italian National Health Service (NHS) was established in 1978 and the principles on which it builds are universal coverage, solidarity and human dignity.[3] The NHS is subdivided into regional health services (RHSs) which are responsible for the local provision of health care services. The NHS, together with the central government, establishes the essential benefit package that RHSs need to deliver and provides financial resources to fund the provision of the services. Both elective and emergency hospital care is included in the essential benefit package.

In 2015, 1,914 hospitals operated in Italy with a total of 217,180 beds. Hospital care is generally provided for free or in exchange of limited out-of-pocket contributions in order to mitigate inefficient hospital utilization. Waiting lists serve as a tool to match scarce supply with the excess of demand for elective hospital admissions generated by free access to hospital services and are based on medical necessity.

Conversely, emergencies are treated in emergency wards that are organized across the country according to a hub-and-spoke model. Residents can access emergency wards across the entire country for free when in need.[4] The order in which patients are treated in emergency wards is related to the severity of the illness, with the more severe cases having the highest priority over less urgent cases. If the emergency does not allow the sick person to reach the emergency ward, an emergency call center can be contacted for free and the Italian Red Cross reaches the sick individual, provides first aid and transports him/her to the closest hospital.[5]

[3] Law 833/1978.

[4] Some regions, such as Trentino Alto Adige and Lombardia, adopt a co-payment system (*ticket*) for non urgent illnesses as a deterrent for over-utilization of emergency wards.

[5] The Italian Red Cross is a charitable organization born in the 19$^{\text{th}}$ century with the aim to support the sick and war refugees.

3.2.2 Social expenditure in Italy

In Italy, the organization and provision of social assistance is delegated to local public authorities, namely regions, provinces and municipalities.[6] Municipalities are the main providers and funders of social care services and have administrative and organizational responsibilities on the provision of social assistance and charity.[7,8] However, regions have the task to determine the local scope for the provision of health and social services by promoting or imposing cooperation between municipalities.

Since 2000, municipalities need to organize, plan and realize the local system of the social care network and provide economic and non-economic services to the community.[9] In practice, it happens often, especially for small municipalities, that social care is provided by unions of municipality (*Unioni di comuni*) or mountain communities (*Comunità montane*), which are funded by transfers from member municipalities, to achieve a more efficient service provision. Differently, the integration of social care with health care services can be provided by local health authorities (LHA), as it happens, for example, in Lombardy.

In 2015, total social expenditure in Italy amounted to almost 7 billion euro, which corresponds to about 112 Euro per individual. About 67% of total social expenditure was funded by local governments, unions of municipalities and mountain communities. The main social services provided by municipalities are targeted to families with children, the disabled and the elderly, who consumed 38.5%, 25.4% and 18.9% of the social care budget, respectively. The remaining 17.2% of the resources is allocated to the poor (7%), immigrants (4.2%), the addicted (0.4%) and administration (5.6%) (Italian Institute for Statistics, 2017b).

Resources allocated to families with children were used mainly to provide subsidies (32.8%) and semi-residential services (32.0%). Subsidies take different forms and mainly fund early childhood day care (3.6%), foster care (2.8%), residential care (9.4%), school services (2.9%) and household income (5.8%). Semi-residential ser-

[6]This was established with the Italian Presidential Decree 616/1977. Before this decree, social assistance was provided by the central government through a network of local institutions and organizations.

[7]Art. 118 of the Italian Constitution.

[8]An exception is the special-statute region of Valle d'Aosta where social care is provided by the province.

[9]Law 328/2000.

vices mainly foster access to kindergartens for early childhood day care (23.6%) and to other daily centers (5.9%). The other main services provided to this consumer category are professional services for foster care, child adoption and parental support (13.2%), education and employment (8.8%), and residential institutes (7.5%).

Among the resources allocated to the elderly, 44.2% were allocated to home services (mainly home care) and 25.3% to residential services (mainly nursing home providers). The remaining resources mainly funded subsidies for income integration, nursing home and home care taxes, families treating the elderly at home (15.5%), and professional services (7.4%).

3.3 Data and descriptive statistics

3.3.1 Data and variables

Our dataset includes data from several data sources. We collect data on the monthly number of deaths by municipality for the period 2003-2015 from the Italian Institute for Statistics (ISTAT). We express mortality rates as the number of deaths per 10,000 individuals. Then, we collect data on the universe of hospital discharge records relative to hospital admissions for cardiovascular and respiratory diseases for the period 2001-2015 provided by the Italian Ministry of Health. These data include personal information on patients (age, gender and municipality of residence) and on the hospitalization (day of admission and ICD9 code of the primary disease). In this study, we focus on hospital admissions of the youngest (0-5 years) and oldest age groups (over 75 years) since they are among the main consumers of social services (see Section 3.2.2) and they represent the age groups facing the highest health risks when extremely hot or col days occur (Deschênes, 2014). Moreover, we limit hospital admissions to emergency cases because temperature shocks likely have an immediate effect on health and, thus, are not expected to affect elective hospitalizations. Since many municipalities are small and the occurrence of both hospitalizations and temperature anomalies may be spurious, we aggregate hospital admissions by municipality and month and express emergency hospital admissions in rates per 10,000 age-group-specific individuals.[10] To this aim, we collect yearly population data from the Italian Institute for Statistics (ISTAT).

Data on daily weather conditions for the period 2001-2015 are provided by the National Climatic Data Center (NCDC). In particular, we use Global Surface Summary of the Day (GSOD) data. These data include information on average daily temperatures, precipitation rates and dew point temperatures by weather station. On average, the number of weather stations are 110 (about one per province), but the number varies over time. We describe how we measure weather variables at municipal level in the later Section 3.3.2.

An important measure of weather conditions that is related to both temperature perception and health is humidity, but GSOD data does not include it. Therefore, following Barreca (2012), we derive absolute humidity from the available weather condition data using the following formula:[11,12]

$$H = \frac{6.11 \times 10^{\left[\frac{7.5T_D}{237.7+T_D}-1\right]}}{R_w(273.15+T)} \quad [g/m^3] \tag{3.1}$$

with T being the average daily temperature in °C, T_D the average daily dew point temperature in °C and R_w the gas constant for water vapor (461.5 J/kg °K).

Yearly balance sheet data of Italian municipal governments is provided by the Italian Ministry of the Interior for the period 2000-2015. The spending category of interest is *social expenditure* which aggregates expenditure for the universe of social services provided.[13] We measure social expenditure in Euro per capita and deflate it

[10]Since a small number of municipalities merged over the period 2001-2015, we replicate the 2016 municipality structure to construct a balanced panel.

[11]See for instance Parish and Putnam (1977).

[12]The most common measures of humidity are absolute and relative humidity which measure the amount of water vapor in the air and the proportion of water vapor relative to the amount at the saturation point, respectively. We prefer absolute instead of relative humidity because the denominator of the relative humidity formula, the air saturation point, is an increasing function of temperature and, hence, relative humidity is mechanically determined by temperature. This leads to the risk of bias in presence of temperature measurement errors (Barreca, 2012). Note, however, that the results from our empirical strategy would be similar if we would control for relative instead of absolute humidity.

[13]Balance sheet data include also sub-categories of social expenditure. However, note that sub-categories are default and defined at central level, and, generally, they do not reflect the actual services provided by a municipality. Indeed, a comparison between expenditures reported in balance sheet sub-categories and expenditures reported in the surveys on local government social expenditure performed by ISTAT since 2013 highlights that balance sheet spending categories are not sufficiently detailed to allow an assessment of expenditure by type of service provided.

using the consumer price index to obtain real values 2010 prices.

Finally, we collect data on yearly personal income at municipal level for the period 2001-2015 from the Ministry of Economics and Finance. As for social expenditure, we express income in Euro per individual and deflate it using the consumer price index to obtain real values at 2010 prices. Moreover, we collect data on pollution for the period 2001-2015 from the European air quality database (AirBase) database. This database collects daily station-level data on a large number pollutants. Following Lagravinese, Moscone, Tosetti, and Lee (2014), the pollutants we consider are ozone (O_3), nitrogen dioxide (NO_2), carbon monoxide (CO) and particulate matter with diameter below 10 μm (PM10). We describe how we measure pollution at municipal level in the later Section 3.3.2. We also collect data on regional per capita health care expenditure for the period 1996-2015 from Health For All.

Our dataset is composed of 1,436,568 *municipality*$\times$*year*$\times$*month* observations for the period 2001-2015. We exclude observations from municipalities located in the region Valle D'Aosta since, in this region, social expenditure and care are provided at provincial level (see Section 3.2.2). We further drop municipalities with incomplete data on weather, pollution, personal income and municipal government social expenditure. This leaves us with a final sample composed of 1,304,928 observations. However, when analyzing children hospital admissions, we exclude additional 1,556 observations because there are no children in the age group 0-5 years living in those municipalities. Moreover, we observe mortality only for 1,131,958 observations since mortality data is not available before 2003.

3.3.2 Measurement of temperature shocks

Starting from daily weather station data, we need to generate monthly temperature at municipal level. First, we measure the average daily temperature in a municipality as the distance-weighted average daily temperature measured at weather stations located within a radius of 40 km from a municipality's centroid. For municipalities where the distance between the centroids and the closest weather station exceeds 40 km (20% of the sample), we assign the average daily temperature of the closest weather station.[14] The average temperature in municipality i on day d is given by the following equation:

$$T_{id} = \sum_k w_{ik} T_{kd} / \sum_k w_{ik} \tag{3.2}$$

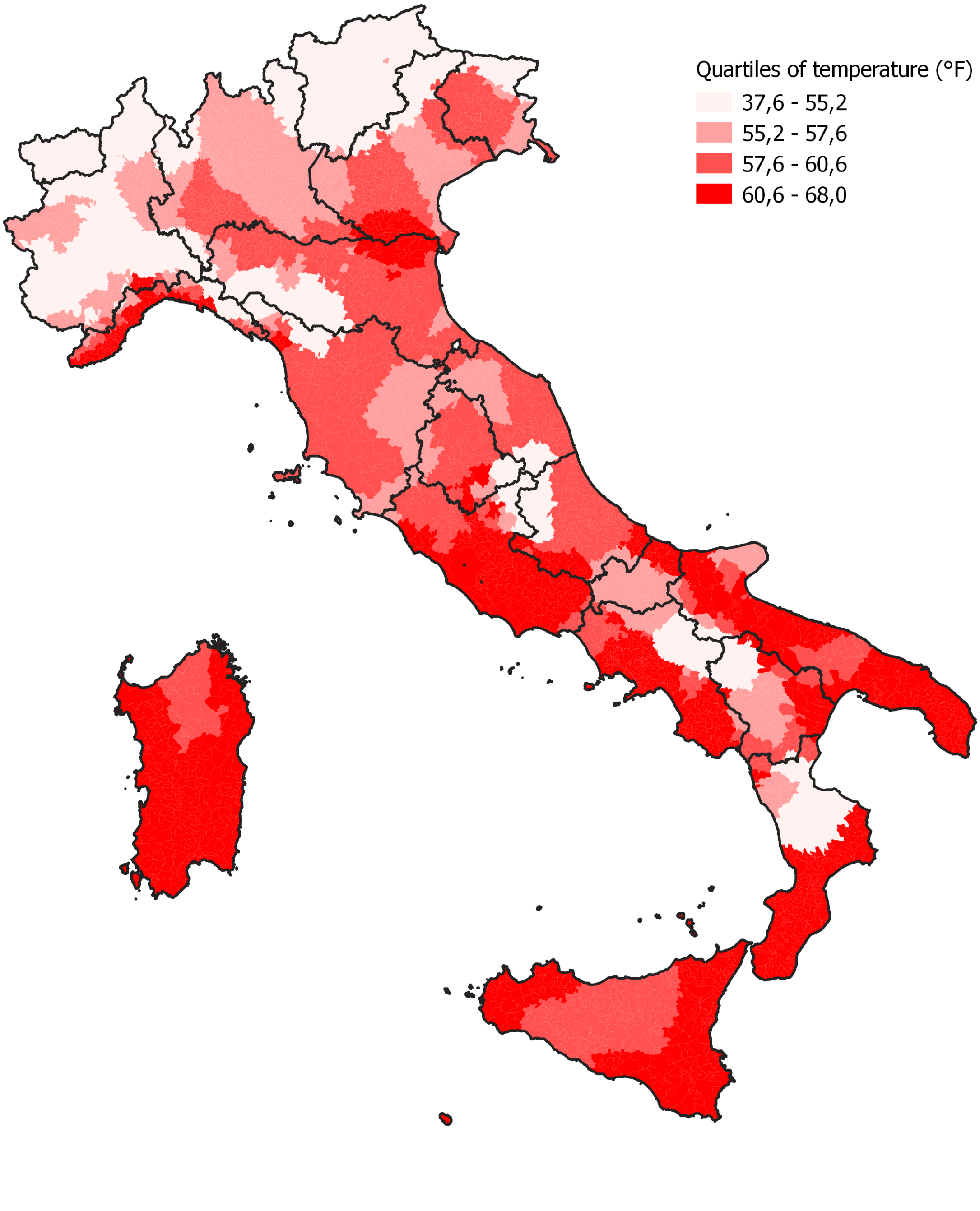
with T_{kd} being the average temperature registered in weather station k on day d, and w_{ik} being the inverse of the distance between the centroid of municipality i and the weather station k. Note that we also use this approach to measure monthly precipitation rates, humidity and pollution at municipality level.

Figure 3.1 illustrates average temperatures for the period 2001-2015 by municipality. It appears that there is spatial correlation in temperatures between municipalities which is due to the construction of municipal temperature measures based on data from a limited number of weather stations. Average temperatures vary strongly across the country, from 37.6°F to 68°F. Temperatures tend to be higher in the South of Italy, especially on the sea side, and on the Islands (Sicily and Sardinia), while temperatures tend to be colder in the North and along the Apennines.

Following Barreca (2012), we classify daily temperatures into temperature bins and collapse the data at monthly level so that each bin measures the number of days per month falling within the specified temperature range. We employ two approaches to define temperature ranges. First, we classify temperatures into 10°F bins, from 30°F to 90°F. Days with temperatures falling below 30°F or above 90°F are grouped into separate variables. This approach allows us to measure the objective exposure of population to temperature levels, but it does not allow us to take into account that temperatures may have heterogeneous effects on population health based on the local resilience to temperatures and offsetting behaviors. Therefore, we build a second set of temperature measures that allows us to address this issue. We classify daily temperatures based on deviations from municipality-specific average temperatures for the period 2001-2015. We create a set of variables measuring the number of days per month with municipality temperatures falling within 0.4 standard deviation (SD) bins relative to the municipality-specific temperature. We create bins ranging from -2 SDs to +2 SDs and group temperatures falling below and above these thresholds, respec-

[14] We test the robustness of our results to the inclusion/exclusion of these municipalities in the later Section 3.5.2.

Figure 3.1: Average temperature by municipality (2001-2015)



Notes - The map shows the average temperature in °F by municipality for a 15-year period (2001-2015). The darker the color, the higher the expenditure per individual.
Source: Our elaboration on GSOD weather data for the period 2001-2015 provided by NCDC. The shapemap of the 2016 administrative borders is provided by ISTAT.

tively, into separate variables. Note that a day with average temperature deviating by more (or less) than +2 SDs (or -2 SDs) from the municipality-specific mean implies that the daily temperature exceeds the percentile 97.7 (or falls below the percentile 2.3) of the local temperature distribution. This corresponds approximately to the definition of extremely hot (or cold) days provided in previous epidemiology studies (e.g. Anderson & Bell, 2009; Gasparrini et al., 2015; Karlsson & Ziebarth, 2018).[15] Moreover, average temperature levels in the most extreme bins, which are equal to 26.5°F and 87.9°F for negative and positive deviations, respectively (see Table 3.1), are close to the thresholds adopted in the economic literature to identify hot (above 80°F) and cold days (below 30°F). Since this measurement procedure is based on the heterogeneous long-run exposure of a municipality-specific population to temperatures, it allows us to account for the fact that temperature levels are different between the North and the South of the country and between mountain and urban areas, and that people may adapt or take offsetting behaviors, such as heating and cooling systems, to mitigate the effect of extreme temperatures on health. Indeed, Table 3.1 shows that temperature level ranges largely overlap between temperature deviation bins, with the minimum temperature in the highest-deviation bin (above 2 SDs) being just 13°F above the maximum temperature in the lowest deviation bin (below -2 SDs). This confirms that different areas of the country are exposed to heterogeneous temperature levels and suggests that temperature deviations may be preferable to temperature levels to measure temperature shocks at local level.

As a robustness check, we extend the temperature-deviation approach to account for seasonal heterogeneity in temperatures between municipalities. To this aim, we generate negative temperature deviation bins relative to the municipality-specific mean temperature during Winter months (October-March), and positive temperature deviation bins relative to the municipality-specific mean temperature during Summer months (April-September). Relative to the baseline temperature deviation approach, using seasonal deviations further accounts for the fact that season-specific temperatures may be heterogeneous among municipalities, but the drawback is that variability

[15] The epidemiology literature defines an extremely hot day as a day with average temperature exceeding the percentile 97.5 of the local temperature distribution and an extremely cold day as a day with average temperature falling below percentile 2.5.

Table 3.1: Descriptive statistics of temperature levels by temperature deviation bin

	(1) Mean	(2) SD	(3) Min	(4) Max
T <-2 SD	26.5	10.2	-15.1	51.6
-2 SD⩽ T <-1.6SD	33.2	7.5	-3.4	55.1
-1.6 SD⩽ T <-1.2 SD	38.6	6.8	1.6	58.4
-1.2SD ⩽ T <-0.8 SD	44.1	6.8	6.7	61.9
-0.8 SD⩽ T <-0.4 SD	49.4	6.9	11.3	66.2
-0.4 SD⩽ T <0 SD	54.3	6.8	16.3	70.8
0 SD⩽ T <+0.4 SD	59.7	6.7	20.9	75.2
+0.4 SD⩽ T <+0.8 SD	65.3	6.4	24.6	80.2
+0.8 SD⩽ T <+1.2 SD	70.8	6.3	28.6	86.5
+1.2 SD⩽ T <+1.6 SD	76.5	6.4	32.5	92.8
+1.6 SD⩽ T <+2 SD	80.6	6.9	36.5	99.3
T ⩾+2 SD	87.9	8.2	64.6	105.9

Notes - The table reports descriptive statistics of temperature levels (in °F) by temperature deviation bin, with each bin representing deviation ranges from the municipality-specific average temperature for the period 2001-2015.

in temperature deviations may be reduced.

3.3.3 Descriptive statistics

Panel A of Table 3.2 reports descriptive statistics of mortality rates and emergency hospital admission rates by age group and type of disease per 10,000 individuals .[16] The average monthly mortality rate is equal to 8.33 and the average monthly emergency hospital admission rate for respiratory diseases of children is equal to 18.73. Among the elderly, the average hospital admission rate for cardiovascular diseases is much higher (62.16), while the rate for respiratory diseases is very close to that of children (26.03). However, hospital admission rates for respiratory diseases among children show much more variation as compared to the elderly since the standard deviation is twice as large for the youngest age group as compared to the oldest age group.

Figure 3.2 illustrates trends in mortality and emergency hospital admission rates aggregated by year. Except for the drops in 2004 and 2014, mortality rates follow an increasing trend between 2003 and 2015 (Figure 3.2a). The prevalence of respiratory diseases of children decreases by 75 yearly admissions (6.25 per month) per 10,000 individuals between 2001 and 2015 (Figure 3.2b), while it increases continuously among

[16]Note that, except for panels B and C of Table 3.2, all statistics presented in this section are weighted by the age-group-specific population.

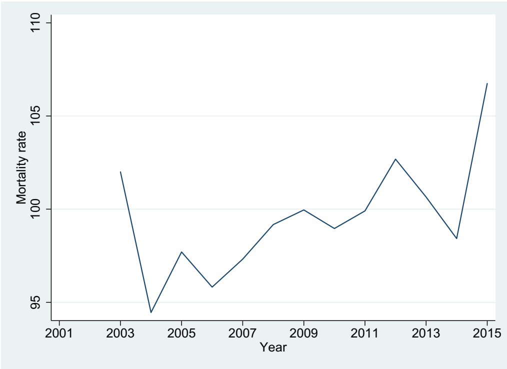
Table 3.2: Descriptive statistics

	Obs	Mean	SD	Min	Max
Panel A: Health outcomes per 10,000 individuals					
Mortality	1131958	8.334	4.400	0	400
Emergency hospital admissions					
Respiratory - Children	1304955	18.732	25.966	0	10000
Cardiovascular - Elderly	1306487	62.160	35.063	0	3333
Respiratory - Elderly	1306487	26.028	21.733	0	2500
Panel B: Temperature level bins (no. of days per month)					
<30°F	1306487	0.737	3.155	0	31
30-40°F	1306487	3.194	6.188	0	30
40-50°F	1306487	5.641	7.300	0	31
50-60°F	1306487	6.615	7.867	0	31
60-70°F	1306487	7.209	8.060	0	31
70-80°F	1306487	5.409	8.259	0	31
80-90°F	1306487	1.588	4.446	0	31
⩾90°F	1306487	0.039	0.483	0	21
Panel C: Temperature deviation bins (no. of days per month)					
T<-2 SD	1306487	0.182	0.855	0	17
-2 SD⩽T<-1.6 SD	1306487	0.926	2.189	0	18
-1.6 SD⩽T<-1.2 SD	1306487	2.873	4.779	0	25
-1.2 SD⩽T<-0.8 SD	1306487	3.804	5.170	0	29
-0.8 SD⩽T<-0.4 SD	1306487	3.617	4.728	0	31
-0.4 SD⩽T<0 SD	1306487	3.413	4.650	0	27
0 SD⩽T<0.4 SD	1306487	4.343	5.537	0	30
0.4 SD⩽T<0.8 SD	1306487	3.531	4.942	0	29
0.8 SD⩽T<1.2 SD	1306487	3.364	4.742	0	31
1.2 SD⩽T<1.6 SD	1306487	3.266	5.818	0	31
1.6 SD⩽T<2 SD	1306487	1.026	2.560	0	24
T⩾2 SD	1306487	0.089	0.516	0	10

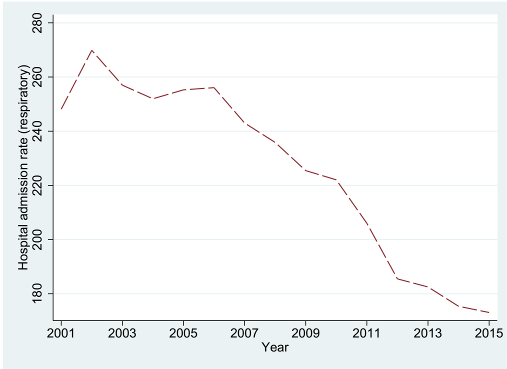
Notes - Panel A reports descriptive statistics of mortality rates for the period 2003-2015 and emergency hospital admission rates by type of diseases and age group for the period 2001-2015 per 10,000 individuals. *Children* are individuals in the age group 0-5 years and *Elderly* are individuals aged over 75 years. Panel B reports statistics on the number of days per month with average daily temperatures falling into 10°F bins. Panel C reports statistics on the number of days per month with average daily temperatures falling into 0.4 standard deviation bins relative to the municipality-specific mean temperature for the period 2001-2015. Statistics in Panel A are weighted by the age-group-specific population

the elderly, from 252 in 2001 to 328 yearly cases per 10,000 elderly individuals in 2015 (red dashed line in Figure 3.2c). Instead, the prevalence of emergency hospital admissions for cardiovascular diseases of the elderly decreases by 262 yearly admissions (about 22 per month) per 10,000 individuals between 2001 and 2015 (blue solid line in Figure 3.2c).

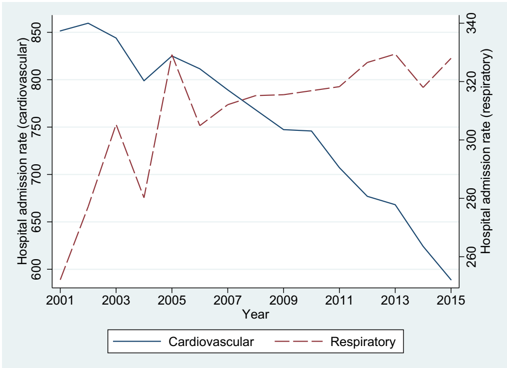
Figure 3.2: Trends in mortality and hospital admission rates



(a) Trend



(b) Children

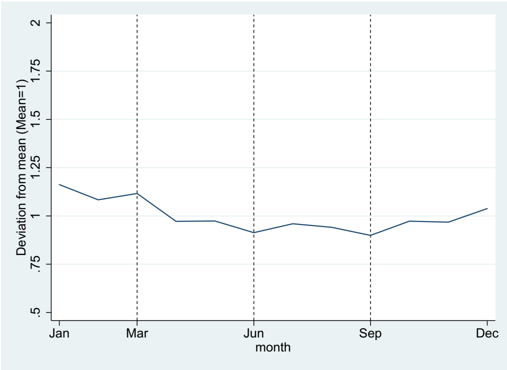


(c) Elderly

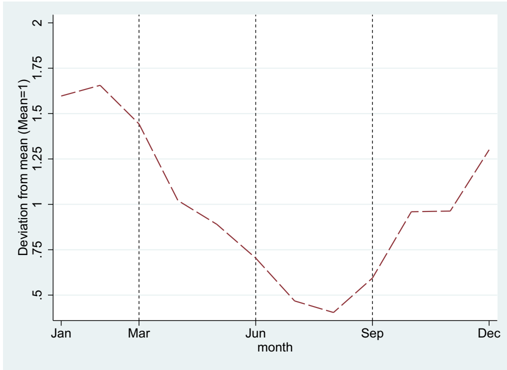
Notes - The figures illustrate trends in the yearly prevalence of mortality for the period 2003-2015 (Figure (a)) and of emergency hospital admissions of children (0-5 years; Figure (b)) and the elderly (over 75 years; Figure (c)) for the period 2001-2015 per 10,000 individuals. In Figures (b) and (c), blue solid lines represent hospital admissions for cardiovascular diseases and red dashed lines represent hospital admissions for respiratory diseases. Mortality and hospital admission rates are weighted by the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT and hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health.

Mortality and emergency hospital admissions follow also seasonal cycles. Figure 3.3 illustrates average normalized yearly cycles in mortality rates and emergency hospital admission rates. Mortality rates show some evidence of seasonal cycles, especially in the first months of the year where mortality is above the mean (Figure 3.3a). Conversely, in the following months, except for December where the rate slightly exceeds the mean, mortality is below but very close to the mean. For both children (Figure 3.3b) and the elderly (red dashed line in Figure 3.3c), respiratory emergency admissions show a decreasing trend from the Winter to the Summer season, and an increasing trend in Autumn, and the seasonal variation is more pronounced for the youngest age group. Hospital admissions for cardiovascular diseases of the elderly show a similar trend to that for respiratory diseases, though less pronounced (blue solid line in Figure

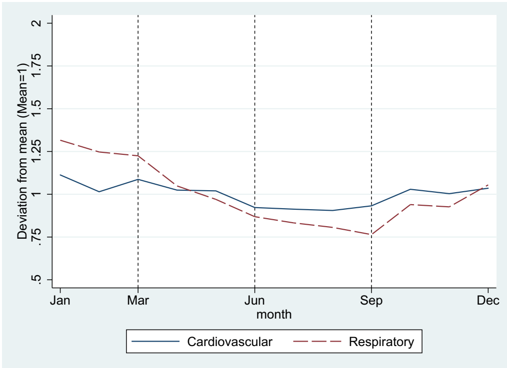
Figure 3.3: Yearly cycles in mortality and hospital admission rates



(a) Trend



(b) Children



(c) Elderly

Notes - The figures illustrate normalized average yearly cycles (mean = 1) in the prevalence of mortality (Figure (a)) and of emergency hospital admissions of children (0-5 years; Figure (b)) and the elderly (over 75 years; Figure (c)) by month of the year. In Figures (b) and (c), blue solid lines represent hospital admissions for cardiovascular diseases and red dashed lines represent hospital admissions for respiratory diseases. Mortality and hospital admission rates are weighted by the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT and hospital discharge data provided by the Italian Ministry of Health.

3.3c).

Figure 3.4 shows maps of average monthly mortality rates for the period 2003-2015 and hospital admission rates of children for respiratory diseases and of the elderly for cardiovascular and respiratory diseases for the period 2001-2015 by municipality. Mortality rates are very heterogeneous across the country, except for the regions Lombardia, Veneto, Trentino Alto Adige and Puglia where mortality tends to be lower as compared to the other regions (Figure 3.4a). The prevalence of hospital admissions of children for respiratory diseases shows a higher prevalence in the Center and South of the country as compared to the northern regions (Figure 3.4b). Among hospital admission rates of the elderly, there do not seem to be areas with systematically higher prevalence for cardiovascular (Figure 3.4c) or respiratory diseases (Figure 3.4d), except for the regions in the North-Eastern part of Italy which show generally higher hospital admission rates.

Panel B of Table 3.2 reports descriptive statistics for the number of days per month per temperature level bin. About 82% of the days have average temperatures ranging between 40°F and 80°F. As the high standard deviations of the bins suggest, there is large variability within each bin which is likely due to the yearly cycles in temperatures. Except for the highest temperature bin (⩾90°F), all of the bins have maximum value of equal or above 30 meaning that there are months where every day has average temperature falling within the same bin.

Panel C of Table 3.2 reports descriptive statistics for the number of days per month per temperature deviation bin. On average, about 93% of the days have temperatures ranging from -1.6 SDs below to 1.6 SDs above the municipality-specific mean. These thresholds correspond to 38.6°F and 76.5°F on average, respectively.[17] However, the large standard deviations of these variables, which exceed the mean values, suggest that there is much heterogeneity in our sample. Days with temperatures falling below -1.6 SDs or exceeding the mean temperature by 1.6 SDs are rare, and the events become even more spurious if we consider the +/- 2 SD threshold (0.18 and 0.09 days per month, respectively). However, these extreme temperature deviations are most likely those that cause surges in mortality and emergency hospital admissions due to their detrimental effect on the cardiovascular and respiratory systems. Differently from temperature level bins (Panel B), only 3 on 12 temperature deviation bins have maximum value equal to 31 which suggests that there may be higher within-month variation in this type of temperature measure as compared to temperature level bins.

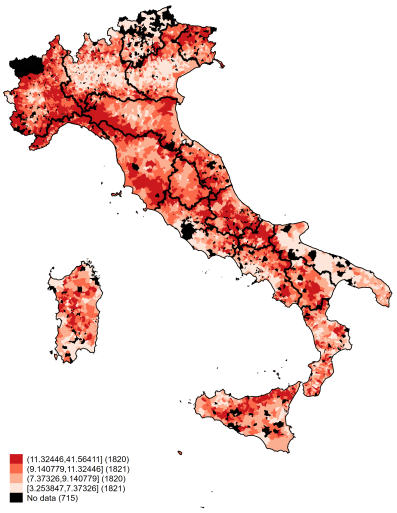
3.4 Identification strategy

3.4.1 Temperature shocks

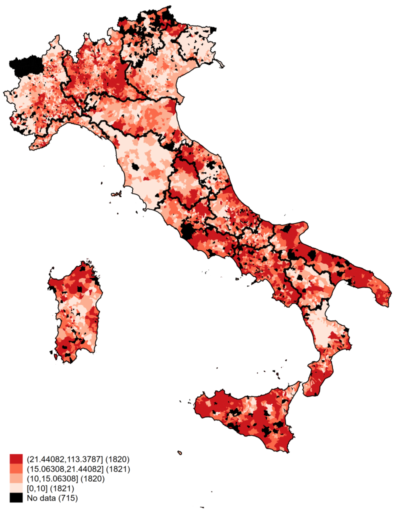
In this study, we want to identify the causal impact of temperature shocks on health outcomes. To this aim, we specify the following flexible temperature bin OLS

[17] Statistics on the relationship between temperature deviation bins and temperature levels are reported in Table 3.1.

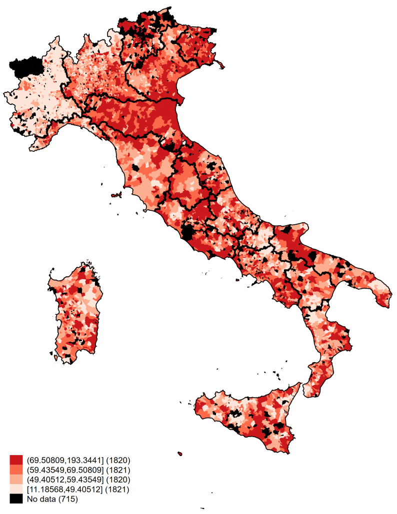
Figure 3.4: Monthly mortality and hospital admission rates by municipality



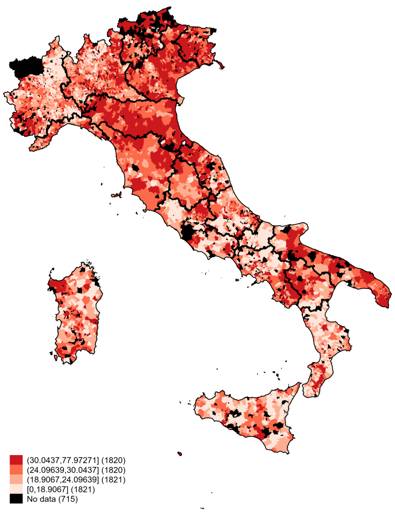
(a) Mortality



(b) Children - Respiratory



(c) Elderly - Cardiovascular



(d) Elderly - Respiratory

Notes - The figures show maps of average mortality rates for the period 2003-2015 (Figure (a)) and emergency hospital admission rates for the period 2001-2015 per 10,000 individuals by municipality. Figure (b) illustrates hospital admission rates of children for respiratory diseases, and Figures (c) and (d) of elderly, for cardiovascular and respiratory diseases, respectively. The darker the color, the higher is the prevalence of hospital admissions. Black areas indicate excluded municipalities or municipalities with missing data. Mortality and hospital admission rates are weighted by the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT and hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health. The shapemap of the 2016 administrative borders is provided by ISTAT.

regression model:[18]

$$H_{ipmy} = \sum_j \beta_j T_{jimy} + \mathbf{X}'_{imy}\boldsymbol{\gamma} + \alpha_i + \theta_{my} + \rho_{pm} + \delta_p t_{pmy} + \varepsilon_{imy} \qquad (3.3)$$

with H_{ipmy} being either the mortality rate per 10,000 individuals or the emergency hospital admission rate of the youngest or oldest age group per 10,000 individuals for cardiovascular or respiratory diseases in municipality i, province p and month m of year y.

T_{jimy} is the number of days in month m of year y with average temperature falling into temperature bin j, and β_j is its parameter. As described in Section 3.3.2, temperature bins are either 10°F bins or 0.4 SD bins relative to the municipality specific mean temperature for the period 2001-2015. When we use bins based on temperature levels, the reference temperature effect is provided by the 60-70°F bin. When we use bins based on temperature deviations, the reference effect of temperature deviations is provided by the 0 to 0.4 SDs bin. This flexible specification of population exposure to temperature allows us to identify a non-linear relationship between weather conditions and hospital admission rates.

$\mathbf{X}'_{imy}$ is a vector of time-varying control variables, namely the average monthly precipitation rate, average monthly humidity, average monthly pollution (O_3, NO_2, CO and PM10), the cumulative regional per capita health care expenditure in the 5 years before the current year and the natural logarithm of the yearly average personal income, and $\boldsymbol{\gamma}$ is the vector of their parameters. When the dependent variable is the mortality rate, we further control for population age structure (share of people in the age groups 0-5 years, 6-14 years and over 75 years). α_i are municipality fixed effects and capture time-invariant unobserved municipality characteristics that determine heterogeneity in mortality and hospital admission rates. θ_{my} are *month×year* fixed effects and capture period-specific shocks common to all municipalities, including the yearly cycles in mortality and hospital care utilization described in Section 3.3.3,

[18]Since the data-generation process has a count nature, count data models may be preferable to OLS models. However, count data models rely on maximum likelihood estimation (MLE) and, since the size of the dataset is very large and we need to control for a very large set of fixed effects for a valid identification of the effect of temperatures on health, the computational time is extremely high (e.g. 160 iterations in one week) and the MLE hardly converges.

and in temperature levels and deviations. Moreover, we control for $province \times month$ fixed effects (ρ_{pm}) and province-specific time-trends ($\delta_p t_{pmy}$) to account for heterogeneity in yearly cycles and trends in mortality and hospital admission rates between provinces. Finally, ε_{imy} is an *iid* error term.

The parameters of main interest are the β_js which measure the causal effect of temperatures on health outcomes. In particular, they measure the effect of an additional day with average temperature in temperature bin j on mortality and hospital admission rates. The validity of our identification strategy is ensured by the inclusion of temporal and spatial fixed effects which account for unobservable differences characterizing heterogeneity in health outcomes and exposure to extreme temperatures between municipalities and over time, of environmental factors correlated with temperatures that affect the population health status, and of supply-side characteristics that influence the capability to deal with peaks in health emergencies. Clearly, cold shocks may be more frequent in mountain areas in Winter periods, while hot shocks in the South and in large urban centers during Summer. These issues justify the inclusion of a large set of fixed effects. Indeed, municipality fixed effects account for fixed differences in both health outcomes and exposure to temperature levels between municipalities, and $month \times year$ fixed effects capture seasonal differences in mortality and hospital admission rates (e.g. January vs. June) and differences between months of different years (e.g. January 2001 vs. June 2003) common to all municipalities. Moreover, $province \times month$ fixed effects capture fixed heterogeneity in health outcomes and temperature variations within (e.g. January vs. June in the province of Bergamo) and between provinces (e.g. June in the province of Bergamo vs. June in the province of Palermo), including offsetting behaviors such as migration to areas that allow to avoid extreme temperatures, and province-specific time trends allow for heterogeneous trends in mortality and hospital admission rates between provinces.[19] Then, controlling for time-varying environmental factors allows to account for the role of the perception of ambient temperatures, driven by humidity, in determining adverse health outcomes when extreme temperature shocks occur (e.g. Karlsson & Ziebarth, 2018) and for the detrimental effect of air pollution on the respiratory and

[19] In preliminary analysis, we tried to include also second-order terms of province-specific time-trends into Equation 3.3. We did not find results different from those presented later in this paper.

cardiovascular systems.

By construction, temperature shocks are spatially correlated because temperature measures at municipal level are weighted sums of temperatures measured at nearby weather stations (see Section 3.3.2). Since spatial correlation may bias estimates of standard errors, we use robust standard errors clustered by province to account for spatial and serial correlation within provinces. Moreover, following previous studies (e.g. Barreca et al., 2015; Deschênes & Moretti, 2009), we weight regressions by the age-group-specific population since municipalities differ in size and, therefore, in the amount of people exposed to extreme temperatures.

To ensure the validity of our identification strategy, we run several robustness checks. First, we use an alternative measure of exposure to temperatures based on deviations from seasonal municipality-specific average temperatures (see Section 3.3.2 for further details). This approach should confirm the results obtained from our baseline temperature deviation approach. However, the identification of temperature effects on hospital admission rates using deviations from seasonal mean temperatures may be more challenging because less variability is left in temperature deviations. Second, we control the sensitiveness of our results when accounting for short-term displacement (or harvesting) in health outcomes since several studies show that health issues are anticipated by extreme weather shocks, but would have occurred shortly after even in the absence of these events (e.g. Barreca, 2012; Deschênes & Moretti, 2009). Third, since extreme cold and hot shocks may emphasize the frailty of the vulnerable population and, hence, may increase the risk of contracting severe illnesses also after several months since shock occurrences (e.g. Simón, Lopez-Abente, Ballester, & Martínez, 2005), we verify that our results are not confounded by possible delayed effects of extreme temperature shocks on health. Elective hospital admissions are not expected to be affected by temperature variations conditional on municipality, $month \times year$ and $province \times month$ fixed effects because they are planned and regulated by waiting lists (see Section 3.2.1). However, finding a significant relationship between temperatures and elective hospital admissions would suggest that our model may not account for all of the unobserved factors affecting hospital admissions. Then, we estimate the impact of temperatures on hospital admission rates of the age group from 6 to 74 years to verify that extreme temperatures do not have adverse effects on hospital admission rates independently from age.

Finally, note that the model specified in Equation 3.3 provides an intrinsic robustness check for the effect of temperatures on emergency hospital admissions. The central temperature bins should not cause significant effects on health outcomes, and the effect should grow, both in magnitude and significance, as days become hotter or colder. Therefore, coefficients of the temperature bins close to the reference bin should be lower in magnitude and less significant as compared to coefficients of bins more distant from the reference bin.

3.4.2 Social expenditure

The identification of the causal effect of social expenditure on health outcomes is a challenging exercise since the relationship is endogenous and exogenous instruments are hard to identify because factors determining social expenditure likely affect also health care utilization and, hence, mortality and hospital admission rates. To our knowledge, there is only one previous study analyzing the relationship between hospital admission rates and social expenditure which exploits a reform of subsidies for social care and compares hospital care utilization among subsidy receivers and non-receivers before and after the reform (Costa-Font et al., 2018). Other studies analyze the direct effect of social expenditure on other health outcomes, but they do not account for endogeneity (e.g. Bilal et al., 2017; Bradley et al., 2011).

We propose an alternative identification strategy that exploits exogenous temperature shocks. We want to analyze whether areas with higher social expenditure face lower mortality and emergency hospital admission rates when extreme temperature shocks occur since the higher availability of social care may allow to take care of the vulnerable population at home or in institutes, and, therefore, to prevent the adverse effects of weather conditions on health. To this aim, we classify observations into 5 equal-sized groups based on quintiles of the year-specific distribution of per capita municipal government social expenditure lagged by one year and re-estimate an extended version of Equation 3.3 that further controls for interaction terms between temperature bins and dummies identifying the groups formed by the highest and lowest quintiles, and social-expenditure group fixed effects (highest, lowest and central quintiles).[20,21] Repeating the classification of municipalities for each year allows to create time-varying groups and, therefore, to account for social expenditure adjustment over time. Indeed, generating time-invariant groups would require to assume that municipalities do not adjust social expenditure levels over a 15-year period which is very unlikely since policies and budget constraints varied between 2001 and 2015. If the group composed of the lowest-spending municipalities shows higher effects of extreme temperatures on mortality and hospital admission rates as compared to groups composed of higher-spending municipalities, this would suggest that social expenditure has a mitigating effect on adverse health outcomes. Note that this strategy does not allow us to estimate the size of the effect of social expenditure on hospital admission rates since we measure its effect mediated by temperature variables. However, it provides evidence of the role of social expenditure as an alternative to mitigate mortality and hospital care utilization.

Since extreme temperature shocks are predictable only in the very short-run (about a week of prediction), municipal governments cannot adjust social expenditure to prevent surges in mortality and emergency hospital admission rates. Therefore, if social expenditure is able to mitigate the adverse impact of temperatures on health, this is an exogenous effect determined by local government decisions on the provision of social care services which are established before the occurrence of, and therefore independently from, temperature shocks.

Since local government balance sheet data does not allow us to disentangle the fraction of social care budget allocated to each age group, our identification strategy for hospital admission rates of the youngest and oldest age groups risks to be undermined if unobserved factors correlated with social expenditure for the other age groups affect hospital admission rates. To address this issue we run two robustness checks. First, we aggregate hospital admissions for children and elderly, and re-estimate the extended version of Equation 3.3. This strategy improves the measurement of social expenditure

[20]In this model, the baseline effect of temperature bins is estimated within the group formed by municipalities in the 2nd to 4th quintiles, and coefficients of interaction terms represent the additional effect in highest- and lowest-spending municipalities relative to the baseline.

[21]We tried to run also separate regressions by quintiles of the year-specific distribution of per capita municipal social expenditure lagged by one year. The results are in line with those presented in the remainder of this essay.

since children and elderly together consume more than 50% of the budget for social care, and, therefore, unobservable factors correlated with social expenditure for other age groups are less likely to confound the results. Second, we run a falsification test and we repeat the analysis using per capita municipal government expenditure for general administration lagged by on year to classify municipalities. Indeed, general administration does not provide health- or social-care-related services and, hence, is not expected to affect health outcomes when extreme temperature shocks occur. This strategy allows us to exclude that there are unobserved confounders that relate social expenditure to health outcomes when extreme weather conditions occur.

To further ensure the validity of our identification strategy, we repeat the above described approach by splitting the sample into 3 equal-sized groups based on tertiles of the year-specific distribution of per capita municipal government social expenditure lagged by one year and re-estimate the extended version Equation 3.3. This ensures that our results are independent from the way in which we split the sample. Then, we repeat the analysis and replace temperature deviation bins with temperature level bins to ensure that findings of the effect of social expenditure are not related to the temperature measurement approach.

3.5 Effect of temperatures on emergency hospital admissions

3.5.1 Results

The impact of temperatures on mortality and emergency hospital admission rates from the estimation of Equation 3.3 using temperature level bins is illustrated in Figure 3.5. Figure 3.5a illustrates the impact of temperatures on mortality rates, Figure 3.5b the impact on emergency hospital admission rates of children for respiratory diseases, and Figures 3.5c and 3.5d the impact on emergency hospital admission rates of the elderly for cardiovascular and respiratory diseases, respectively. In each graph, dots represent coefficients and vertical lines represent 95% confidence intervals. Each coefficient measures the impact of an additional day in a temperature bin on health outcomes relative to the impact of a day in the reference bin (60-70°F). To facilitate the interpretation of the results and the comparability of temperature-related effects between the different health outcomes, we normalize the illustrated coefficients by the population-weighted mean of the dependent variable. Therefore, coefficients can be interpreted as relative percentage changes.[22,23]

Mortality rates significantly increase when temperatures exceed 70°F. An additional day with average temperature between 70°F and 80°F increase the mortality rate by 0.08% and the effect increases to 0.41% when temperatures exceed 90°F. Conversely, cold days do not show significant effects on mortality. Instead, the hospital admission rate of children for respiratory diseases significantly increases with an additional day with average temperature in the 50-60°F bin, but the coefficients of all other temperature bins are not significant. Conversely, as the average temperature level decreases relative to the reference bin, the hospital admission rate of elderly significantly increases for both cardiovascular and respiratory diseases. However, as extremely low temperatures are approached (less than 40°F), the coefficients become smaller in magnitude and lose significance for cardiovascular diseases, while significance is lost in the lowest temperature bin for respiratory diseases. Temperatures above the reference bin do not significantly affect hospital admissions of elderly for cardiovascular diseases, except for temperatures in the 70-80°F bin which have a negative and significant, though very small impact. Conversely, the impact on hospital admission rates of the elderly for respiratory diseases is significant and equal to 0.24% and 0.53% for an additional day in the 80-90°F and and above 90°F bins.

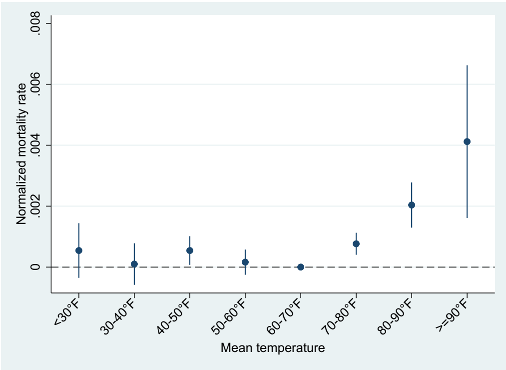
Figure 3.6 illustrates regression results (normalized coefficients with 95% confidence intervals) from the estimation of Equation 3.3 using temperature deviation bins with the number of days in the 0-0.4 SDs bin providing the reference effect of temperature deviations from the municipality-specific mean on hospital admission rates.[24] We find

[22]Expressing the dependent variable in its natural logarithm would have allowed a similar interpretation. However, note that a large number of observations has mortality and hospital admission rates equal to zero and, hence, log-transformation would have implied the loss of relevant information which contributes to the identification of the adverse effects of temperatures on health. Alternatively, we could have summed a constant amount to the dependent variable to avoid information loss after log-transformation, but since the number of zeros is large, we would have risked to influence estimated elasticities. Nevertheless, regressions using log-transformed dependent variables (not reported here) provide coefficients that are very similar to the results presented in this paper.

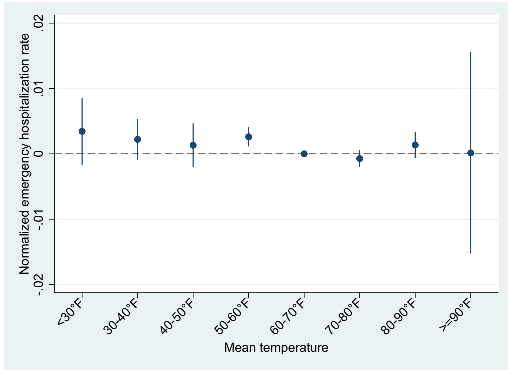
[23]Non-transformed regression results are reported in Table C.1 in the Appendix.

[24]Non-transformed regression results are reported in Table C.2 in the Appendix.

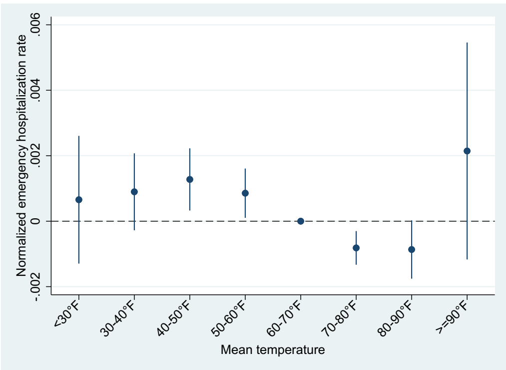
Figure 3.5: Regression results of mortality and emergency hospital admission rates on temperature level bins



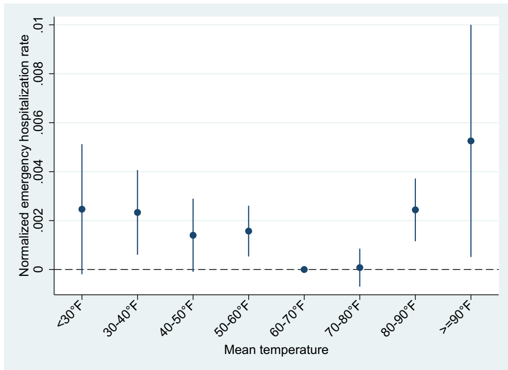
(a) Mortality



(b) Children - Respiratory



(c) Elderly - Cardiovascular



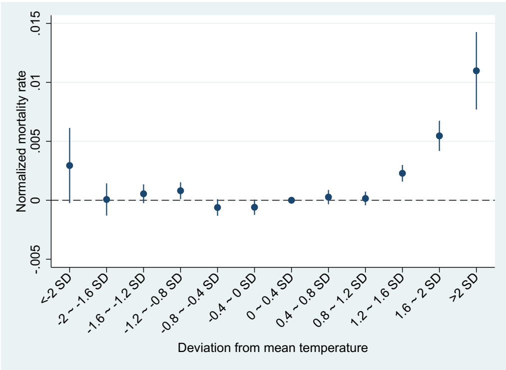
(d) Elderly - Respiratory

Notes - The figures illustrate regression results of monthly mortality rates for the period 2003-2015 (Figure (a)) and of emergency hospital admission rates for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 10°F bins, with the baseline being the number of days with temperatures between 60°F and 70°F. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model of mortality rates further controls for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health and GSOD weather data provided by NCDC.

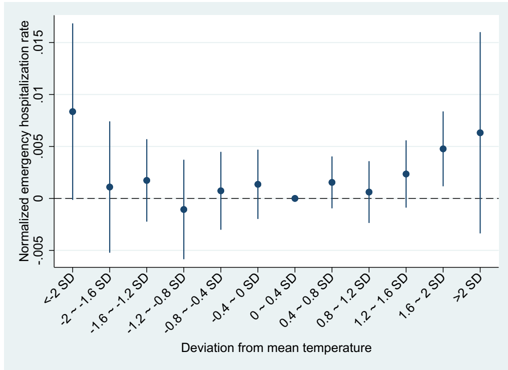
significant surges in mortality rates when deviations from mean temperatures exceed +1.2 SDs (see Figure 3.6a). The effect is growing with the size of the deviation and is equal to 0.23%, 0.55% and 1.10% for an additional day in the bins from 1.2 SDs to 1.6 SDs, from 1.6 to 2 SDs and above 2 SDs, respectively. Also temperatures deviating by less than -2 SDs show an increase in mortality rates, though not significant.

Hospital admission rates of children for respiratory diseases increase with extremely large deviations from mean temperatures, but the effect is significant only for devi-

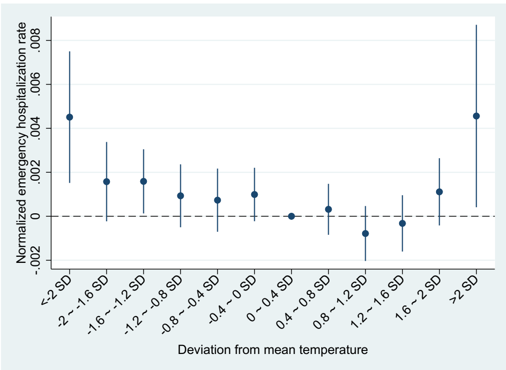
Figure 3.6: Regression results of mortality and emergency hospital admission rates on temperature deviation bins



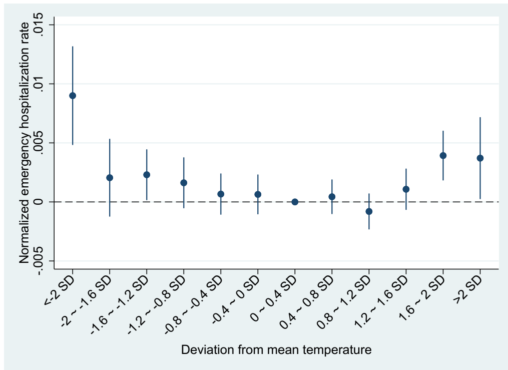
(a) Mortality



(b) Children - Respiratory



(c) Elderly - Cardiovascular



(d) Elderly - Respiratory

Notes - The figures illustrate regression results of monthly mortality rates for the period 2003-2015 (Figure (a)) and of emergency hospital admission rates for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The models of mortality rates further controls for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health and GSOD weather data provided by NCDC.

ations between 1.6 SDs and 2 SDs above the mean (see Figure 3.6b). The effect is equal to 0.83% for an additional extremely cold (below -2 SDs), and 0.48% and 0.63% for an additional hot day with temperatures deviating by more than 1.6 SDs and 2 SDs, respectively. Similarly, the elderly hospital admission rate for respiratory diseases grows as temperature deviates from the mean, and the effects become significant for the most extreme bins (see Figure 3.6d). The elderly seem to be more sensitive to temperature variations as compared to children since significant effects are visible when extremely cold and hot days occur (below -2 SDs and above 2 SDs, respectively). An additional extremely cold and hot day raise hospital admission rates of the elderly for respiratory diseases by 0.90% and 0.37%, respectively. Moreover, the elderly show significant surges in hospital admission rates for cardiovascular diseases of 0.45% and 0.46% for an additional extremely cold and hot day, respectively (see Figure 3.6c).

Except for the impact of extremely hot days on mortality and emergency hospital admissions of the elderly for respiratory diseases, the results obtained from the temperature level approach are in contrast with the existing literature and strongly differ from the temperature deviation approach. This is likely due to the heterogeneous exposure to temperature levels across Italy. Using temperature levels to analyze the impact of weather conditions on health outcomes does not allow to take into account offsetting behaviors and resilience to extreme temperatures at local level. This issue is offset when using the temperature deviation approach, but the drawback is that it does not allow to identify absolute temperature thresholds above or below which weather conditions have adverse effects on health. However, since Italy is a country with a very heterogeneous exposure to temperature levels as the remarkable overlapping of temperature ranges between temperature deviation bins suggests (see Section 3.3.2 and Table 3.1), the temperature deviation approach likely provides a more precise identification of the impact of temperature variations on health. Therefore, we prefer this approach as compared to temperature levels.

Our results of heat-related mortality are in line with previous studies. As compared to the findings of Burgess, Deschênes, Donaldson, and Greenstone (2011) in India and of Karlsson and Ziebarth (2018) in Germany, our results point into the same direction but the magnitude of the impact of extreme temperatures is lower. Conversely, as compared to findings in the US for the period 1960-2004 (Barreca, 2012; Barreca et al., 2016; Deschênes & Greenstone, 2011), the effect of an additional day with average temperature above 90°F is larger in Italy, but we do not find significant cold-related effects on mortality. These differences may be due to different degrees of diffusion of air conditioning systems, climatic conditions or time periods under investigation. Note, however, that our findings from the temperature-deviation approach, which accounts for local resilience to temperature exposure, highlight much larger effects of relative hot temperatures on mortality. Although we cannot compare these results with the findings of the above mentioned studies because they do not use similar approaches, it may be the case that these studies are under-estimating the effect of extreme temperatures because they do not account for resilience to weather conditions in a country as the US which may faces even more pronounced regional heterogeneity in climatic conditions as compared to Italy.

Regarding the impact of hot shocks on hospital admission rates, regardless of the adopted temperature measurement approach, the results point into the same direction of Karlsson and Ziebarth (2018) in Germany, but the magnitude of the impact of hot shocks in Italy is remarkably lower by about 8%-9% for both children and the elderly. Conversely, our findings on cold-related hospital admission surges of the elderly provide strong evidence of the adverse effects of extremely cold days on the health status of vulnerable age groups, which was sometimes inconclusive in previous studies (e.g. Karlsson & Ziebarth, 2018; Son, Bell, & Lee, 2014). Our findings of surges in hospital admission rates of the elderly for cardiovascular diseases driven by extremely hot and cold days are in line with Morabito et al. (2005) who use data on hospital admissions for myocardial infarction for a 5 year period in the Italian region Tuscany and find that the elderly face hospital admission above the average when weather discomfort conditions worsens.[25]

Clearly, these results capture the effect of extreme temperatures on health if the large set of fixed effects for which we control in Equation 3.3 are sufficient to capture all of the unobservable effects correlated with temperature variations and affecting hospital admissions (see Section 3.4.1). Since in our preferred approach temperature deviation bins close to the reference bin do not show significant effects on hospital admission rates and the effect grows in magnitude and significance as the deviation of temperatures from the mean grows, we argue that our results are robust. Nevertheless, in the next Section 3.5.2 we further verify the robustness of our results using alternative temperature and health outcome measures.

[25] In Morabito et al. (2005), weather discomfort is measured using composite indexes of temperature, humidity and wind velocity.

3.5.2 Robustness checks

To validate the robustness of our identification strategy, we run several robustness checks using an alternative measure of temperature deviations based on seasonal temperatures and elective hospital admission rates, which should be unrelated to temperature variations conditional on the set of fixed effects, as the dependent variable. Moreover, we control for short-term displacement and delayed effects of extreme temperature shocks on health. Then, we analyze the relationship between weather conditions and emergency hospital admission rates for the age group 6-74 years which is not expected to be affected by extreme temperature shocks. Finally, we test the robustness of our estimates to the inclusion/exclusion of municipalities where the distance between the centroid and the closest weather station exceeds 40 km because, for these municipalities, we assigned temperatures measured at the closest weather station independently from the distance from the station and this may confound our results due to imprecise temperature measurement (see Section 3.3.2).

First, we re-estimate Equation 3.3 using alternative measures of temperatures based on deviations from municipality- and season-specific mean temperatures. In particular, we generate 0.4 SD bins and consider positive deviations during Summer months (April-September) and negative deviations during Winter months (October-March). Using seasonal means as a reference for temperature deviations differs from our baseline temperature deviation approach since it takes into account that municipalities having the same average temperature may differ in the yearly temperature variations between hot and cold months.[26] For both mortality and hospital admission rates, we find that the results using this alternative temperature measure are very similar to our preferred results from the temperature deviation approach (see Figure C.1 and Table C.3 in the Appendix). This is likely due to the fact that the model in Equation 3.3 controls for $province \times month$ fixed effects which account for fixed heterogeneity in yearly cycles in temperatures between provinces.

Second, we estimate Equation 3.3 using elective hospital admission rates per 10,000 individuals as the dependent variables for both children and elderly. The results do

[26] It may be the case that two municipalities have the same average temperatures, but one municipality has hotter Summers and colder Winters as compared to the other municipality.

not show significant coefficients for any age group and type of disease, except for two coefficients in the model of children hospital admission rates for respiratory diseases, one of which is negative and the other slightly positive (see Figure C.2 and Table C.4).[27] This result provides strong support for our identification strategy since it confirms that the effect of extreme temperatures on emergency hospital admissions is causal and not determined by other unobserved factors correlated with temperatures.

Third, we re-estimate Equation 3.3 using the temperature deviation approach and account for the harvesting effect. We follow the approach used by Barreca (2012) and express temperature bins as two-month moving averages.[28] Results are very similar to our baseline estimates, except for hospital admission rates of children for respiratory diseases where coefficients are similar but we less significant (see Figure C.3 and Table C.5).

Fourth, we investigate whether our results are confounded by possible delayed effects of extreme temperature shocks on health conditions. To this aim, we re-estimate Equation 3.3 using the temperature deviation approach and further include 6 lags of the most extreme temperature bins (below -2 SDs and above 2 SDs).[29] We find that the impact of current temperature deviations is confirmed and that extreme temperature peaks in the past months do not significantly affect current health outcomes, except for emergency hospital admissions for cardiovascular diseases of the elderly which are significantly affected by cold shocks occurred in the previous month (see Figure C.4 and Table C.6).

Then, we re-estimate Equation 3.3 using hospital admission rates for cardiovascular and respiratory diseases of the age group from 6 to 74 years as dependent variables. We find that only days with average temperature between 1.6 and 2 SDs above the mean have a significant effect on hospital admission rates for respiratory diseases which may be justified by the effect of heat on outdoor workers (Dillender, 2019), but the impact is not significant for extremely hot days (see Figure C.5 and Table C.7).[30] Even if

[27]Note that this result would be confirmed if we used temperature level bins instead of temperature deviation bins.

[28]We tried to use the approach proposed by Barreca et al. (2016) who sum coefficients of current and lagged temperature bins, and results are similar to the results from the moving-average approach.

[29]Note that including a higher or lower number of lags, or including lags separately, provides similar results.

[30]Note that the results would not change if we analyzed 10-year age groups separately.

there is spurious correlation between extreme temperatures and hospital admissions for the age group 6-74 years, none of the other coefficients is significant suggesting that our selection of age groups is robust.

Finally, we re-estimate Equation 3.3 and exclude municipalities where the distance between the centroid and the closest weather station exceeds 40 km (20% of the sample). We find that coefficients of temperature deviation bins are very similar to our baseline estimates both in magnitude and significance (see Figure C.6 and Table C.8). Therefore, we argue that our identification strategy is robust and provides causal interpretation of the impact of extreme temperatures on health outcomes.

3.6 The mitigating effect of social expenditure

3.6.1 Results

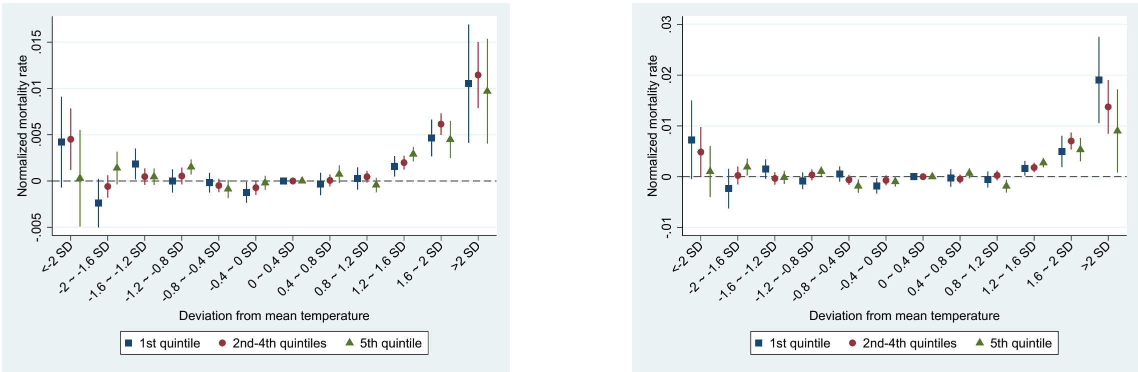
The results presented in Section 3.5 provide evidence of the adverse impact of extremely hot and cold days on health outcomes. The question we address in this section is whether social expenditure allows to mitigate this effect thanks to subsidies to families, prevention and easier access to alternative services, such as home care, residential and semi-residential centers, and proximity services. Following the strategy described in Section 3.4.2, we estimate an extension of Equation 3.3 using our preferred specification with temperature deviation bins and further control for interaction terms between temperature bins and dummy variables identifying municipalities belonging to the groups formed by the first and fifth quintiles of the year-specific distribution of per capita local government social expenditure lagged by one year. Then, we compare marginal effects of temperature bins on health outcomes between the baseline group (2nd to 4th quintiles) and the lowest- (first quintile) and highest-spending groups (5th quintile) to identify whether heterogeneity in spending levels for social services mitigates the adverse effects of extreme temperatures on health. Since quintiles are calculated for each year's distribution, there is overlapping between the group-specific distributions of social expenditure (see Table C.9 in the Appendix). However, the mean, minimum and maximum spending levels grow with the quintiles and this should allow us to identify heterogeneity in mortality and emergency hospital care utilization among municipalities with different social spending levels.

The results of the impact of temperatures on mortality rates from the estimation of Equation 3.3 that includes interaction terms between temperature bins and social expenditure groups are illustrated in Figure 3.7. Dots represent normalized coefficients of temperature deviation bins and vertical lines are 95% confidence intervals.[31] Blue squares, red dots and green triangles represent marginal effects of temperature bins for the groups formed by the first, central and fifth quintiles, respectively. When using current temperature bins, social expenditure does not seem to mitigate the adverse effects of extreme temperatures on mortality (Figure 3.7a). Indeed, there is no clear pattern in the effects of temperatures across the groups formed by social expenditure quintiles. Also Dunn et al. (2005) in the US and Ko et al. (2013) in Korea do not find significant associations between local government social expenditure and standardized mortality rates, although these studies do not account for endogeneity of social expenditure. Similarly, Bilal et al. (2017) in their cross-country analysis find that social expenditure does not have a direct effect on mortality rates, but its effect is mediated by unemployment. However, we cannot exclude that the insignificant effect of social expenditure is driven by the fact that heat- and cold-related deaths, which would have occurred shortly after even in the absence of weather shocks, are anticipated.

To address this issue, we repeat the analysis and specify temperature bins as 2-month moving averages. This approach allows us to account for short-term temporal displacement of mortality (Barreca, 2012). The results reveal that there is evidence of a negative gradient in mortality rates from the lowest- to the highest-spending municipalities when extremely hot (above 2 SDs) or cold days (below -2 SDs) occur (Figure 3.7b).[32] This finding suggests that social expenditure mitigates the adverse effects on health caused by extreme temperatures by reducing the harvesting effect. This finding is in line with Bradley et al. (2011) who find in their cross-country analysis that social expenditure improves life expectancy and reduces infant mortality. Therefore, previous studies may have failed in identifying a significant relationship between social expenditure and mortality rates because they do not account for endogeneity

[31] Non-transformed regression results are reported in column 1 of Table C.10 in the Appendix.
[32] Non-transformed regression results are reported in column 2 of Table C.10 in the Appendix.

Figure 3.7: Regression results of mortality rates by quintiles of per capita municipal social expenditure



(a) Current temperature bins

(b) 2-month moving average temperature bins

Notes - The figures illustrate regression results of monthly mortality rates per 10,000 individuals for the period 2003-2015. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. In Figure (a) current temperature bins are used, and in Figure (b) 2-month moving-average temperature bins are used. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. Temperature bins are also interacted with dummy variables identifying the first and fifth quintiles of the year-specific per capita social expenditure distribution lagged by one year. Blue squares represent marginal effects for municipalities in the first social expenditure quintile, red dots for municipalities in the second, third and fourth quintiles, and green triangles for municipalities in the fifth quintile. All models control for the average monthly precipitation rate and humidity, the cumulative regional health care expenditure for the past 5 years, the natural logarithm of the yearly personal income, municipality, month×year, province×month and social expenditure group fixed effects, province-specific time trends, pollution and population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, GSOD weather data provided by NCDC and municipality balance sheet data provided by the Italian Ministry of Interior.

of social expenditure and may not properly account for the mechanism that relates social expenditure to mortality.

The evidence of a negative gradient relating health outcomes to social expenditure emerges also from hospital admission rates.[33] The results from the estimation of Equation 3.3 with the inclusion of interaction terms between temperature bins and social expenditure groups are illustrated in Figure 3.8.[34] For both cardiovascular and respiratory diseases, extreme temperature deviations have the highest effects on emergency hospital admissions of the elderly in the lowest-spending municipalities and the lowest effects in the highest-spending municipalities (see Figures 3.8b and 3.8c for cardiovascular and respiratory diseases, respectively). The only exception is the effect of cold shocks on respiratory diseases where the highest spending group faces an impact which is larger than in the baseline group, but still lower than in the lowest-spending group.

[33]Here we only present results using current temperature bins. Note, however, that using 2-month moving averages of bins provides similar results.

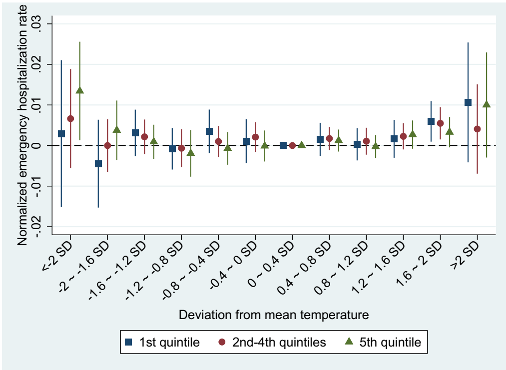
[34]Non-transformed regression results are reported in columns 3-5 of Table C.10 in the Appendix.

The effect of extremely cold days (below -2 SDs) on hospital admission rates for cardiovascular diseases is 2.85 and 1.76 times larger in the lowest-spending municipalities as compared to the middle- and highest-spending municipalities, respectively, while for hot shocks (above 2 SDs) the multipliers are 1.90 and 2.41. The gap in admission rates between spending groups is lower for respiratory diseases, with cold shocks having a 1.85 and 1.79 times larger effect in the lowest-spending municipalities as compared to the middle- and highest-spending municipalities, respectively, and hot shocks having 2.71 and 2.83 times larger effects. However, note that the differences between groups are not significant since confidence intervals of coefficients largely overlap. Conversely, the evidence on effect of social expenditure in mitigating emergency hospital admission rates of children for respiratory diseases is inconclusive for both cold and hot shocks (see Figure 3.8a). Indeed, the highest-spending group shows similar emergency hospital admission rates to the lowest-spending group when hot shocks occur, and for cold shocks the gradient relating social expenditure to hospital admissions is positive.

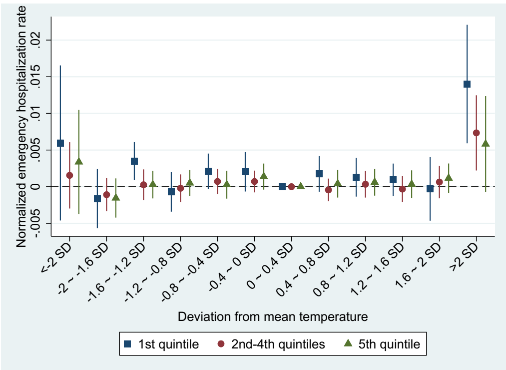
Our results of the effect of social expenditure on hospital admission rates are in line with the findings of Costa-Font et al. (2018) who show that subsidizing social care decreases hospital admissions in favor of less expensive social services. Municipalities with higher spending levels for social care face lower emergency hospital admissions when extreme temperature shocks occur because the population at risk, i.e. the children and the elderly, are better assisted and monitored, and have access to alternative services to hospital care, such as kindergartens for children and nursing homes for the elderly. This allows to mitigate the adverse effects of extreme temperatures on health thanks to offsetting behaviors, such as air conditioners, and easier access to health care and, therefore, prevention (Bradley et al., 2011; Vavken et al., 2012).

Finally, note that the fact that the age group 6-74 years is included in the analysis of mortality and, hence, seems to face lower mortality rates when extreme weather shocks occur thanks to higher social expenditure, suggests that it is likely that this age group benefits from social expenditure also in terms of lower hospitalization rates. However, we did not analyze this aspect for this age group because we found that extreme temperatures do not significantly affect hospital admission rates of this age group (see Section 3.5.2). Nevertheless, repeating the approach described in Section

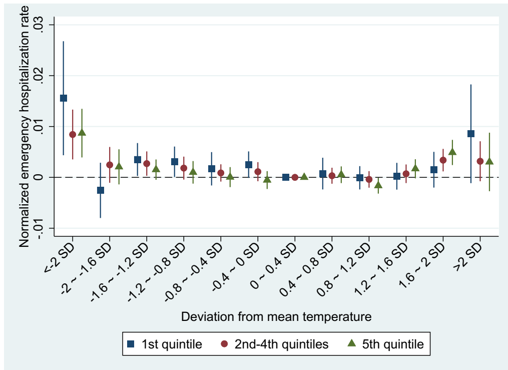
Figure 3.8: Regression results of emergency hospital admission rates by quintiles of per capita municipal social expenditure



(a) Children - Respiratory diseases



(b) Elderly - Cardiovascular diseases



(c) Elderly - Respiratory diseases

Notes - The figures illustrate regression results of monthly emergency hospital admission rates per 10,000 individuals for the period 2001-2015. Figure (a) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (b) and (c) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. Temperature bins are also interacted with dummy variables identifying the first and fifth quintiles of the year-specific per capita social expenditure distribution lagged by one year. Blue squares represent marginal effects for municipalities in the first social expenditure quintile, red dots for municipalities in the second, third and fourth quintiles, and green triangles for municipalities in the fifth quintile. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health, GSOD weather data provided by NCDC and municipality balance sheet data provided by the Italian Ministry of Interior.

3.4.2 for the age group 6-74 years reveals that also for this age group there is a negative gradient relating social expenditure to hospital admission rates in several temperature bins, especially for cold shocks on respiratory diseases and hot shocks on cardiovascular diseases (see Figure C.7 and columns 1 and 2 of Table C.11 in the Appendix). This confirms that the results on mortality and hospital admission rates are in line and provides support for a valid identification of the relationship between social expenditure and health outcomes when extreme weather events occur.

3.6.2 Robustness checks

To ensure the validity of the strategy used to identify the mitigating effect of social expenditure on health outcomes, we first address the fact that our strategy is limited by the inability to measure the fraction of social expenditure allocated to each age group. Then we use alternative municipality classification procedures based on tertiles of social expenditure and on other local government expenditure components. Finally, we use temperature level instead of temperature deviation bins.

First, we aggregate hospital admissions for children and elderly since together they consume more than half of the resources allocated to social care on average, and re-estimate Equation 3.3 including interaction terms of temperature bins with dummies identifying the groups formed by the first and fifth quintiles of the year-specific per capita local government social expenditure distribution lagged by one year. This strategy allows us to reduce the potential effect of unobserved confounders correlated with the fraction of social expenditure allocated to other age groups. The results for cardiovascular diseases are almost identical to the baseline results for the elderly since the prevalence of hospital admissions for cardiovascular diseases of children is very low (0.44 with almost 75% of observations having a rate equal to 0) as compared to the elderly population (see Figure C.8a and column 3 of Table C.11 in the Appendix). Moreover, the results for respiratory diseases confirm our baseline results, although we lose some evidence on the gradient due to the inclusion of hospital admissions of children which do not seem to be mitigated by social expenditure (see Figure C.8b and column 4 of Table C.11).

Second, we classify municipalities based on tertiles of the year-specific distribution of per capita local government social expenditure and re-estimate Equation 3.3 including interaction terms between temperature bins and dummies identifying the groups formed by the first and third tertiles. As in our baseline results, we find that the adverse effect of extreme temperature shocks on health are the highest in the lowest-spending group of municipalities, and the lowest in the highest-spending group, except for hospital admission rates of children for respiratory diseases (see Figure C.9

and Table C.12). This confirms that our identification strategy is not affected by the procedure used to classify municipalities.

Then, we classify municipalities based on quintiles of the year-specific distribution of per capita local government expenditure for general administration and re-estimate Equation 3.3 including interaction terms between temperature bins and dummies identifying groups formed by the first and fifth quintiles. Except for a few bins where we find the same gradient observed in our baseline results, the findings suggest that there is no clear pattern that relates expenditure for general administration to hospital admission rates (see Figure C.10 and Table C.13). This result is expected since services provided by general administration are not related to health and social care provision, and suggests that the mitigating effect of social expenditure is not confounded by unobserved factors.

Finally, we repeat the analysis using temperature level instead of temperature deviation bins. Again, the results are confirmed (see Figure C.11 and Table C.14).

3.7 Conclusions

The adverse effects of extreme weather conditions on health will likely determine an increase in future health care expenditure due to population aging and climate change and, therefore, investigating on alternative services that may allow to mitigate adverse health outcomes and the utilization of expensive health care services becomes a crucial policy question for the NHS. The aim of this essay was to analyze the impact of extreme temperatures on mortality and emergency hospital admission rates, and to investigate if local government social expenditure allows to mitigate this impact. We used mortality data for the period 2003-2015 and hospital discharge data for cardiovascular and respiratory diseases for the period 2001-2015 aggregated by municipality and month, and merged these data with weather and local government balance sheet data. We defined an identification strategy that allows for non-linear temperature effects and accounts for humidity, precipitation, personal income, cumulative per capita regional health care expenditure, pollution, province-specific time trends and municipality, $month \times year$ and $province \times month$ fixed effects to estimate the causal effect of temperatures on mortality and hospital admission rates. Then, we analyzed the heterogeneous effect of temperature shocks on health outcomes among municipalities classified by quintiles of the year-specific distribution of per capita local government social expenditure lagged by one year.

We found that temperature levels are an inappropriate measure for temperature shocks in Italy because they do not account for local resilience to temperatures driven by offsetting behavior and adaptation. Our preferred model based on deviations from municipality-specific mean temperatures shows that an additional extremely cold (below -2 SDs from the mean) and hot day (above 2 SDs from the mean) in a month increase the emergency hospital admission rate of children for respiratory diseases by 083% and 0.63%, respectively, but the effect is not significant. Conversely, for the elderly the impact is 0.37% and 0.90% for an additional hot or cold day, respectively. The effect on hospital admission rates of the elderly for cardiovascular diseases is lower and equal to 0.46% and 0.45% for an additional extremely hot or cold day, respectively. Moreover, the effect of an additional extremely hot day on mortality is equal to 1.10%, while cold days do not have significant effects.

In line with Bradley et al. (2011) and Costa-Font et al. (2018), we find that municipalities in the lowest social expenditure group face higher mortality and emergency hospital admission rates as compared to municipalities with higher per capita expenditure on social services, but the effect for mortality is driven by reduced short-run temporal displacement. Indeed, social expenditure allows to mitigate the effect of extreme temperatures because access to alternative services, such as nursing homes, and health care services is improved, and subsidies are distributed to the poor and needing (Bradley et al., 2011; Vavken et al., 2012). However, children do not appear to benefit from higher social expenditure levels.

Even if our identification strategy does not allow to measure the direct effect of social expenditure on health outcomes, our results provide strong support for social expenditure as a tool to improve health outcomes and reduce costly hospital care utilization. Future research could try to quantify the degree of substitution between health and social care services, and investigate on the efficient allocation of public resources to health and social care services with the aim to maximize health outcomes and to minimize costs.

The internal validity of our results is ensured by a the large set of fixed effects included in our regression models. Indeed, the fixed effects allow to account for both temporal and spacial heterogeneity affecting health outcomes when extreme temperature shocks occur. Different from Essays 1 and 2, this study allows to achieve also external validity. Since information on weather conditions is available everywhere and easily accessible by everyone, any selection effect caused by relocation choices based on weather conditions occurring in Italy is expected to take place also in other countries. This argument is also supported by the comparability of our results with findings of studies using data from other countries (e.g. Barreca, 2012; Barreca et al., 2016; Burgess et al., 2011).

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Appendix A

A.1 Matching approach

To construct a counterfactual group of municipalities, we apply a matching procedure starting from the full sample of 1129 municipalities struck at least once by an earthquake over the period 2000-2015. We exclude 252 municipalities affected by an earthquake in year 2000 because we lack data on pre-treatment characteristics before that year. Moreover, we keep only municipalities with complete data for the period 2000-2015. The resulting sub-sample of treated municipalities is composed of 743 units.

To build an equal-sized control group of municipalities not struck by earthquakes, we use the remaining 5339 municipalities with complete data for the period 2000-2015. Moreover, we exclude 1001 municipalities that share part of the border with struck municipalities to abstract from possible spillover effects of earthquake occurrence. Therefore, our final donor pool is composed of 4338 unaffected municipalities. Since geographical proximity may be not sufficient to build a control group with similar institutional characteristics in the pre-treatment period, especially if contiguous municipalities are located in other regions, we build a control based on institutional proximity, intended as similarity in institutional factors.[1] To this aim, we force the

[1]Cipollone and Rosolia (2007) construct a control group of municipalities using geographical proximity as a proxy for the similarity of treated and controlled municipalities to analyze social interactions in high school after an earthquake. While the schooling system is mostly centralized, local institutional aspects related to spending levels and funding sources may be quite heterogeneous, especially across regions.

matching with municipalities in the same region. This procedure guarantees that matched municipalities are subject to the same institutional setting and have little geographical discontinuity. We also match pre-treatment average transfers from the central government and from the regions, personal income, population size (less or greater than 15,000 people), the budget share allocated to local services, the propensity to face an earthquake (using seismic zones, see Section 2.1) and historical earthquake experience. To measure historical earthquake experience, we define the index $EQL_{i,2000} = \sum_{t=1000}^{1999}(EQ_{i,t}/(2000-t))$. This is the sum of earthquakes with intensity $\geqslant$5 occurred before 2000 weighted by the inverse of the number of years passed since the occurrence of the shocks. Due to data limitations, the index accounts only for earthquakes occurred since 1000 AD.

To perform the matching we use the coarsened exact matching (CEM) applied with the *cem* command in Stata 13 developed by Blackwell, Iacus, King, and Porro (2009). The advantage of CEM compared to other matching procedures is that the matching imbalance is lower, model dependence and bias in postmatching estimation are reduced, and efficiency is improved. Since the treatment occurs at different points in time for different municipalities, we repeat the matching procedure for each period between 2001 and 2015 by allowing replacement of matched untreated municipalities. We do not impose any custom restrictions on the cutpoints that define the coarsening and use the standards. Since we want exact matching to occur on the region, we repeat the CEM algorithm for each regional sub-sample.

CEM was able to match 347 municipalities out of the 743 treated municipalities. Indeed, t-tests on mean differences show that matching characteristics and per capita local government expenditure are not significantly different between the two groups before the occurrence of an earthquake (see columns 1 and 2 of Table A.1 below). Conversely, average characteristics of the universe of municipalities (column 3) differ significantly from the characteristics of the treated group, except for budget share allocated to local services.

Table A.1: Balancing properties resulting from the matching approach

	(1) Treated	(2) Matched	(3) All unaffected
Expenditure p/c	1199.9	1207.4	1509.0***
Transfers p/c	515.4	525.2	549.4***
Income	10639.8	10676.5	11803.6***
Population	5158.1	4892.4	6254.9***
Local services	21.96	22.52	21.74
Seismic zone 1	0.0994	0.0994	0.0581***
Seismic zone 2	0.519	0.519	0.187***
Seismic zone 3	0.306	0.306	0.191***
EQL_{2000}	0.125	0.118	0.0278***
Observations	3458	3458	84967

Notes - The table reports mean characteristics of 347 municipalities struck by an earthquake with intensity $\geqslant 5$ (column 1) and their matched unaffected municipalities (column 2) before the occurrence of an earthquake, and of the universe of unaffected municipalities for the period 2000-2015 (column 3). Except for expenditure, the reported characteristics are those used to build the group of matched municipalities (institutional proximity is omitted because of exact matching on that characteristic - see Section A.1). Stars in column 3 indicate significance levels of t-tests on mean differences between column 1 and 3. t-tests on mean differences between column 1 and 2 reveal not significant differences for all characteristics. Significance level: *** $p < 0.001$. Monetary values are discounted at 2010 prices.

Table A.2: Impact of earthquakes on local government expenditure using alternative model specifications

	(1)	(2)	(3)	(4)
	Excluding covariates		Spatial correlation	
	FE	FE (AR1)	FE	FE (AR1)
EQ_t	0.00000850	0.00723	0.0193*	0.0190**
	(0.00971)	(0.00797)	(0.00861)	(0.00736)
EQ_{t-1}	0.0582***	0.0566***	0.0667***	0.0609***
	(0.0112)	(0.00889)	(0.00977)	(0.00808)
$\text{EQ}_{t-d} \times \text{Dist}$	0.0354***	0.0190***	0.0302***	0.0164***
	(0.00495)	(0.00294)	(0.00397)	(0.00254)
$\text{EQ}_{t-d} \times \text{Dist}^2$	-0.00592***	-0.00345***	-0.00451***	-0.00257***
	(0.000756)	(0.000459)	(0.000616)	(0.000404)
$\text{EQ}_{t-d} \times \text{Dist}^3$	0.000231***	0.000141***	0.000161***	0.0000947***
	(0.0000303)	(0.0000189)	(0.0000251)	(0.0000170)
$\text{EQ}_{-i,t}$			0.00642	0.00609
			(0.00499)	(0.00443)
$\text{EQ}_{-i,t-1}$			0.0187***	0.0173***
			(0.00498)	(0.00438)
Observations	119816	119102	119816	119102
Overall R-squared	0.178	0.761	0.382	0.760
Within R-squared	0.518	0.616	0.599	0.663
Between R-squared	0.0128	0.994	0.278	0.824
Municipality fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Financial time-variant controls	No	No	Yes	Yes
Political controls	No	No	Yes	Yes
Socioeconomic controls	No	No	Yes	Yes
Sociodemographic controls	No	No	Yes	Yes

Notes - The table presents fixed effects regression results for the log of per capita local government expenditure. In columns 1 and 2, we include only the variables measuring earthquake occurrence. In columns 3 and 4, we control for the full set of covariates and further account for spatial correlation of earthquake occurrence. EQ_t and EQ_{t-1} are dummy variables equal to one if there has been an earthquake in the current year and in the previous year, respectively, and zero otherwise. EQ_{t-d} is a dummy variable equal to one measuring the occurrence of the latest earthquake within the last 15 years, and zero otherwise. $1 < d \leqslant 15$ measures the temporal distance from the latest earthquake. $EQ_{-i,t}$ and $EQ_{-i,t-1}$ are dummy variables equal to one if there has been an earthquake in a neighboring municipality in the current year and in the previous year, respectively, and zero otherwise. All models control for year fixed effects. Models 3 and 4 also control for financial time-variant (logs of per capita transfers from the central and regional governments and revenues from local taxation), political (center-right government, vote concentration, term limit, years before elections), socioeconomic (average income and percent of low-income population) and sociodemographic factors (population density, percent of young and percent of old population). Models 2 and 4 further control for the lag of the dependent variable. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices.

Table A.3: Impact of earthquakes on local government expenditure using the matching sample

	(1) OLS	(2) RE	(3) FE	(4) FE (AR1)
EQ_t	0.0443	0.0261	0.0248	0.0338**
	(0.0236)	(0.0148)	(0.0151)	(0.0129)
EQ_{t-1}	0.113***	0.0883***	0.0868***	0.0804***
	(0.0271)	(0.0195)	(0.0198)	(0.0155)
$EQ_{t-d} \times$ Dist	0.0399**	0.0280**	0.0273**	0.0129*
	(0.0132)	(0.00959)	(0.00970)	(0.00533)
$EQ_{t-d} \times$ Dist^2	-0.00558**	-0.00422**	-0.00414*	-0.00191*
	(0.00206)	(0.00162)	(0.00162)	(0.000905)
$EQ_{t-d} \times$ Dist^3	0.000175*	0.000155*	0.000153*	0.0000687
	(0.0000891)	(0.0000727)	(0.0000727)	(0.0000420)
Observations	11104	11104	11104	11104
Overall R-squared	0.350	0.349	0.221	0.744
Within R-squared		0.514	0.514	0.628
Between R-squared		0.227	0.00631	0.992
Region fixed effects	Yes	Yes	No	No
Year fixed effects	Yes	Yes	Yes	Yes

Notes - The table presents regression results for the log of per capita local government expenditure using a sample composed by 347 treated and 347 matched municipalities identified with coarsened exact matching (*cem* command in Stata 13) on average pre-treatment institutional, sociodemographic, and environmental characteristics. Model 1 is an OLS regression, model 2 a random effects regressions, and models 3 and 4 are fixed effects regressions. EQ_t and EQ_{t-1} are dummy variables equal to one if there has been an earthquake in the current year and in the previous year, respectively, and zero otherwise. EQ_{t-d} is a dummy variable equal to one measuring the occurrence of the latest earthquake within the last 15 years, and zero otherwise. $1 < d \leqslant 15$ measures the temporal distance from the latest earthquake. All models control for year fixed effects. Models 1 and 2 further control for region fixed effects, which are time-invariant, and model 4 for the lag of the dependent variable. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices.

Table A.4: Sensitivity analysis of the impact of earthquakes on local government expenditure

	(1)	(2)	(3)	(4)	(5)	(6)
	Single earthquake		No earthquakes 1988-1999		No earthquakes 2010-2015	
	FE	FE (AR1)	FE	FE (AR1)	FE	FE (AR1)
EQ_t	0.0164	0.0168*	0.0554***	0.0450***	0.0221*	0.0186*
	(0.00891)	(0.00802)	(0.0113)	(0.00965)	(0.00917)	(0.00794)
EQ_{t-1}	0.0659***	0.0627***	0.110***	0.0933***	0.0710***	0.0620***
	(0.0105)	(0.00882)	(0.0137)	(0.0111)	(0.0106)	(0.00875)
$EQ_{t-d} \times$ Dist	0.0308***	0.0168***	0.0420***	0.0248***	0.0317***	0.0173***
	(0.00405)	(0.00259)	(0.00649)	(0.00423)	(0.00416)	(0.00266)
$EQ_{t-d} \times$ Dist^2	-0.00465***	-0.00268***	-0.00526***	-0.00306***	-0.00485***	-0.00279***
	(0.000629)	(0.000412)	(0.00102)	(0.000685)	(0.000645)	(0.000423)
$EQ_{t-d} \times$ Dist^3	0.000168***	0.000100***	0.000181***	0.000105***	0.000177***	0.000106***
	(0.0000257)	(0.0000173)	(0.0000441)	(0.0000307)	(0.0000262)	(0.0000177)
Observations	118176	117470	93314	92782	117882	117181
Struck municipalities	1025	1025	819	819	1004	1004
Overall R-squared	0.384	0.760	0.362	0.732	0.384	0.761
Within R-squared	0.599	0.663	0.607	0.665	0.599	0.663
Between R-squared	0.281	0.824	0.251	0.777	0.281	0.826
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Financial time-variant controls	Yes	Yes	Yes	Yes	Yes	Yes
Political controls	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Sociodemographic controls	Yes	Yes	Yes	Yes	Yes	Yes

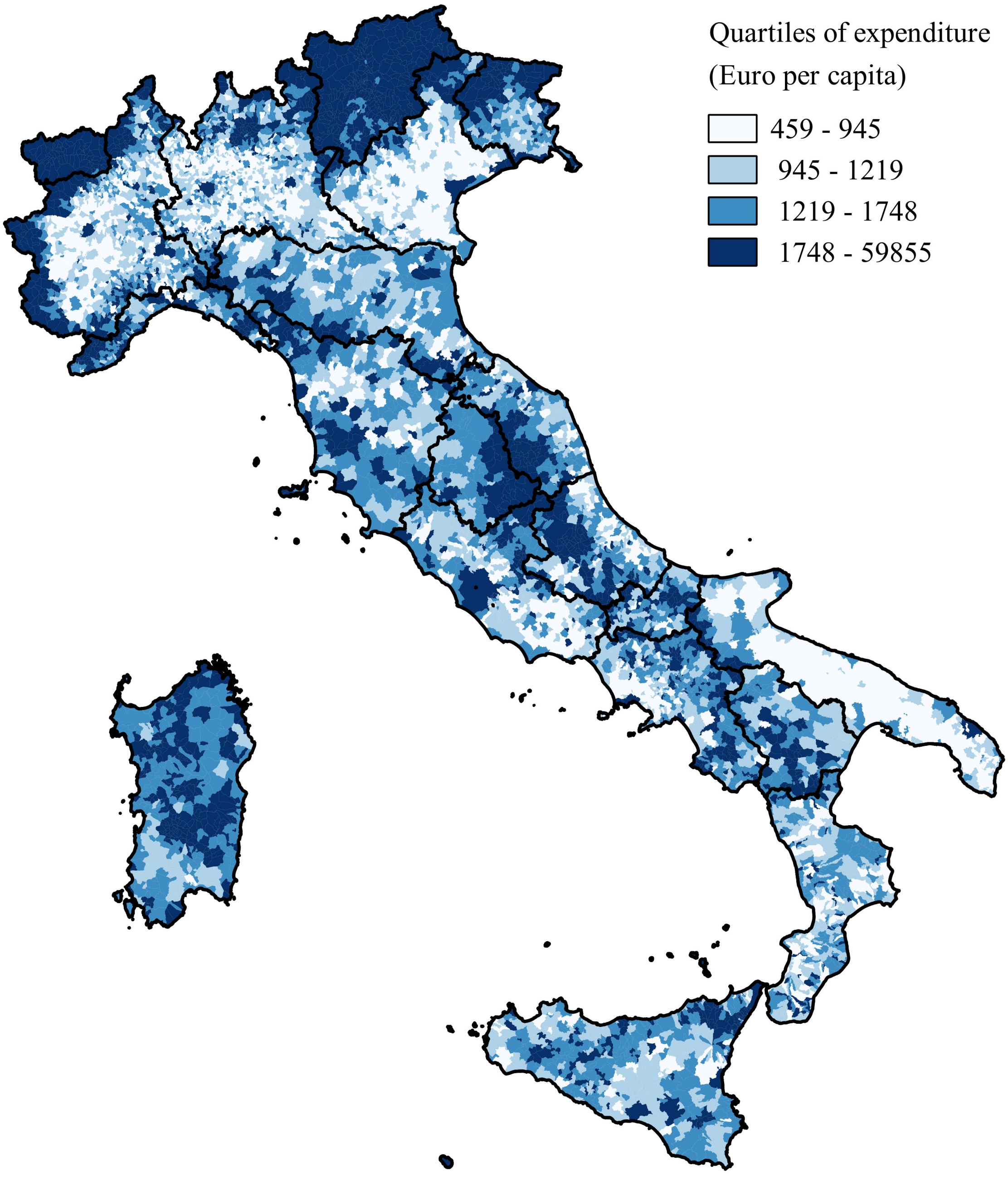
Notes - The table presents fixed effects regression results for the log of per capita local government expenditure. In columns 1 and 2, municipalities that faced more than one earthquake between 2000 and 2015 are excluded. In columns 3 and 4, municipalities struck in the 12 years before 2000 are excluded. In columns 5 and 6, municipalities struck after 2009 are excluded. EQ_t and EQ_{t-1} are dummy variables equal to one if there has been an earthquake in the current year and in the previous year, respectively, and zero otherwise. EQ_{t-d} is a dummy variable equal to one measuring the occurrence of the latest earthquake within the last 15 years, and zero otherwise. $1 < d \leqslant 15$ measures the temporal distance from the latest earthquake. All models control for financial time-variant (logs of per capita transfers from the central and regional governments and revenues from local taxation), political (center-right government, vote concentration, term limit, years before elections), socioeconomic (average income and percent of low-income population) and sociodemographic factors (population density, percent of young and percent of old population), and year fixed effects. Models 2, 4 and 6 further control for the lag of the dependent variable. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices.

Table A.5: Impact of earthquakes on local government expenditure using different intensity-based earthquake occurrence measures

	(1)	(2)	(3)	(4)	(5)
	Intensity-based measures		Magnitude-based measures		
	I⩾6	I⩾7	D⩽10 km	D⩽20 km	D⩽30 km
EQ_t	0.0554**	0.156**	0.0182*	0.0133**	0.0101**
	(0.0203)	(0.0562)	(0.00914)	(0.00485)	(0.00389)
EQ_{t-1}	0.250***	0.550***	0.0602***	0.0427***	0.0328***
	(0.0262)	(0.0717)	(0.0107)	(0.00549)	(0.00422)
$EQ_{t-d} \times$ Dist	0.120***	0.262***	0.0231***	0.0168***	0.00739*
	(0.0102)	(0.0294)	(0.00694)	(0.00384)	(0.00307)
$EQ_{t-d} \times \text{Dist}^2$	-0.0165***	-0.0343***	-0.00393**	-0.00301***	-0.000955
	(0.00159)	(0.00425)	(0.00129)	(0.000739)	(0.000611)
$EQ_{t-d} \times \text{Dist}^3$	0.000565***	0.00112***	0.000160*	0.000134***	0.0000271
	(0.0000636)	(0.000165)	(0.0000655)	(0.0000390)	(0.0000333)
Observations	119816	119816	119816	119816	119816
Overall R-squared	0.389	0.396	0.391	0.391	0.392
Within R-squared	0.603	0.602	0.598	0.598	0.598
Between R-squared	0.285	0.294	0.290	0.290	0.290
Municipality and year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes - The table presents fixed effects regression results for the log of per capita local government expenditure using earthquakes with intensity ⩾6 (column 1) and ⩾7 (column 2), and magnitude ⩾4 (columns 3-5) for the identification of treated municipalities. In columns 3, 4 and 5, treatment is assigned if the centroid of a municipality is located within 10 km, 20 km and 30 km, respectively. EQ_t and EQ_{t-1} are dummy variables equal to one if there has been an earthquake in the current year and in the previous year, respectively, and zero otherwise. EQ_{t-d} is a dummy variable equal to one measuring the occurrence of the latest earthquake within the last 15 years, and zero otherwise. $1 < d \leqslant 15$ measures the temporal distance from the latest earthquake. All models control for financial time-variant (logs of per capita transfers from the central and regional governments and revenues from local taxation), political (center-right government, vote concentration, term limit, years before elections), socioeconomic (average income and percent of low-income population) and sociodemographic factors (population density, percent of young and percent of old population), and year fixed effects. Models 2 and 4 further control for the lag of the dependent variable. Significance levels: *** $p < .001$, ** $p < .01$, * $p < .05$. Standard errors (in parentheses) are robust and clustered by municipality. Monetary values are discounted at 2010 prices.

Figure A.1: Local government expenditure (2000-2015)



Notes - The map shows the average per capita local government expenditure in Euro by municipality for a 16-year period (2000-2015). The darker the color, the higher the expenditure per individual. Expenditure is discounted at 2010 prices.
Source: Our elaboration on balance sheet data of Italian local governments for the period 2000-2015 provided by the Ministry of Interior. The shapemap of the 2016 administrative borders is provided by ISTAT.

Appendix B

B.1 Theoretical framework

We consider a voter with the following expected utility function depending on wealth (w):

$$EU_I[w] = log(w) \qquad w > 0. \tag{B.1}$$

The voter observes policies by incumbent politicians while he/she is uncertain about the effect of policies by alternative candidates (challengers). Therefore, the voter's expected utility from choosing the challenger is:

$$EU_C[w, \varepsilon, \pi] = \pi \; log(w - \varepsilon) + (1 - \pi) \; log(w + \varepsilon) \qquad \pi \in [0, 1], \; 0 < \varepsilon < w \tag{B.2}$$

where π is the probability attached to outcomes lower than the current level of wealth, and ε is the loss/gain from policies in terms of wealth. Using (B.1) and (B.2), we can write a critical value of π that makes the individual indifferent between choosing the incumbent or the competitor:

$$\hat{\pi} = \frac{log(w + \varepsilon) - log(w)}{log(w + \varepsilon) - log(w - \varepsilon)} \tag{B.3}$$

For $\pi \geqslant \hat{\pi}$, the individual will vote for the incumbent.

Now, assume that an earthquake occurs and the voter faces a loss of wealth L (with $0 < L < w - \varepsilon$). The incumbent and the competitor's ability to recover from the loss is assumed to be the same: $\rho \in [0, 1]$. However, the incumbent can send a signal δ ($\delta \in [-\rho, 1-\rho]$) at no cost regarding his/her commitment in restoring initial wealth, which affects voter's expectations. Using (B.1) and (B.2), we can write the voter's expected utility from the incumbent and the competitor as:

$$EU_I[w|L,\rho] = (\rho + \delta)\ log(w) + (1 - \rho - \delta)\ log(w - L) \tag{B.4}$$

and

$$\begin{aligned} EU_C[w, \varepsilon, \pi|L, \rho] = \rho[\pi\ log(w - \varepsilon) + (1 - \pi)\ log(w + \varepsilon)] \\ + (1 - \rho)[\pi\ log(w - \varepsilon - L) + (1 - \pi)\ log(w + \varepsilon - L)]. \end{aligned} \tag{B.5}$$

Hence, defining $\Delta = \delta[log(w) - log(w - L)]$, the new value of π for which the individual is indifferent between choosing the incumbent or the competitor is:

$$\hat{\pi}_s = \frac{\rho[log(w + \varepsilon) - log(w)] + (1 - \rho)[log(w + \varepsilon - L) - log(w - L)] - \Delta}{\rho[log(w + \varepsilon) - log(w - \varepsilon)] + (1 - \rho)[log(w + \varepsilon - L) - log(w - \varepsilon - L)]} \tag{B.6}$$

which is a decreasing function of L and δ. From Equation B.6 we see that the individual will vote for the incumbent if the probability of negative outcomes is $\pi \geqslant \hat{\pi}_s$. A positive threshold $\bar{\delta}$ exists for which $\hat{\pi}_s$ does not vary with ρ:

$$\bar{\delta} = \frac{\beta(\gamma - \eta) + \alpha(\eta - \phi) + \lambda(\phi - \gamma)}{(\alpha - \gamma)(\lambda - \beta + \phi - \eta)} \tag{B.7}$$

where $\alpha = log(w)$, $\beta = log(w + \varepsilon)$, $\lambda = log(w - \varepsilon)$, $\gamma = log(w - L)$, $\eta = log(w - \varepsilon - L)$ and $\phi = log(w + \varepsilon - L)$. For $\delta < \bar{\delta}$, we have that $\hat{\pi}_s$ is an increasing function of ρ. Conversely, $\hat{\pi}_s$ decreases with p if $\delta > \bar{\delta}$.

To compare vote choices before and after the shock, consider first the extreme case of full recovery with $\rho = 1$ and no signal by the incumbent ($\delta = 0$). In this case we obtain $\hat{\pi}_s = \hat{\pi}$ meaning that the chances of reelection of the incumbent do not change. However, if the incumbent sends a negative signal, he/she could reduce the likelihood of reelection since Δ is an increasing function of δ and $\hat{\pi}_s$ would increase.

Consider now the most realistic case in which full recovery is not expected (at least within a relatively short period of time or within one electoral cycle). For $\rho < 1$ and no signal by the incumbent ($\delta = 0$), we have $\hat{\pi}_s < \hat{\pi}$. Moreover, if a positive signal is sent ($\delta > 0$), the likelihood of supporting the incumbent increases since Δ has a negative effect on $\hat{\pi}_s$. Finally, if the incumbent sends a negative signal ($\delta < 0$), then a threshold $\hat{\delta}$ exists for which $\hat{\pi}_s \lesseqgtr \hat{\pi}$. Using (B.3) and (B.6), we solve $\hat{\pi} = \hat{\pi}_s$ for δ ($\delta = \Delta/[log(w) - log(w - L)]$) and get the critical value:

$$\hat{\delta} = -(1-\rho)\frac{\beta(\gamma-\eta) + \lambda(\phi-\gamma) + \alpha(\phi-\eta)}{(\beta-\lambda)(\alpha-\gamma)} \tag{B.8}$$

For $\delta \geqslant \hat{\delta}$, we have $\hat{\pi}_s \leqslant \hat{\pi}$ and the incumbent mayor benefits from the shock even though a negative signal is sent, provided this is not too negative.

Table B.1: Balancing properties: Kernel matching

Variable	U/M	Treated	Control	% bias	t	p> |t|
Panel A: Predictors of earthquake occurrence						
Election year$_{t-1}$	U	2003.4	2005.6	-38.4	-4.87	0.000
	M	2003.4	2002.9	7.5	0.72	0.473
Seismic zone 1	U	.15294	.08963	19.4	2.85	0.004
	M	.15385	.14174	3.7	0.31	0.755
Seismic zone 2	U	.61765	.2457	80.9	11.15	0.000
	M	.61538	.57898	7.9	0.68	0.497
Seismic zone 3	U	.2	.21828	-4.5	-0.57	0.567
	M	.20118	.19214	2.2	0.21	0.835
Mountain municipality	U	.61176	.38716	46.0	5.96	0.000
	M	.60947	.62078	-2.3	-0.21	0.831
Coastal municipality	U	.00588	.06933	-33.8	-3.25	0.001
	M	.00592	.01442	-4.5	-0.78	0.437
Center (=1)	U	.46471	.11948	81.9	13.62	0.000
	M	.46154	.49478	-7.9	-0.61	0.542
South (=1)	U	.27647	.26609	2.3	0.30	0.761
	M	.27811	.23532	9.6	0.90	0.369
Per captia local government expenditure $_{t-1}$	U	1.8244	1.5285	19.6	2.27	0.023
	M	1.7681	1.598	11.3	1.32	0.186
Panel B: Political characteristics						
Incumbent vote share$_{t-1}$	U	55.438	56.483	-7.5	-0.84	0.400
	M	55.415	55.871	-3.3	-0.33	0.743
Incumbent is man (=1)	U	.91765	.92496	-2.7	-0.36	0.720
	M	.92308	.94723	-9.0	-0.90	0.369
Incumbent age	U	45.259	46.727	-16.1	-1.99	0.046
	M	45.367	46.028	-7.2	-0.69	0.491
Inumbent education years	U	14.253	14.369	-3.2	-0.42	0.672
	M	14.231	14.466	-6.5	-0.60	0.547
Center-right local government	U	.10588	.12622	-6.3	-0.79	0.428
	M	.10651	.10445	0.6	0.06	0.951
Civic-list local government	U	.00588	.00281	4.7	0.75	0.456
	M	.00592	.00188	6.1	0.59	0.552
Proportional electoral system (=1)	U	.1	.08243	6.1	0.83	0.409
	M	.10059	.0711	10.2	0.97	0.335

Notes - The table reports balancing properties of a kernel PSM using the Epanechnikov kernel function with bandwidth 0.01. *U* represents the full (unmatched) sample and *M* the matched sample of municipalities.

Table B.2: Balancing properties: Nearest-neighbor matching (n=10)

Variable	U/M	Treated	Control	% bias	t	p> |t|
			Panel A: Predictors of earthquake occurrence			
Election year$_{t-1}$	U	2003.4	2005.6	-38.4	-4.87	0.000
	M	2003.4	2003.2	3.1	0.29	0.771
Seismic zone 1	U	.15294	.08963	19.4	2.85	0.004
	M	.15294	.14529	2.3	0.20	0.844
Seismic zone 2	U	.61765	.2457	80.9	11.15	0.000
	M	.61765	.58235	7.7	0.66	0.508
Seismic zone 3	U	.2	.21828	-4.5	-0.57	0.567
	M	.2	.24118	-10.1	-0.91	0.361
Mountain municipality	U	.61176	.38716	46.0	5.96	0.000
	M	.61176	.59706	3.0	0.28	0.782
Coastal municipality	U	.00588	.06933	-33.8	-3.25	0.001
	M	.00588	.00824	-1.3	-0.26	0.796
Center (=1)	U	.46471	.11948	81.9	13.62	0.000
	M	.46471	.50235	-8.9	-0.69	0.489
South (=1)	U	.27647	.26609	2.3	0.30	0.761
	M	.27647	.23353	9.6	0.91	0.365
Per captia local government expenditure $_{t-1}$	U	1.8244	1.5285	19.6	2.27	0.023
	M	1.8244	1.6063	14.5	1.74	0.082
			Panel B: Political characteristics			
Incumbent vote share$_{t-1}$	U	55.438	56.483	-7.5	-0.84	0.400
	M	55.438	55.589	-1.1	-0.11	0.912
Incumbent is man (=1)	U	.91765	.92496	-2.7	-0.36	0.720
	M	.91765	.94706	-10.9	-1.08	0.282
Incumbent age	U	45.259	46.727	-16.1	-1.99	0.046
	M	45.259	45.918	-7.2	-0.70	0.484
Inumbent education years	U	14.253	14.369	-3.2	-0.42	0.672
	M	14.253	14.578	-9.0	-0.86	0.393
Center-right local government	U	.10588	.12622	-6.3	-0.79	0.428
	M	.10588	.11353	-2.4	-0.22	0.822
Civic-list local government	U	.00588	.00281	4.7	0.75	0.456
	M	.00588	.00118	7.1	0.73	0.466
Proportional electoral system (=1)	U	.1	.08243	6.1	0.83	0.409
	M	.1	.07647	8.2	0.76	0.446

Notes - The table reports balancing properties of a nearest-neighbor matching with 10 neighbors. *U* represents the full (unmatched) sample and *M* the matched sample of municipalities.

Table B.3: PSM regression results using alternative matching algorithms

	(1)	(2)	(3)	(4)	(5)	(6)
Matching algorithm	Kernel			Nearest-neighbor (n=10)		
Dependent variable	Reelected	Vote share	Vote share (DD)	Reelected	Vote share	Vote share (DD)
Earthquake (× Post)	0.0598**	3.198**	3.054***	0.0549*	2.380	2.688*
	(0.0291)	(1.361)	(1.109)	(0.0322)	(1.452)	(1.444)
Municipality fixed effects	No	No	Yes	No	No	Yes
Time fixed effects	No	No	Yes	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10848	10848	21696	1204	1207	2414
(Pseudo) R-sq.	0.0490	0.109	0.618	0.0450	0.109	0.669
Log-likelihood	-150.8			-150.1		

Notes - The table reports regression results of electoral outcomes weighted by the reciprocal of normalized propensity scores. Columns 1-3 are based on kernel matching with bandwith 0.01 and columns 4-6 on nearest-neighbor matching with 10 neighbors. Columns 1 and 4 report marginal effects computed at the mean from probit regression results of incumbent mayor reelection probability. Columns 2 and 5 report OLS regression results of incumbent mayor vote share, and columns 3 and 6 report results using a difference-in-difference strategy. *Earthquake* is a dummy variable equal to 1 if a municipality was struck by an earthquake since the previous electoral period. In columns 5 and 6, *Earthquake* × *Post* is a dummy variable equal to 1 for struck municipalities in the electoral period after earthquake occurrence. All models control for political variables (election year and electoral system), characteristic of the incumbent (education years, age and gender) and geo-institutional characteristics (seismic zones, mountain or coastal jurisdiction, and geographic location). Columns 3 and 6 further control for municipality and time fixed effects (post-earthquake electoral cycle). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered by municipality are in parentheses.

Table B.4: Placebo tests

	(1)	(2)	(3)	(4)	(5)	(6)
	Unaffected election periods			Weak earthquakes		
Dependent variable	Reelection	Vote share	Vote share (DD)	Reelection	Vote share	Vote share (DD)
Placebo earthquake (× Post)	0.0115	0.376	-0.346	0.00802	-0.702	-0.793
	(0.0340)	(1.330)	(1.391)	(0.0183)	(0.710)	(0.665)
Municipality fixed effects	No	No	No	No	No	Yes
Time fixed effects	No	No	Yes	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9965	9965	19930	8914	8914	17828
(Pseudo) R-sq.	0.0567	0.0910	0.511	0.0436	0.0956	0.624
Log-likelihood	-205.6			-617.2		

Notes - The table reports regression results of electoral outcomes weighted by the reciprocal of normalized propensity scores using placebo earthquakes to assign treatment. In columns 1-3, the placebo is assigned to struck by earthquakes in electoral periods when no earthquake occurs (before and after the occurrence of the shock). In columns 4-6, the placebo is assigned to municipalities struck by weak earthquakes (intensity equal to 5). Columns 1 and 4 report marginal effects computed at the mean from probit regression results of incumbent mayor reelection probability. Columns 2 and 5 report OLS regression results of incumbent mayor vote share, and columns 3 and 6 report results using a difference-in-difference strategy. *Placebo earthquake* is a dummy variable equal to 1 for municipalities to which placebo treatments are assigned. In columns 3 and 6, *Placebo earthquake* × *Post* is a dummy variable equal to 1 for struck municipalities in the electoral period after earthquake occurrence. All models control for political variables (election year and electoral system), characteristic of the incumbent (education years, age and gender) and geo-institutional characteristics (seismic zones, mountain or coastal jurisdiction, and geographic location). Columns 3 and 6 further control for municipality and time fixed effects (post-earthquake electoral cycle). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered by municipality are in parentheses.

Appendix C

Table C.1: Regression results of mortality and emergency hospital admission rates on temperature level bins

	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
<30°F	0.00453	0.0644	0.0408	0.0642
	(0.00382)	(0.0492)	(0.0619)	(0.0353)
30-40°F	0.000828	0.0414	0.0558	0.0607**
	(0.00290)	(0.0296)	(0.0373)	(0.0230)
40-50°F	0.00453*	0.0247	0.0793**	0.0365
	(0.00200)	(0.0319)	(0.0301)	(0.0198)
50-60°F	0.00135	0.0488***	0.0532*	0.0409**
	(0.00176)	(0.0141)	(0.0239)	(0.0138)
70-80°F	0.00638***	-0.0135	-0.0507**	0.00203
	(0.00154)	(0.0125)	(0.0163)	(0.0103)
80-90°F	0.0170***	0.0255	-0.0538	0.0635***
	(0.00316)	(0.0186)	(0.0283)	(0.0170)
⩾90°F	0.0343**	0.00267	0.133	0.137*
	(0.0107)	(0.147)	(0.105)	(0.0630)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	8.334	18.73	62.16	26.03
Obs.	1131958	1304955	1306487	1306487
R^2	0.247	0.252	0.200	0.185

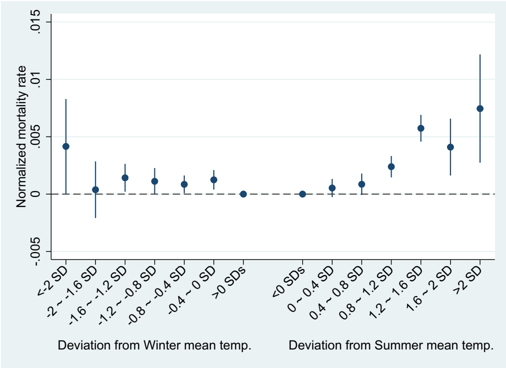
Notes - The table reports regression results of monthly mortality rates for the period 2003-2015 (column 1) and emergency hospital admission rates of children (0-5 years; column 2) and elderly (over 75 years; columns 3 and 4) for the period 2001-2015 per 10,000 individuals. Columns 2 and 4 report results for respiratory diseases, and column 3 for cardiovascular diseases. Temperature bins measure the number of days per month with average temperature falling within 10°F bins, with the baseline being the number of days with temperatures between 60°F and 70°F. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls for the population age structure. We use robust standard errors clustered by province (in parenthesis) and weight regressions by the yearly elderly population. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table C.2: Regression results of mortality and emergency hospital admission rates on temperature deviation bins

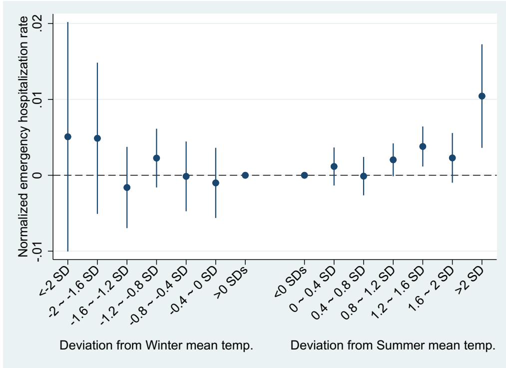
	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
T<-2 SD	0.0245	0.156	0.280**	0.234***
	(0.0135)	(0.0812)	(0.0949)	(0.0555)
-2 SD⩽T<-1.6 SD	0.000559	0.0205	0.0979	0.0534
	(0.00582)	(0.0604)	(0.0572)	(0.0437)
-1.6 SD⩽T<-1.2 SD	0.00458	0.0325	0.0986*	0.0599*
	(0.00339)	(0.0379)	(0.0463)	(0.0286)
-1.2 SD⩽T<-0.8 SD	0.00674*	-0.0199	0.0579	0.0422
	(0.00304)	(0.0457)	(0.0454)	(0.0286)
-0.8 SD⩽T<-0.4 SD	-0.00511	0.0138	0.0455	0.0174
	(0.00299)	(0.0358)	(0.0456)	(0.0231)
-0.4 SD⩽T<0 SD	-0.00493	0.0254	0.0615	0.0166
	(0.00276)	(0.0319)	(0.0386)	(0.0224)
0.4 SD⩽T<0.8 SD	0.00225	0.0289	0.0196	0.0114
	(0.00259)	(0.0239)	(0.0368)	(0.0194)
0.8 SD⩽T<1.2 SD	0.00126	0.0115	-0.0488	-0.0209
	(0.00246)	(0.0284)	(0.0396)	(0.0202)
1.2 SD⩽T<1.6 SD	0.0191***	0.0440	-0.0201	0.0280
	(0.00300)	(0.0310)	(0.0406)	(0.0232)
1.6 SD⩽T<2 SD	0.0455***	0.0894*	0.0691	0.102***
	(0.00545)	(0.0344)	(0.0485)	(0.0279)
T⩾2 SD	0.0915***	0.118	0.283*	0.0966*
	(0.0140)	(0.0925)	(0.132)	(0.0460)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	8.334	18.73	62.16	26.03
Obs.	1131958	1304955	1306487	1306487
R^2	0.248	0.252	0.200	0.185

Notes - The table reports regression results of monthly mortality rates for the period 2003-2015 (column 1) and emergency hospital admission rates of children (0-5 years; column 2) and elderly (over 75 years; columns 3 and 4) for the period 2001-2015 per 10,000 individuals. Columns 2 and 4 report results for respiratory diseases, and column 3 for cardiovascular diseases. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls for the population age structure. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

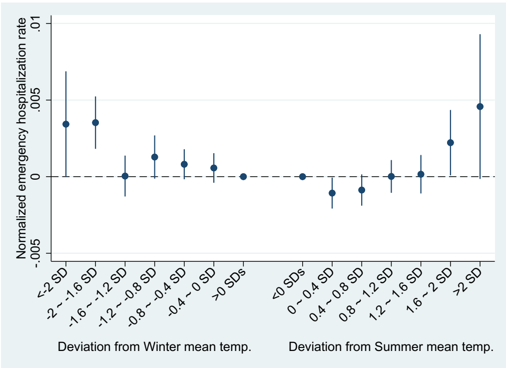
Figure C.1: Regression results of mortality and emergency hospital admission rates on seasonal temperature deviation bins



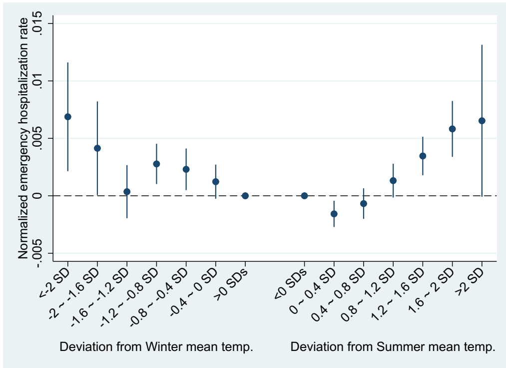
(a) Mortality



(b) Children - Respiratory diseases



(c) Elderly - Cardiovascular diseases



(d) Elderly - Respiratory diseases

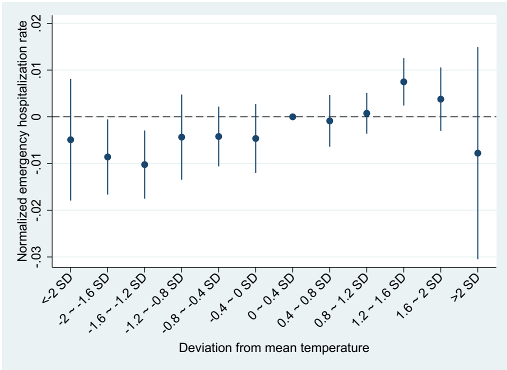
Notes - The figures illustrate regression results of monthly mortality rates for the period 2003-2015 (Figure (a)) and of emergency hospital admission rates for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average seasonal temperature for the period 2001-2015. Negative deviation bins refer to the Winter-specific mean temperature (October-March), and positive deviation bins refer to the Summer-specific mean temperature (April-September). All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model of mortality rates further controls for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health and GSOD weather data provided by NCDC.

Table C.3: Regression results of mortality and emergency hospital admission rates on seasonal temperature deviation bins

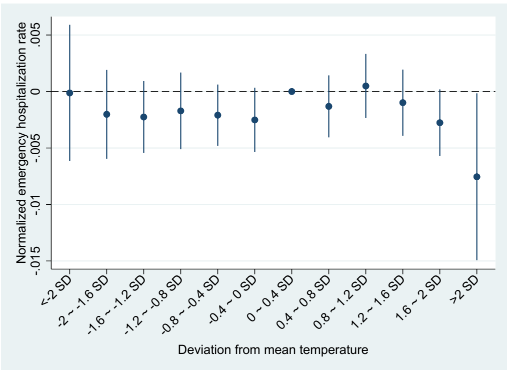
	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
T<-2 SD	0.0347	0.0951	0.213	0.179**
	(0.0176)	(0.145)	(0.109)	(0.0628)
-2 SD⩽T<-1.6 SD	0.00318	0.0913	0.219***	0.108*
	(0.0105)	(0.0952)	(0.0543)	(0.0541)
-1.6 SD⩽T<-1.2 SD	0.0119*	-0.0302	0.00239	0.00932
	(0.00516)	(0.0512)	(0.0423)	(0.0306)
-1.2 SD⩽T<-0.8 SD	0.00930	0.0424	0.0796	0.0722**
	(0.00493)	(0.0370)	(0.0447)	(0.0233)
-0.8 SD⩽T<-0.4 SD	0.00710*	-0.00267	0.0502	0.0600*
	(0.00327)	(0.0439)	(0.0311)	(0.0240)
-0.4 SD⩽T<0 SD	0.0104**	-0.0188	0.0352	0.0319
	(0.00361)	(0.0442)	(0.0306)	(0.0197)
0 SD⩽T<0.4 SD	0.00443	0.0217	-0.0667*	-0.0410**
	(0.00337)	(0.0239)	(0.0320)	(0.0152)
0.4 SD⩽T<0.8 SD	0.00717	-0.00215	-0.0543	-0.0177
	(0.00396)	(0.0242)	(0.0324)	(0.0176)
0.8 SD⩽T<1.2 SD	0.0199***	0.0382	0.000888	0.0343
	(0.00396)	(0.0207)	(0.0339)	(0.0195)
1.2 SD⩽T<1.6 SD	0.0478***	0.0711**	0.00980	0.0902***
	(0.00496)	(0.0252)	(0.0398)	(0.0223)
1.6 SD⩽T<2 SD	0.0341**	0.0429	0.138*	0.152***
	(0.0105)	(0.0313)	(0.0676)	(0.0323)
T⩾2 SD	0.0621**	0.195**	0.284	0.170
	(0.0201)	(0.0652)	(0.150)	(0.0878)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	8.334	18.73	62.16	26.03
Obs.	1131958	1304955	1306487	1306487
R^2	0.248	0.252	0.200	0.185

Notes - The table reports regression results of monthly mortality rates for the period 2003-2015 (column 1) and emergency hospital admission rates for children (0-5 years; column 2) and elderly (over 75 years; columns 3 and 4) for the period 2001-2015 per 10,000 individuals. Columns 2 and 4 report results for respiratory diseases, and column 3 for cardiovascular diseases. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average seasonal temperature for the period 2001-2015. Negative deviation bins refer to the Winter-specific mean temperature (October-March), and positive deviation bins refer to the Summer-specific mean temperature (April-September). All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls for the population age structure. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

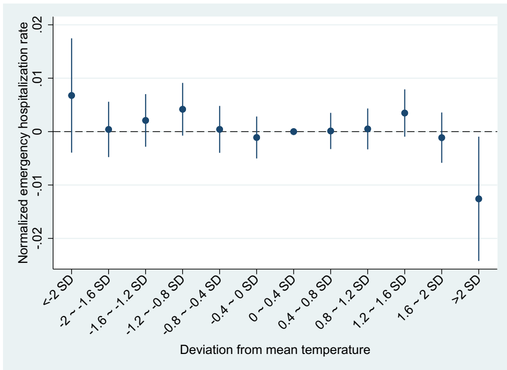
Figure C.2: Regression results of elective hospital admission rates on temperature deviation bins



(a) Children - Respiratory diseases



(b) Elderly - Cardiovascular diseases



(c) Elderly - Respiratory diseases

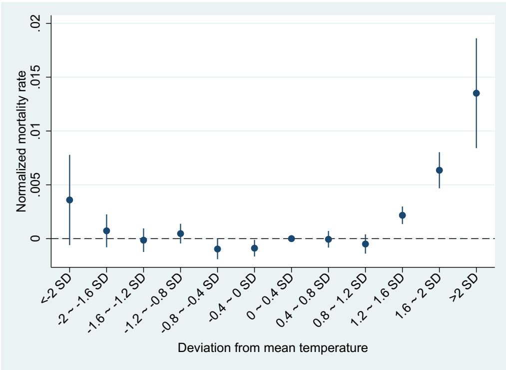
Notes - The figures illustrate regression results of emergency hospital admission rates per 10,000 individuals for the period 2001-2015. Figure (a) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (b) and (c) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health and GSOD weather data provided by NCDC.

Table C.4: Regression results of elective hospital admission rates on temperature deviation bins

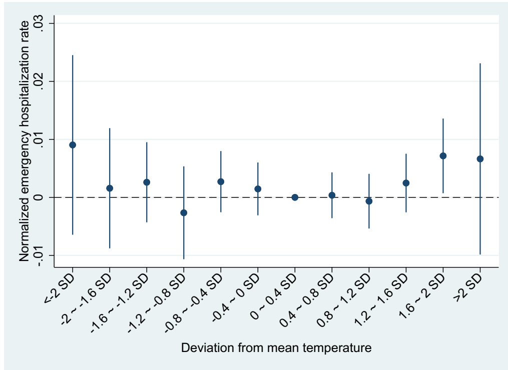
	(1)	(2)	(3)
	Children	Elderly	
	Resp.	Cardio.	Resp.
T<-2 SD	-0.0375	-0.00344	0.0418
	(0.0508)	(0.0821)	(0.0337)
-2 SD⩽T<-1.6 SD	-0.0658*	-0.0539	0.00252
	(0.0314)	(0.0534)	(0.0163)
-1.6 SD⩽T<-1.2 SD	-0.0782**	-0.0602	0.0129
	(0.0285)	(0.0433)	(0.0155)
-1.2 SD⩽T<-0.8 SD	-0.0333	-0.0458	0.0258
	(0.0356)	(0.0462)	(0.0155)
-0.8 SD⩽T<-0.4 SD	-0.0322	-0.0558	0.00256
	(0.0249)	(0.0369)	(0.0138)
-0.4 SD⩽T<0 SD	-0.0355	-0.0671	-0.00679
	(0.0288)	(0.0388)	(0.0124)
0.4 SD⩽T<0.8 SD	-0.00669	-0.0351	0.000746
	(0.0216)	(0.0374)	(0.0107)
0.8 SD⩽T<1.2 SD	0.00579	0.0130	0.00311
	(0.0171)	(0.0386)	(0.0121)
1.2 SD⩽T<1.6 SD	0.0572**	-0.0263	0.0215
	(0.0198)	(0.0398)	(0.0139)
1.6 SD⩽T<2 SD	0.0289	-0.0737	-0.00698
	(0.0265)	(0.0402)	(0.0148)
T⩾2 SD	-0.0595	-0.201*	-0.0777*
	(0.0886)	(0.101)	(0.0367)
Municipality fixed effects	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Mean of dep. var.	7.651	26.67	6.172
Obs.	1304955	1306487	1306487
R^2	0.177	0.242	0.164

Notes - The table reports regression results of monthly elective hospital admission rates of children (0-5 years; column 1) and the elderly (over 75 years; columns 2 and 3) per 10,000 individuals for the period 2001-2015. Columns 1 and 3 report results for respiratory diseases, and column 2 reports results for cardiovascular disease. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

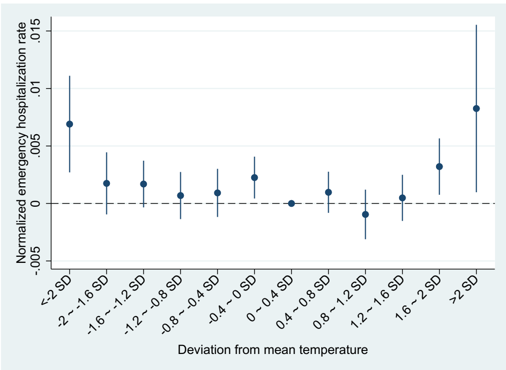
Figure C.3: Regression results of mortality and emergency hospital admission rates on 2-month moving-average temperature deviation bins



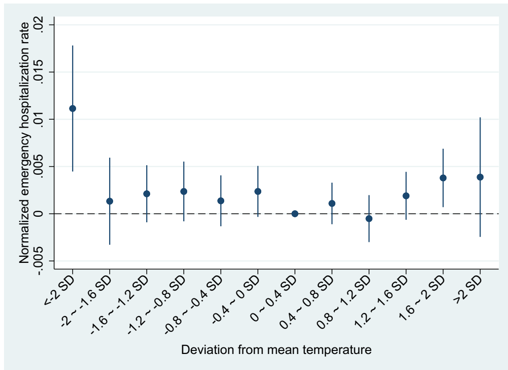
(a) Mortality



(b) Children - Respiratory



(c) Elderly - Cardiovascular



(d) Elderly - Respiratory

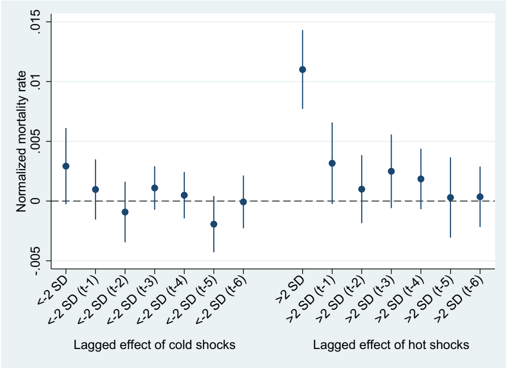
Notes - The figures illustrate regression results of monthly mortality rates for the period 2003-2015 (Figure (a)) and of emergency hospital admission rate for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins, and vertical lines represent 95% confidence intervals. Temperature bins measure the 2-month moving average of the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model of mortality rates further controls for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health and GSOD weather data provided by NCDC.

Table C.5: Regression results of mortality and emergency hospital admission rates on 2-month moving-average temperature deviation bins

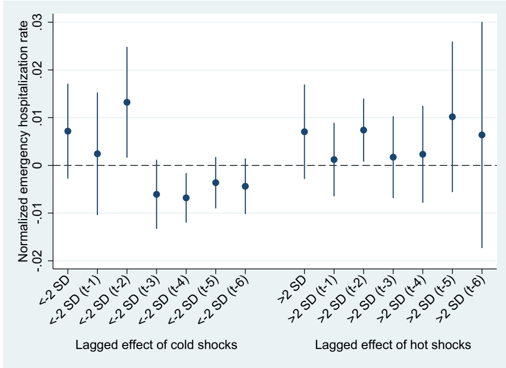
	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
T<-2 SD	0.0299	0.169	0.429**	0.290**
	(0.0178)	(0.148)	(0.133)	(0.0886)
-2 SD⩽T<-1.6 SD	0.00608	0.0294	0.109	0.0345
	(0.00650)	(0.0988)	(0.0855)	(0.0612)
-1.6 SD⩽T<-1.2 SD	-0.00119	0.0487	0.105	0.0550
	(0.00466)	(0.0658)	(0.0643)	(0.0401)
-1.2 SD⩽T<-0.8 SD	0.00391	-0.0496	0.0428	0.0614
	(0.00389)	(0.0763)	(0.0649)	(0.0420)
-0.8 SD⩽T<-0.4 SD	-0.00801*	0.0506	0.0572	0.0357
	(0.00404)	(0.0503)	(0.0663)	(0.0358)
-0.4 SD⩽T<0 SD	-0.00737*	0.0273	0.140*	0.0615
	(0.00329)	(0.0434)	(0.0577)	(0.0358)
0.4 SD⩽T<0.8 SD	-0.000501	0.00682	0.0604	0.0284
	(0.00328)	(0.0377)	(0.0567)	(0.0292)
0.8 SD⩽T<1.2 SD	-0.00413	-0.0122	-0.0591	-0.0134
	(0.00381)	(0.0449)	(0.0683)	(0.0330)
1.2 SD⩽T<1.6 SD	0.0181***	0.0462	0.0303	0.0494
	(0.00349)	(0.0482)	(0.0636)	(0.0337)
1.6 SD⩽T<2 SD	0.0530***	0.134*	0.199*	0.0987*
	(0.00713)	(0.0613)	(0.0776)	(0.0411)
T⩾2 SD	0.113***	0.124	0.513*	0.101
	(0.0217)	(0.157)	(0.231)	(0.0840)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	8.334	18.69	62.09	26.03
Obs.	1131791	1297524	1299041	1299041
R^2	0.248	0.253	0.200	0.185

Notes - The table reports regression results of monthly mortality rates for the period 2003-2015 (column 1) and of emergency hospital admission rates of children (0-5 years; column 2) and the elderly (over 75 years; columns 3 and 4) individuals for the period 2001-2015 per 10,000 individuals. Columns 2 and 4 report results for respiratory diseases, and column 2 for cardiovascular disease. Temperature bins measure the 2-month moving average of the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls for the population age structure. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

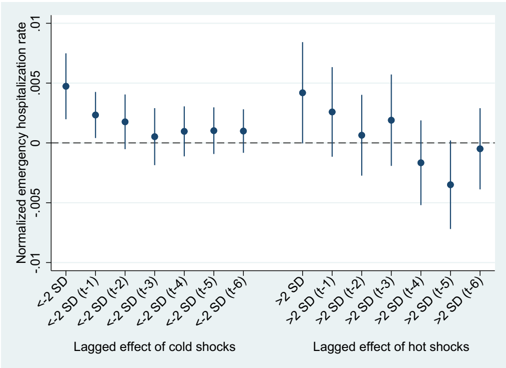
Figure C.4: Delayed effect of extreme temperature deviations



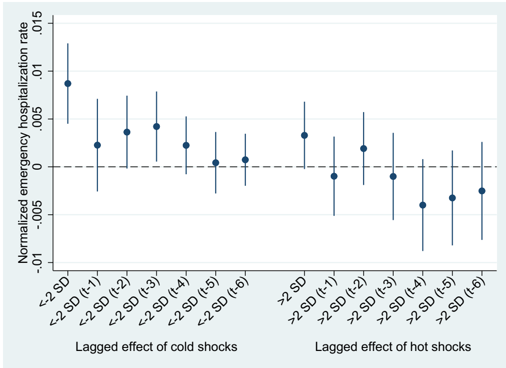
(a) Mortality



(b) Children - Respiratory



(c) Elderly - Cardiovascular



(d) Elderly - Respiratory

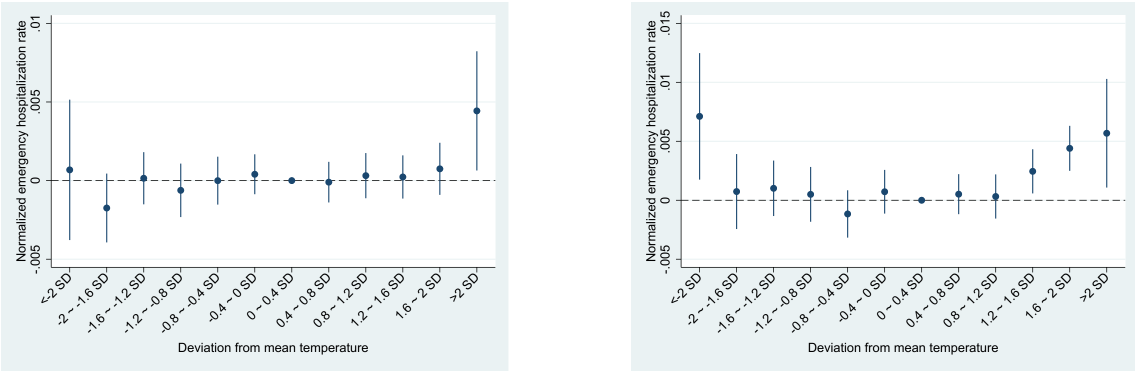
Notes - The figures illustrate regression results of monthly mortality rates for the period 2003-2015 (Figure (a)) and of emergency hospital admission rates for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. The figure illustrates results only for the highest and lowest temperature deviation bins which are both current and lagged for 6 periods. All models further control for the central current temperature deviation bins (above -2 SDs and below 2 SDs), average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The models of mortality rates further controls for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health and GSOD weather data provided by NCDC.

Table C.6: Delayed effect of extreme temperature deviations

	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
T<-2 SD	0.0244	0.133	0.293**	0.227***
	(0.0136)	(0.0939)	(0.0870)	(0.0560)
T<-2 SD (t-1)	0.00810	0.0451	0.144*	0.0592
	(0.0107)	(0.121)	(0.0608)	(0.0645)
T<-2 SD (t-2)	-0.00765	0.245*	0.109	0.0949
	(0.0108)	(0.110)	(0.0722)	(0.0507)
T<-2 SD (t-3)	0.00914	-0.112	0.0324	0.110*
	(0.00775)	(0.0685)	(0.0752)	(0.0488)
T<-2 SD (t-4)	0.00409	-0.126*	0.0598	0.0587
	(0.00826)	(0.0490)	(0.0659)	(0.0403)
T<-2 SD (t-5)	-0.0161	-0.0671	0.0633	0.0113
	(0.01000)	(0.0509)	(0.0615)	(0.0428)
T<-2 SD (t-6)	-0.000597	-0.0810	0.0613	0.0193
	(0.00940)	(0.0552)	(0.0574)	(0.0362)
T⩾2 SD	0.0917***	0.131	0.259	0.0860
	(0.0140)	(0.0934)	(0.134)	(0.0469)
T⩾2 SD (t-1)	0.0264	0.0226	0.160	-0.0256
	(0.0145)	(0.0728)	(0.118)	(0.0552)
T⩾2 SD (t-2)	0.00830	0.137*	0.0397	0.0500
	(0.0121)	(0.0623)	(0.107)	(0.0508)
T⩾2 SD (t-3)	0.0208	0.0320	0.118	-0.0262
	(0.0131)	(0.0809)	(0.121)	(0.0607)
T⩾2 SD (t-4)	0.0154	0.0430	-0.103	-0.104
	(0.0108)	(0.0959)	(0.112)	(0.0640)
T⩾2 SD (t-5)	0.00246	0.188	-0.216	-0.0848
	(0.0143)	(0.149)	(0.117)	(0.0661)
T⩾2 SD (t-6)	0.00299	0.118	-0.0303	-0.0657
	(0.0107)	(0.224)	(0.107)	(0.0682)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Central temperature bins	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	8.334	18.51	61.87	26.13
Obs.	1130958	1260371	1261813	1261813
R^2	0.248	0.255	0.201	0.187

Notes - The table reports regression results of monthly mortality rates for the period 2003-2015 (column 1) and of emergency hospital admission rates of children (0-5 years; column 2) and the elderly (over 75 years; columns 3 and 4) individuals for the period 2001-2015 per 10,000 individuals. Columns 2 and 4 report results for respiratory diseases, and column 2 for cardiovascular disease. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for current temperature bins, 6-months lags of the highest and lowest temperature deviation bins, the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls for the population age structure. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

Figure C.5: Regression results of emergency hospital admission rates of the age group 6-74 years on temperature deviation bins



(a) Cardiovascular diseases (b) Respiratory diseases

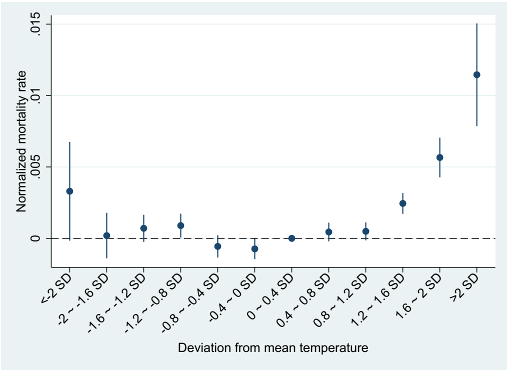
Notes - The figures illustrate regression results of monthly emergency hospital admission rates of individuals of the age group 6-74 years per 10,000 individuals for the period 2001-2015. Figure (a) illustrates results for cardiovascular diseases and Figure (b) illustrates regression results for respiratory disease. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health and GSOD weather data provided by NCDC.

Table C.7: Regression results of emergency hospital admission rates of the age group 6-74 years on temperature deviation bins

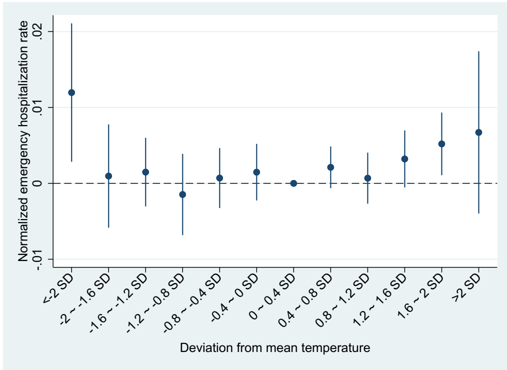
	(1) Cardio.	(2) Resp.
T<-2 SD	-0.000607	0.00860
	(0.00797)	(0.00581)
-2 SD⩽T<-1.6 SD	-0.00359	-0.00179
	(0.00541)	(0.00325)
-1.6 SD⩽T<-1.2 SD	0.000995	-0.00121
	(0.00324)	(0.00249)
-1.2 SD⩽T<-0.8 SD	-0.00166	-0.00277
	(0.00364)	(0.00243)
-0.8 SD⩽T<-0.4 SD	0.00159	-0.00357
	(0.00308)	(0.00215)
-0.4 SD⩽T<0 SD	0.00249	-0.0000660
	(0.00261)	(0.00212)
0.4 SD⩽T<0.8 SD	0.000491	-0.000912
	(0.00249)	(0.00185)
0.8 SD⩽T<1.2 SD	0.000269	-0.000937
	(0.00264)	(0.00198)
1.2 SD⩽T<1.6 SD	0.00213	0.00236
	(0.00309)	(0.00209)
1.6 SD⩽T<2 SD	0.00504	0.00580**
	(0.00351)	(0.00209)
T⩾2 SD	0.0145	0.00888
	(0.00948)	(0.00599)
Average precipitation	0.172**	0.0995*
	(0.0601)	(0.0397)
log Personal income	0.637***	0.159
	(0.188)	(0.141)
Municipality fixed effects	Yes	Yes
Year × month fixed effects	Yes	Yes
Province × month fixed effects	Yes	Yes
Province-specific time-trends	Yes	Yes
Pollution	Yes	Yes
Mean of dep. var.	3.515	1.820
Obs.	1306487	1306487
R^2	0.122	0.0977

Notes - The table reports regression results of monthly emergency hospital admission rates of individuals in the age group 6-74 years per 10,000 individuals for the period 2001-2015. Columns 1 and 2 report results for cardiovascular and respiratory diseases, respectively. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

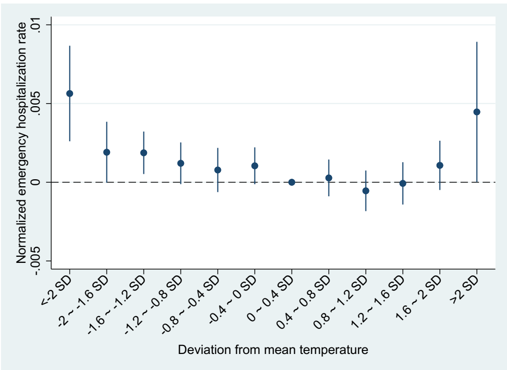
Figure C.6: Regression results of mortality and emergency hospital admission rates excluding municipalities far from weather stations



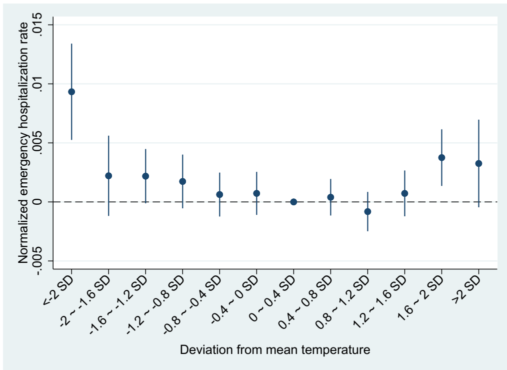
(a) Mortality



(b) Children - Respiratory diseases



(c) Elderly - Cardiovascular diseases



(d) Elderly - Respiratory diseases

Notes - The figures illustrate regression results of monthly mortality rates for the period 2003-2015 (Figure (a)) and of emergency hospital admission rates for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals using the sub-sample of municipalities where the distance between the centroid and the closest weather station is equal to or less than 40 km. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model of mortality rates further controls for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health and GSOD weather data provided by NCDC.

Table C.8: Regression results of mortality and emergency hospital admission rates excluding municipalities far from weather stations

	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
T<-2 SD	0.0272	0.224*	0.350***	0.245***
	(0.0145)	(0.0872)	(0.0962)	(0.0547)
-2 SD⩽T<-1.6 SD	0.00160	0.0180	0.118	0.0582
	(0.00670)	(0.0650)	(0.0613)	(0.0456)
-1.6 SD⩽T<-1.2 SD	0.00579	0.0277	0.116**	0.0574
	(0.00398)	(0.0432)	(0.0427)	(0.0309)
-1.2 SD⩽T<-0.8 SD	0.00737*	-0.0275	0.0748	0.0456
	(0.00350)	(0.0512)	(0.0420)	(0.0305)
-0.8 SD⩽T<-0.4 SD	-0.00465	0.0130	0.0484	0.0165
	(0.00328)	(0.0377)	(0.0445)	(0.0249)
-0.4 SD⩽T<0 SD	-0.00607*	0.0276	0.0649	0.0191
	(0.00305)	(0.0356)	(0.0371)	(0.0244)
0.4 SD⩽T<0.8 SD	0.00366	0.0396	0.0171	0.0105
	(0.00276)	(0.0263)	(0.0370)	(0.0208)
0.8 SD⩽T<1.2 SD	0.00404	0.0127	-0.0337	-0.0215
	(0.00264)	(0.0321)	(0.0409)	(0.0224)
1.2 SD⩽T<1.6 SD	0.0201***	0.0602	-0.00441	0.0190
	(0.00305)	(0.0359)	(0.0426)	(0.0260)
1.6 SD⩽T<2 SD	0.0467***	0.0973*	0.0666	0.0987**
	(0.00584)	(0.0395)	(0.0496)	(0.0322)
T⩾2 SD	0.0944***	0.126	0.277	0.0856
	(0.0151)	(0.102)	(0.141)	(0.0498)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	8.242	18.73	62.11	26.29
Obs.	883917	1017313	1018270	1018270
R^2	0.270	0.279	0.216	0.200

Notes - The table reports regression results of monthly mortality rates for the period 2003-2015 (column 1) and of emergency hospital admission rates of children (0-5 years; column 2) and the elderly (over 75 years; columns 3 and 4) for the period 2001-2015 per 10,000 individuals using the sub-sample of municipalities where the distance between the centroid and the closest weather station is equal to or less than 40 km. Columns 2 and 4 report results for respiratory diseases, and column 3 for cardiovascular diseases. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls also for the population age structure. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

Table C.9: Descriptive statistics of per capita municipal social expenditure by quintiles of the year-specific distribution

	Mean	SD	Min	Max
Quintile 1	24.13	10.04	0.00	42.82
Quintile 2	50.35	7.92	31.52	69.47
Quintile 3	77.74	10.47	52.69	103.08
Quintile 4	117.87	17.41	81.58	165.40
Quintile 5	289.37	210.83	128.45	4694.29

Notes - The table reports descriptive statistics of per capita municipal expenditure on social services lagged by on year by quintiles of the year-specific expenditure distribution.

Table C.10: Regression results of mortality and emergency hospital admission rates by quintiles of per capita municipal social expenditure

	(1)	(2)	(3)	(4)	(5)
	Mortality		Children	Elderly	
	Current	MA2	Resp.	Cardio.	Resp.
T<-2 SD	0.0360**	0.0496	0.124	0.0396	0.219**
	(0.0136)	(0.0737)	(0.117)	(0.0591)	(0.0650)
-2 SD⩽T<-1.6 SD	-0.00471	-0.0337	0.0000347	-0.0279	0.0639
	(0.00495)	(0.0382)	(0.0618)	(0.0296)	(0.0467)
-1.6 SD⩽T<-1.2 SD	0.00378	0.00650	0.0403	0.00673	0.0704*
	(0.00365)	(0.0270)	(0.0408)	(0.0274)	(0.0318)
-1.2 SD⩽T<-0.8 SD	0.00433	0.0308	-0.0124	-0.00539	0.0474
	(0.00370)	(0.0248)	(0.0448)	(0.0247)	(0.0300)
-0.8 SD⩽T<-0.4 SD	-0.00390	0.0533*	0.0188	0.0182	0.0227
	(0.00295)	(0.0268)	(0.0366)	(0.0225)	(0.0226)
-0.4 SD⩽T<0 SD	-0.00575	0.0433	0.0391	0.0182	0.0290
	(0.00320)	(0.0259)	(0.0349)	(0.0194)	(0.0249)
0.4 SD⩽T<0.8 SD	0.000536	-0.0266	0.0326	-0.0113	0.00831
	(0.00266)	(0.0307)	(0.0272)	(0.0203)	(0.0209)
0.8 SD⩽T<1.2 SD	0.00366	0.00980	0.0200	0.00866	-0.0104
	(0.00258)	(0.0358)	(0.0317)	(0.0238)	(0.0216)
1.2 SD⩽T<1.6 SD	0.0158***	0.000305	0.0425	-0.00833	0.0184
	(0.00306)	(0.0309)	(0.0308)	(0.0229)	(0.0243)
1.6 SD⩽T<2 SD	0.0490***	0.100*	0.103**	0.0163	0.0881**
	(0.00477)	(0.0431)	(0.0380)	(0.0290)	(0.0293)
T⩾2 SD	0.0912***	0.299**	0.0764	0.188**	0.0824
	(0.0146)	(0.0959)	(0.105)	(0.0671)	(0.0522)
T<-2 SD × Q1	-0.00177	0.0570	-0.0693	0.113	0.186
	(0.0229)	(0.121)	(0.146)	(0.132)	(0.146)
-2 SD⩽T<-1.6 SD × Q1	-0.0148	-0.0291	-0.0836	-0.0138	-0.131
	(0.0108)	(0.0618)	(0.0896)	(0.0559)	(0.0664)
-1.6 SD⩽T<-1.2 SD × Q1	0.0112	0.0432	0.0181	0.0830*	0.0210
	(0.00604)	(0.0401)	(0.0533)	(0.0318)	(0.0301)
-1.2 SD⩽T<-0.8 SD × Q1	-0.00429	-0.0365	-0.00261	-0.0129	0.0325
	(0.00439)	(0.0391)	(0.0436)	(0.0275)	(0.0283)
-0.8 SD⩽T<-0.4 SD × Q1	0.00239	0.0658	0.0468	0.0353	0.0213
	(0.00446)	(0.0520)	(0.0421)	(0.0274)	(0.0363)
-0.4 SD⩽T<0 SD × Q1	-0.00424	-0.0168	-0.0189	0.0338	0.0361
	(0.00457)	(0.0518)	(0.0506)	(0.0309)	(0.0286)
0.4 SD⩽T<0.8 SD × Q1	-0.00318	-0.00997	-0.00405	0.0560	0.0110
	(0.00526)	(0.0537)	(0.0385)	(0.0297)	(0.0348)
0.8 SD⩽T<1.2 SD × Q1	-0.00147	0.105	-0.0143	0.0245	0.00824
	(0.00491)	(0.0536)	(0.0371)	(0.0271)	(0.0257)
1.2 SD⩽T<1.6 SD × Q1	-0.00286	-0.0273	-0.0113	0.0323	-0.0126
	(0.00358)	(0.0426)	(0.0330)	(0.0244)	(0.0238)
1.6 SD⩽T<2 SD × Q1	-0.0111	-0.0175	0.00897	-0.0241	-0.0490
	(0.00741)	(0.0755)	(0.0472)	(0.0533)	(0.0381)
T⩾2 SD × Q1	-0.00547	-0.280	0.123	0.171	0.141
	(0.0287)	(0.187)	(0.140)	(0.114)	(0.128)

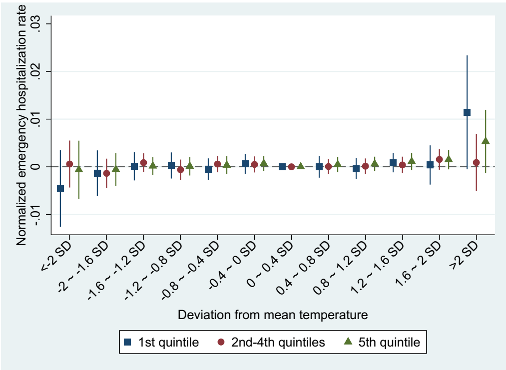
Continued on next page

Table C.10 – continued from previous page

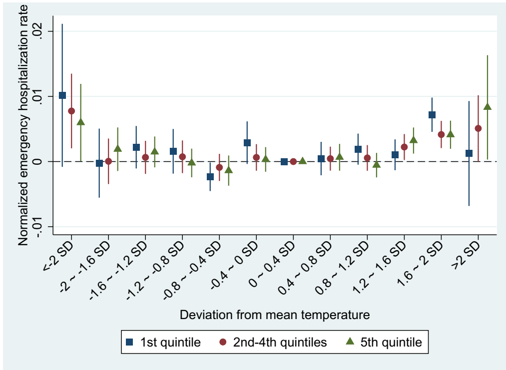
	(1)	(2)	(3)	(4)	(5)
	Mortality		Children	Elderly	
	Current	MA2	Resp.	Cardio.	Resp.
Q1	0.0228	-0.0975	-0.336	-0.941	-0.262
	(0.0866)	(0.889)	(0.738)	(0.613)	(0.587)
T<-2 SD × Q5	-0.0333	0.0246	0.128	0.0469	0.00703
	(0.0242)	(0.0791)	(0.173)	(0.0720)	(0.0697)
-2 SD⩽T<-1.6 SD × Q5	0.0172*	0.0328	0.0706	-0.0116	-0.0101
	(0.00680)	(0.0405)	(0.0543)	(0.0349)	(0.0277)
-1.6 SD⩽T<-1.2 SD × Q5	0.000358	-0.0703*	-0.0229	0.000693	-0.0309
	(0.00378)	(0.0287)	(0.0248)	(0.0187)	(0.0196)
-1.2 SD⩽T<-0.8 SD × Q5	0.00923	-0.0352	-0.0237	0.0184	-0.0217
	(0.00473)	(0.0304)	(0.0276)	(0.0144)	(0.0182)
-0.8 SD⩽T<-0.4 SD × Q5	-0.00390	-0.0514	-0.0319	-0.0111	-0.0213
	(0.00385)	(0.0261)	(0.0214)	(0.0140)	(0.0179)
-0.4 SD⩽T<0 SD × Q5	0.00394	-0.0251	-0.0411	0.0172	-0.0428*
	(0.00355)	(0.0318)	(0.0334)	(0.0220)	(0.0210)
0.4 SD⩽T<0.8 SD × Q5	0.00606	-0.101*	-0.00952	0.0218	0.00511
	(0.00420)	(0.0392)	(0.0250)	(0.0213)	(0.0196)
0.8 SD⩽T<1.2 SD × Q5	-0.00757*	-0.0854*	-0.0248	0.00674	-0.0322*
	(0.00328)	(0.0340)	(0.0189)	(0.0148)	(0.0135)
1.2 SD⩽T<1.6 SD × Q5	0.0103***	0.0311	0.00810	0.0169	0.0254
	(0.00292)	(0.0299)	(0.0182)	(0.0173)	(0.0179)
1.6 SD⩽T<2 SD × Q5	-0.00865	-0.103**	-0.0410	0.0134	0.0393
	(0.00825)	(0.0385)	(0.0257)	(0.0208)	(0.0259)
T⩾2 SD × Q5	-0.00408	0.215	0.111	-0.0390	-0.00350
	(0.0240)	(0.193)	(0.129)	(0.100)	(0.0853)
Q5	-0.0704	1.347*	0.150	-0.257	0.299
	(0.0744)	(0.667)	(0.516)	(0.407)	(0.379)
Municipality fixed effects	Yes	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	8.334	93.42	18.73	25.63	26.03
Obs.	1131958	1299041	1304955	1306487	1306487
R^2	0.248	0.839	0.252	0.155	0.185

Notes - The table reports regression results of monthly mortality rates per 10,000 individuals for the period 2003-2015 (columns 1 and 2) and of emergency hospital admission rates of children (0-5 years; column 3) and the elderly (over 75 years; columns 4-5). Columns 3 and 5 report results for respiratory diseases, and column 4 reports results for cardiovascular diseases. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. In columns 1 and 3-5, current temperature bins are used, and in column 2 temperature bins are 2-month moving averages. *Q1* and *Q5* are dummy variables equal to one for municipalities belonging to the first of fifth quintile of the per capita local government social expenditure distribution lagged by one year, respectively. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Models in columns 1 and 2 further control for population age structure. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

Figure C.7: Regression results of emergency hospital admission rates of the age group 6-74 years by quintiles of per capita municipal social expenditure



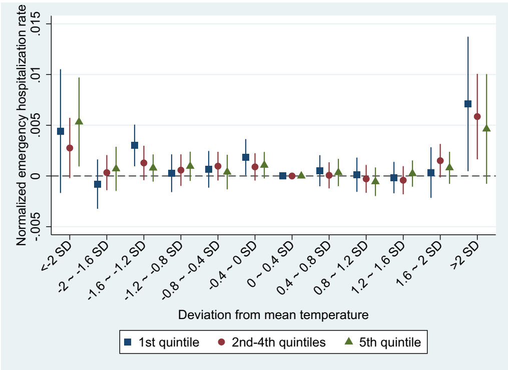
(a) Cardiovascular diseases



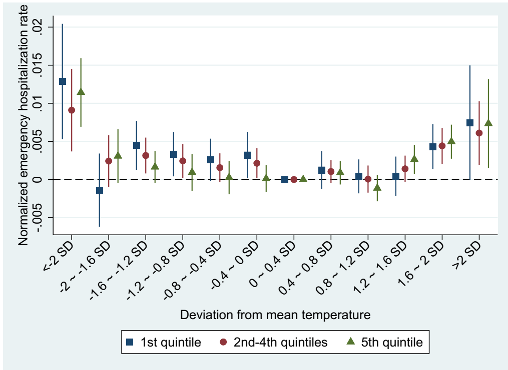
(b) Respiratory diseases

Notes - The figures illustrate separate regression results of monthly emergency hospital admission rates of the age group 6-74 years per 10,000 individuals by quintiles (1st, 2nd to 4th, and 5th) of the year-specific distribution of per capita municipal social expenditure lagged by one year. Figures (a) and (b) illustrate regression results for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. Blue squares represent marginal effects for municipalities in the first social expenditure quintile, red dots for municipalities in the second, third and fourth quintiles, and green triangles for municipalities in the fifth quintile. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health, GSOD weather data provided by NCDC and municipality balance sheet data provided by the Italian Ministry of Interior.

Figure C.8: Regression results of aggregated emergency hospital admission rates by quintiles of per capita municipal social expenditure



(a) Cardiovascular diseases



(b) Respiratory diseases

Notes - The figures illustrate separate regression results of aggregated monthly emergency hospital admission rates of children (0-5 years) and the elderly (over 75 years) per 10,000 individuals by quintiles (1st, 2nd to 4th, and 5th) of the year-specific distribution of per capita municipal social expenditure lagged by one year. Figure (a) illustrates regression results for cardiovascular diseases and Figure (b) illustrates regression results for respiratory diseases. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. Blue squares represent marginal effects for municipalities in the first social expenditure quintile, red dots for municipalities in the second, third and fourth quintiles, and green triangles for municipalities in the fifth quintile. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health, GSOD weather data provided by NCDC and municipality balance sheet data provided by the Italian Ministry of Interior.

Table C.11: Regression results of emergency hospital admission rates of the age group 6-74 years and the aggregated vulnerable population

	(1)	(2)	(3)	(4)
	6-74 years		Dependent population	
	Cardio.	Resp.	Cardio.	Resp.
T<-2 SD	0.00205	0.0100	0.0942	0.160**
	(0.00884)	(0.00621)	(0.0517)	(0.0486)
-2 SD⩽T<-1.6 SD	-0.00481	-0.00324	0.0113	0.0427
	(0.00552)	(0.00312)	(0.0301)	(0.0304)
-1.6 SD⩽T<-1.2 SD	0.00307	-0.00131	0.0438	0.0555**
	(0.00351)	(0.00267)	(0.0296)	(0.0211)
-1.2 SD⩽T<-0.8 SD	-0.00212	-0.00212	0.0196	0.0431*
	(0.00382)	(0.00249)	(0.0271)	(0.0200)
-0.8 SD⩽T<-0.4 SD	0.00203	-0.00319	0.0331	0.0275
	(0.00309)	(0.00217)	(0.0246)	(0.0169)
-0.4 SD⩽T<0 SD	0.00176	-0.00123	0.0306	0.0376*
	(0.00302)	(0.00225)	(0.0235)	(0.0177)
0.4 SD⩽T<0.8 SD	0.000205	-0.000668	0.00225	0.0185
	(0.00276)	(0.00196)	(0.0224)	(0.0133)
0.8 SD⩽T<1.2 SD	0.000462	-0.0000663	-0.00977	0.00103
	(0.00291)	(0.00216)	(0.0239)	(0.0160)
1.2 SD⩽T<1.6 SD	0.00139	0.00262	-0.0143	0.0248
	(0.00311)	(0.00209)	(0.0242)	(0.0155)
1.6 SD⩽T<2 SD	0.00546	0.00533*	0.0515	0.0778***
	(0.00388)	(0.00223)	(0.0287)	(0.0212)
T⩾2 SD	0.00317	0.000895	0.200**	0.107**
	(0.0108)	(0.00660)	(0.0734)	(0.0375)
T<-2 SD × Q1	-0.0180	-0.00411	0.0568	0.0663
	(0.0174)	(0.0107)	(0.103)	(0.0779)
-2 SD⩽T<-1.6 SD × Q1	0.000173	0.00167	-0.0387	-0.0672
	(0.00693)	(0.00484)	(0.0315)	(0.0406)
-1.6 SD⩽T<-1.2 SD × Q1	-0.00271	0.00401	0.0589*	0.0235
	(0.00387)	(0.00267)	(0.0238)	(0.0224)
-1.2 SD⩽T<-0.8 SD × Q1	0.00311	0.00338	-0.0104	0.0156
	(0.00365)	(0.00278)	(0.0201)	(0.0172)
-0.8 SD⩽T<-0.4 SD × Q1	-0.00370	-0.00219	-0.0106	0.0183
	(0.00291)	(0.00215)	(0.0187)	(0.0203)
-0.4 SD⩽T<0 SD × Q1	0.000484	0.00619*	0.0327	0.0190
	(0.00378)	(0.00246)	(0.0237)	(0.0240)
0.4 SD⩽T<0.8 SD × Q1	-0.000171	0.00153	0.0154	0.00352
	(0.00377)	(0.00252)	(0.0214)	(0.0189)
0.8 SD⩽T<1.2 SD × Q1	-0.00174	0.00326	0.0140	0.00624
	(0.00318)	(0.00201)	(0.0204)	(0.0169)
1.2 SD⩽T<1.6 SD × Q1	0.00170	-0.0000836	0.00887	-0.0173
	(0.00242)	(0.00170)	(0.0161)	(0.0167)
1.6 SD⩽T<2 SD × Q1	-0.00410	0.00716*	-0.0400	-0.00172
	(0.00668)	(0.00320)	(0.0379)	(0.0237)
T⩾2 SD × Q1	0.0370	0.0131	0.0425	0.0238
	(0.0222)	(0.0126)	(0.109)	(0.0667)

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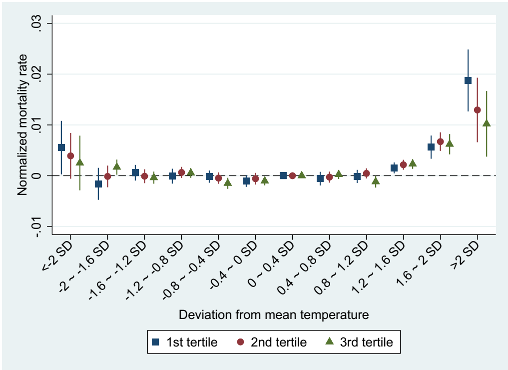
Table C.11 – continued from previous page

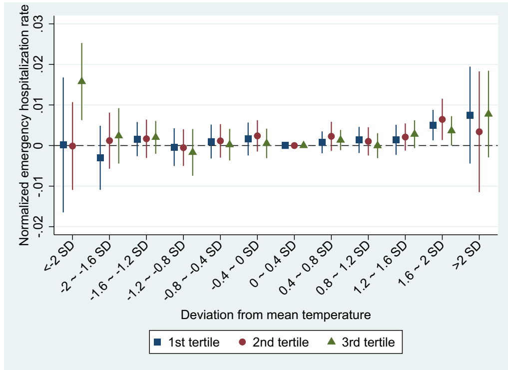
	(1)	(2)	(3)	(4)
	6-74 years		Dependent population	
	Cardio.	Resp.	Cardio.	Resp.
Q1	-0.00529	-0.0812	-0.363	-0.202
	(0.0666)	(0.0422)	(0.459)	(0.375)
T<-2 SD × Q5	-0.00424	-0.00448	0.0875	0.0410
	(0.00732)	(0.00519)	(0.0602)	(0.0530)
-2 SD⩽T<-1.6 SD × Q5	0.00286	0.00220	0.0126	0.0114
	(0.00486)	(0.00247)	(0.0326)	(0.0153)
-1.6 SD⩽T<-1.2 SD × Q5	-0.00247	0.00173	-0.0170	-0.0265*
	(0.00280)	(0.00166)	(0.0174)	(0.0123)
-1.2 SD⩽T<-0.8 SD × Q5	0.00256	-0.00220	0.0129	-0.0266*
	(0.00204)	(0.00153)	(0.0135)	(0.0120)
-0.8 SD⩽T<-0.4 SD × Q5	-0.000855	-0.00165	-0.0198	-0.0229*
	(0.00208)	(0.00168)	(0.0158)	(0.0109)
-0.4 SD⩽T<0 SD × Q5	0.000677	0.000367	0.00565	-0.0353*
	(0.00270)	(0.00181)	(0.0207)	(0.0150)
0.4 SD⩽T<0.8 SD × Q5	0.00145	-0.000488	0.00941	-0.00286
	(0.00281)	(0.00167)	(0.0201)	(0.0126)
0.8 SD⩽T<1.2 SD × Q5	0.00170	-0.00153	-0.00958	-0.0210*
	(0.00174)	(0.00140)	(0.0138)	(0.00896)
1.2 SD⩽T<1.6 SD × Q5	0.00250	0.000796	0.0224	0.0216
	(0.00216)	(0.00147)	(0.0153)	(0.0115)
1.6 SD⩽T<2 SD × Q5	-0.000149	-0.000496	-0.0240	0.00970
	(0.00337)	(0.00224)	(0.0205)	(0.0146)
T⩾2 SD × Q5	0.0155	0.00824	-0.0417	0.0219
	(0.0138)	(0.0102)	(0.103)	(0.0567)
Q5	-0.0444	-0.00549	-0.136	0.263
	(0.0514)	(0.0331)	(0.415)	(0.250)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	3.515	1.820	34.13	17.61
Obs.	1306487	1306487	1306487	1306487
R^2	0.122	0.0980	0.251	0.272

Notes - The table reports regression results of monthly emergency hospital admission rates of the age group 6-74 years (columns 1 and 2) and of the dependent population (children 0-4 years and elderly over 75 years; columns 3 and 4) per 10,000 individuals for the period 2001-2015. Columns 1 and 3 report results for cardiovascular diseases, and columns 2 and 4 report results for respiratory disease. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. *Q1* and *Q5* are dummy variables equal to one for municipalities belonging to the first of fifth quintile of the per capita local government social expenditure distribution lagged by one year, respectively. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

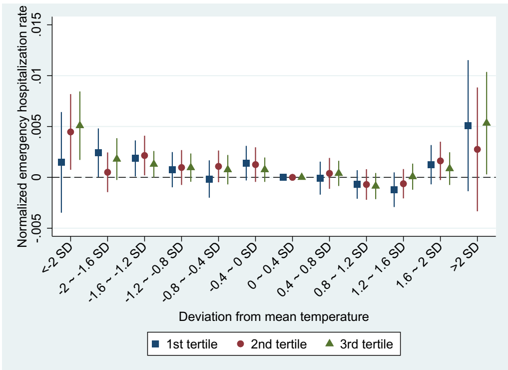
Figure C.9: Regression results of mortality and emergency hospital admission rates by tertiles of per capita municipal social expenditure



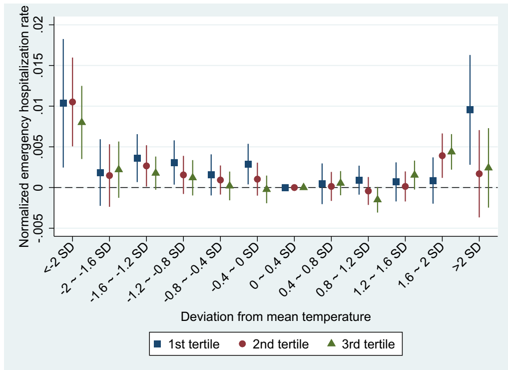
(a) Mortality



(b) Children - Respiratory diseases



(c) Elderly - Cardiovascular diseases



(d) Elderly - Respiratory diseases

Notes - The figures illustrate regression results of monthly mortality ratesfor the period 2003-2015 (Figure (a)) and of emergency hospital admission rates for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals by tertiles of the year-specific distribution of per capita municipal social expenditure lagged by one year. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. In Figures (b)-(d), current temperature bins are used, and in Figure (a) temperature bins are 2-month moving averages. Blue squares represent marginal effects for municipalities in the first social expenditure tertile, red dots for municipalities in the second tertile, and green triangles for municipalities in the third teritle. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Models of mortality rates further control for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health, GSOD weather data provided by NCDC and municipality balance sheet data provided by the Italian Ministry of Interior.

Table C.12: Regression results of mortality and emergency hospital admission rates by tertiles of per capita municipal social expenditure

	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
T<-2 SD	0.00428	-0.00227	0.278*	0.274***
	(0.0940)	(0.103)	(0.118)	(0.0725)
-2 SD⩽T<-1.6 SD	-0.0249	0.0226	0.0310	0.0384
	(0.0435)	(0.0660)	(0.0619)	(0.0510)
-1.6 SD⩽T<-1.2 SD	0.00194	0.0313	0.134*	0.0692*
	(0.0304)	(0.0452)	(0.0618)	(0.0337)
-1.2 SD⩽T<-0.8 SD	0.0327	-0.00968	0.0602	0.0404
	(0.0273)	(0.0432)	(0.0544)	(0.0311)
-0.8 SD⩽T<-0.4 SD	0.0641*	0.0215	0.0671	0.0240
	(0.0279)	(0.0394)	(0.0494)	(0.0237)
-0.4 SD⩽T<0 SD	0.0373	0.0447	0.0780	0.0268
	(0.0296)	(0.0369)	(0.0539)	(0.0269)
0.4 SD⩽T<0.8 SD	-0.0270	0.0425	0.0243	0.00357
	(0.0336)	(0.0343)	(0.0481)	(0.0237)
0.8 SD⩽T<1.2 SD	0.0173	0.0194	-0.0437	-0.0110
	(0.0355)	(0.0333)	(0.0477)	(0.0228)
1.2 SD⩽T<1.6 SD	0.000366	0.0393	-0.0389	0.00349
	(0.0325)	(0.0320)	(0.0457)	(0.0245)
1.6 SD⩽T<2 SD	0.0954*	0.121*	0.101	0.102**
	(0.0454)	(0.0487)	(0.0598)	(0.0363)
T⩾2 SD	0.297*	0.0636	0.171	0.0441
	(0.125)	(0.142)	(0.193)	(0.0712)
T<-2 SD × T1	0.0622	0.00522	-0.186	-0.00423
	(0.104)	(0.121)	(0.153)	(0.108)
-2 SD⩽T<-1.6 SD × T1	-0.0445	-0.0791	0.119	0.00954
	(0.0553)	(0.0567)	(0.0674)	(0.0522)
-1.6 SD⩽T<-1.2 SD × T1	0.0440	-0.00158	-0.0177	0.0249
	(0.0281)	(0.0316)	(0.0372)	(0.0295)
-1.2 SD⩽T<-0.8 SD × T1	-0.0204	0.00222	-0.0133	0.0397
	(0.0313)	(0.0319)	(0.0402)	(0.0244)
-0.8 SD⩽T<-0.4 SD × T1	0.0199	-0.00304	-0.0773*	0.0163
	(0.0367)	(0.0284)	(0.0342)	(0.0258)
-0.4 SD⩽T<0 SD × T1	0.00705	-0.0144	0.00888	0.0482
	(0.0394)	(0.0345)	(0.0494)	(0.0326)
0.4 SD⩽T<0.8 SD × T1	-0.0141	-0.0277	-0.0291	0.00841
	(0.0403)	(0.0319)	(0.0427)	(0.0308)
0.8 SD⩽T<1.2 SD × T1	0.0757	0.00640	0.000148	0.0346
	(0.0413)	(0.0273)	(0.0384)	(0.0205)
1.2 SD⩽T<1.6 SD × T1	-0.0227	-0.0129	-0.0365	0.0145
	(0.0360)	(0.0242)	(0.0321)	(0.0203)
1.6 SD⩽T<2 SD × T1	-0.00562	-0.0264	-0.0234	-0.0795*
	(0.0504)	(0.0486)	(0.0440)	(0.0336)
T⩾2 SD × T1	-0.161	0.0771	0.145	0.204
	(0.144)	(0.130)	(0.210)	(0.107)

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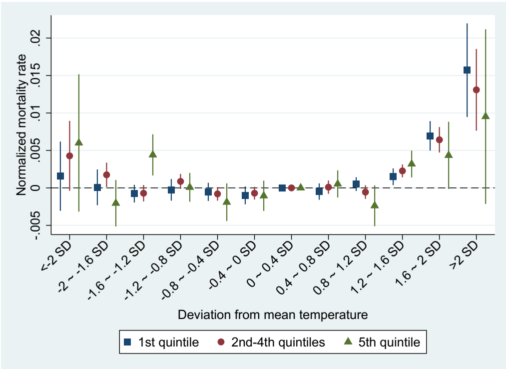
Table C.12 – continued from previous page

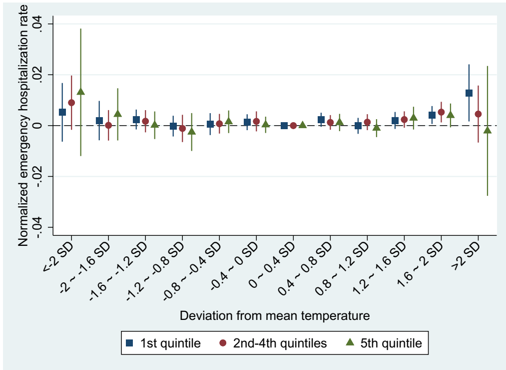
	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
T1	-0.159	-0.107	-0.0149	-0.735
	(0.675)	(0.582)	(0.802)	(0.522)
T<-2 SD × T3	0.0839	0.298**	0.0382	-0.0655
	(0.0858)	(0.112)	(0.121)	(0.0644)
-2 SD⩽T<-1.6 SD × T3	0.0165	0.0221	0.0807	0.0188
	(0.0485)	(0.0553)	(0.0567)	(0.0332)
-1.6 SD⩽T<-1.2 SD × T3	-0.0438	0.00635	-0.0536	-0.0232
	(0.0283)	(0.0262)	(0.0374)	(0.0198)
-1.2 SD⩽T<-0.8 SD × T3	-0.0260	-0.0219	-0.000710	-0.00923
	(0.0273)	(0.0316)	(0.0288)	(0.0182)
-0.8 SD⩽T<-0.4 SD × T3	-0.0495*	-0.0174	-0.0203	-0.0189
	(0.0230)	(0.0217)	(0.0287)	(0.0156)
-0.4 SD⩽T<0 SD × T3	-0.00862	-0.0350	-0.0311	-0.0328
	(0.0297)	(0.0291)	(0.0415)	(0.0202)
0.4 SD⩽T<0.8 SD × T3	-0.0594	-0.0173	-0.0000715	0.0103
	(0.0350)	(0.0244)	(0.0420)	(0.0192)
0.8 SD⩽T<1.2 SD × T3	-0.0743*	-0.0200	-0.00965	-0.0282*
	(0.0304)	(0.0201)	(0.0286)	(0.0134)
1.2 SD⩽T<1.6 SD × T3	0.0225	0.0131	0.0432	0.0364*
	(0.0261)	(0.0195)	(0.0307)	(0.0157)
1.6 SD⩽T<2 SD × T3	-0.0602	-0.0524	-0.0474	0.0121
	(0.0354)	(0.0309)	(0.0476)	(0.0296)
T⩾2 SD × T3	0.142	0.0817	0.160	0.0188
	(0.168)	(0.148)	(0.224)	(0.0905)
T3	0.985	0.426	-0.167	0.260
	(0.560)	(0.603)	(0.827)	(0.362)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	93.42	18.73	62.16	26.03
Obs.	1299041	1304955	1306487	1306487
R^2	0.839	0.252	0.200	0.185

Notes - The table reports regression results of monthly mortality rates per 10,000 individuals for the period 2003-2015 (column 1) and of emergency hospital admission rates of children (0-5 years; column 2) and the elderly (over 75 years; columns 3-4). Columns 2 and 4 report results for respiratory diseases, and column 3 reports results for cardiovascular diseases. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. In columns 2-4, current temperature bins are used, and in column 1 temperature bins are 2-month moving averages. *T1* and *T3* are dummy variables equal to one for municipalities belonging to the first of third tertile of the per capita local government social expenditure distribution lagged by one year, respectively. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls for population age structure.. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

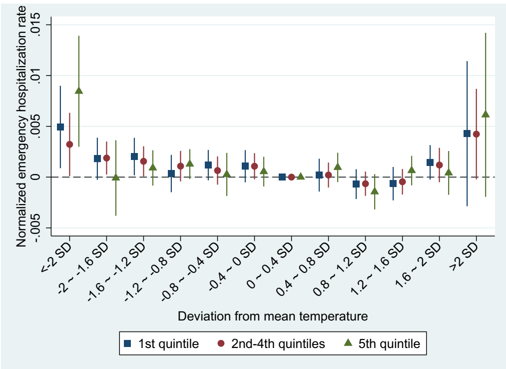
Figure C.10: Regression results of mortality and emergency hospital admission rates by quintiles of per capita municipal expenditure for general administration



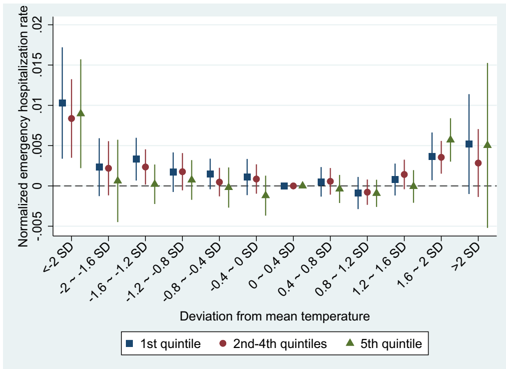
(a) Mortality



(b) Children - Respiratory diseases



(c) Elderly - Cardiovascular diseases



(d) Elderly - Respiratory diseases

Notes - The figures illustrate regression results of monthly mortality rates for the period 2003-2015 (Figure (a)) and of emergency hospital admission rates for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals by quintiles (1st, 2nd to 4th, and 5th) of the year-specific distribution of per capita municipal expenditure for general administration lagged by one year. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. In Figures (b)-(d), current temperature bins are used, and in Figure (a) temperature bins are 2-month moving averages. Blue squares represent marginal effects for municipalities in the first social expenditure quintile, red dots for municipalities in the second, third and fourth quintiles, and green triangles for municipalities in the fifth quintile. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Models of mortality rates further control for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health, GSOD weather data provided by NCDC and municipality balance sheet data provided by the Italian Ministry of Interior.

Table C.13: Regression results of mortality and emergency hospital admission rates by quintiles of per capita municipal expenditure for general administration

	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
T<-2 SD	0.0169	0.169	0.200*	0.218**
	(0.0786)	(0.102)	(0.0987)	(0.0648)
-2 SD⩽T<-1.6 SD	0.00645	0.00199	0.117*	0.0570
	(0.0317)	(0.0573)	(0.0515)	(0.0446)
-1.6 SD⩽T<-1.2 SD	-0.0301	0.0321	0.0968*	0.0612*
	(0.0266)	(0.0417)	(0.0469)	(0.0291)
-1.2 SD⩽T<-0.8 SD	0.0280	-0.0210	0.0672	0.0459
	(0.0246)	(0.0512)	(0.0476)	(0.0307)
-0.8 SD⩽T<-0.4 SD	0.0450	0.0138	0.0403	0.0124
	(0.0294)	(0.0370)	(0.0440)	(0.0235)
-0.4 SD⩽T<0 SD	0.0383	0.0312	0.0666	0.0223
	(0.0241)	(0.0376)	(0.0409)	(0.0242)
0.4 SD⩽T<0.8 SD	-0.0479	0.0234	0.0128	0.0148
	(0.0249)	(0.0276)	(0.0389)	(0.0219)
0.8 SD⩽T<1.2 SD	-0.0313	0.0253	-0.0404	-0.0202
	(0.0316)	(0.0300)	(0.0380)	(0.0209)
1.2 SD⩽T<1.6 SD	0.0310	0.0446	-0.0283	0.0370
	(0.0295)	(0.0308)	(0.0399)	(0.0244)
1.6 SD⩽T<2 SD	0.0647	0.0994*	0.0740	0.0924***
	(0.0401)	(0.0387)	(0.0537)	(0.0270)
T⩾2 SD	0.452***	0.0851	0.263	0.0739
	(0.0926)	(0.107)	(0.141)	(0.0559)
T<-2 SD × Q1	0.0998	-0.0711	0.107	0.0500
	(0.0782)	(0.0972)	(0.105)	(0.0714)
-2 SD⩽T<-1.6 SD × Q1	-0.00474	0.0348	-0.00429	0.00349
	(0.0459)	(0.0528)	(0.0508)	(0.0391)
-1.6 SD⩽T<-1.2 SD × Q1	0.0205	0.0128	0.0288	0.0252
	(0.0242)	(0.0277)	(0.0332)	(0.0214)
-1.2 SD⩽T<-0.8 SD × Q1	0.000191	0.0172	-0.0453	-0.00158
	(0.0238)	(0.0331)	(0.0367)	(0.0197)
-0.8 SD⩽T<-0.4 SD × Q1	0.0323	-0.00290	0.0331	0.0262
	(0.0221)	(0.0228)	(0.0231)	(0.0183)
-0.4 SD⩽T<0 SD × Q1	-0.00349	-0.00631	-0.0000351	0.00633
	(0.0290)	(0.0269)	(0.0411)	(0.0244)
0.4 SD⩽T<0.8 SD × Q1	0.0209	0.0196	-0.000727	-0.00162
	(0.0310)	(0.0262)	(0.0420)	(0.0210)
0.8 SD⩽T<1.2 SD × Q1	0.110***	-0.0272	-0.00252	-0.00273
	(0.0297)	(0.0173)	(0.0246)	(0.0201)
1.2 SD⩽T<1.6 SD × Q1	-0.0679**	-0.00663	-0.0117	-0.0164
	(0.0250)	(0.0187)	(0.0305)	(0.0157)
1.6 SD⩽T<2 SD × Q1	0.0759*	-0.0213	0.0166	0.00310
	(0.0344)	(0.0284)	(0.0448)	(0.0299)
T⩾2 SD × Q1	-0.480***	0.156	0.00288	0.0612
	(0.139)	(0.114)	(0.216)	(0.0967)

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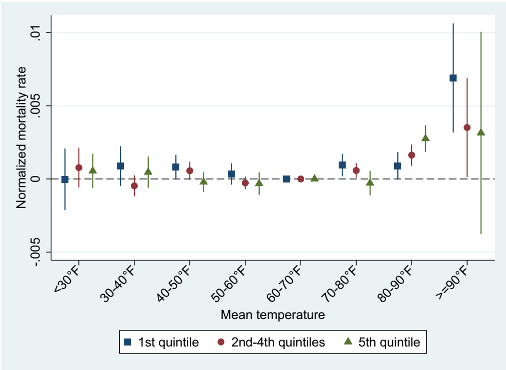
Table C.13 – continued from previous page

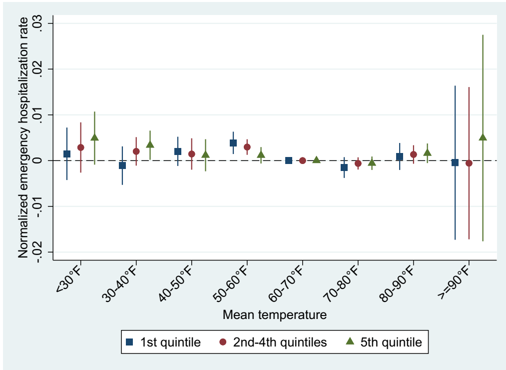
	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
Q1	-0.966	-0.0258	-0.132	-0.00536
	(0.501)	(0.476)	(0.733)	(0.410)
T<-2 SD × Q5	0.190	0.0764	0.325*	0.0154
	(0.171)	(0.279)	(0.162)	(0.115)
-2 SD⩽T<-1.6 SD × Q5	-0.173*	0.0808	-0.122	-0.0409
	(0.0837)	(0.0751)	(0.0996)	(0.0481)
-1.6 SD⩽T<-1.2 SD × Q5	0.0903	-0.0294	-0.0408	-0.0558*
	(0.0493)	(0.0418)	(0.0488)	(0.0258)
-1.2 SD⩽T<-0.8 SD × Q5	-0.0995	-0.0264	0.0124	-0.0267
	(0.0755)	(0.0594)	(0.0465)	(0.0296)
-0.8 SD⩽T<-0.4 SD × Q5	-0.0523	0.0145	-0.0238	-0.0176
	(0.0503)	(0.0361)	(0.0452)	(0.0233)
-0.4 SD⩽T<0 SD × Q5	-0.00105	-0.0254	-0.0330	-0.0537
	(0.0743)	(0.0311)	(0.0409)	(0.0315)
0.4 SD⩽T<0.8 SD × Q5	-0.140	-0.000567	0.0466	-0.0247
	(0.0733)	(0.0296)	(0.0417)	(0.0228)
0.8 SD⩽T<1.2 SD × Q5	-0.0278	-0.0439	-0.0493	-0.00375
	(0.0712)	(0.0247)	(0.0407)	(0.0183)
1.2 SD⩽T<1.6 SD × Q5	0.0138	0.0104	0.0682*	-0.0388
	(0.0619)	(0.0286)	(0.0310)	(0.0212)
1.6 SD⩽T<2 SD × Q5	-0.102	-0.0245	-0.0482	0.0561
	(0.0785)	(0.0353)	(0.0611)	(0.0291)
T⩾2 SD × Q5	0.108	-0.124	0.118	0.0569
	(0.239)	(0.240)	(0.261)	(0.147)
Q5	2.105	0.942	0.338	0.463
	(1.296)	(0.557)	(1.018)	(0.456)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	93.42	18.73	62.16	26.03
Obs.	1299041	1304955	1306487	1306487
R^2	0.839	0.252	0.200	0.185

Notes - The table reports regression results of monthly mortality rates per 10,000 individuals for the period 2003-2015 (column 1) and of emergency hospital admission rates of children (0-5 years; column 2) and the elderly (over 75 years; columns 3-4). Columns 2 and 4 report results for respiratory diseases, and column 3 reports results for cardiovascular diseases. Temperature bins measure the number of days per month with average temperature falling within 0.4 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001-2015, with the baseline being the number of days with temperatures deviating from the mean between 0 and +0.4 SDs. In columns 2-4, current temperature bins are used, and in column 1 temperature bins are 2-month moving averages. *Q1* and *Q5* are dummy variables equal to one for municipalities belonging to the first of fifth quintile of the per capita local government administrative expenditure distribution lagged by one year, respectively. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls for population age structure. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.

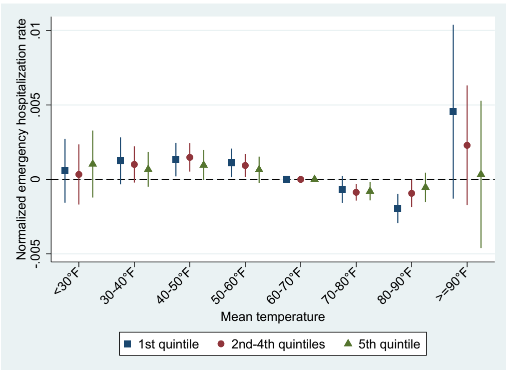
Figure C.11: Regression results of mortality and emergency hospital admission rates by quintiles of per capita municipal social expenditure using temperature level bins



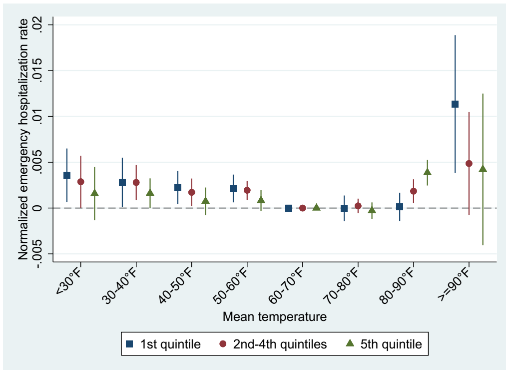
(a) Mortality



(b) Children - Respiratory diseases



(c) Elderly - Cardiovascular diseases



(d) Elderly - Respiratory diseases

Notes - The figures illustrate regression results of monthly mortality rates for the period 2003-2015 (Figure (a)) and of emergency hospital admission rates for the period 2001-2015 (Figures (b)-(d)) per 10,000 individuals by quintiles (1st, 2nd to 4th, and 5th) of the year-specific distribution of per capita municipal social expenditure lagged by one year. Figure (b) illustrates results for hospital admissions of children (0-5 years) for respiratory diseases, and Figures (c) and (d) illustrate results for hospital admissions of the elderly (over 75 years) for cardiovascular and respiratory diseases, respectively. Dots represent normalized coefficients of temperature bins and vertical lines represent 95% confidence intervals. Temperature bins measure the number of days per month with average temperature falling within 10°F bins, with the baseline being the number of days with temperatures between 60°F and 70°F. In Figures (b)-(d), current temperature bins are used, and in Figure (a) temperature bins are 2-month moving averages. Blue squares represent marginal effects for municipalities in the first social expenditure quintile, red dots for municipalities in the second, third and fourth quintiles, and green triangles for municipalities in the fifth quintile. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. Models of mortality rates further control for the population age structure. Standard errors are robust and clustered by province. All regressions are weighted by the the age-group-specific population.
Source: Our elaboration on mortality data for the period 2003-2015 provided by ISTAT, hospital discharge data for the period 2001-2015 provided by the Italian Ministry of Health, GSOD weather data provided by NCDC and municipality balance sheet data provided by the Italian Ministry of Interior.

Table C.14: Regression results of mortality and emergency hospital admission rates by quintiles of per capita municipal social expenditure using temperature level bins

	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
<30°F	0.0515	0.0538	0.0207	0.0748
	(0.0324)	(0.0525)	(0.0641)	(0.0377)
30-40°F	0.00938	0.0378	0.0625	0.0727**
	(0.0198)	(0.0298)	(0.0386)	(0.0254)
40-50°F	0.0396**	0.0271	0.0918**	0.0447*
	(0.0133)	(0.0328)	(0.0302)	(0.0200)
50-60°F	0.0161	0.0556***	0.0581*	0.0505***
	(0.00853)	(0.0163)	(0.0241)	(0.0138)
70-80°F	0.00203	-0.0115	-0.0539**	0.00623
	(0.0137)	(0.0127)	(0.0176)	(0.0104)
80-90°F	-0.0359	0.0251	-0.0582*	0.0479**
	(0.0186)	(0.0194)	(0.0293)	(0.0172)
⩾90°F	0.0849	-0.0105	0.142	0.127
	(0.0554)	(0.159)	(0.128)	(0.0745)
<30°F × Q1	0.0568	-0.0259	0.0152	0.0184
	(0.0539)	(0.0436)	(0.0572)	(0.0344)
30-40°F × Q1	0.0414**	-0.0583**	0.0149	0.000581
	(0.0140)	(0.0217)	(0.0262)	(0.0284)
40-50°F × Q1	-0.00370	0.0108	-0.00950	0.0141
	(0.00830)	(0.0191)	(0.0207)	(0.0141)
50-60°F × Q1	0.0253*	0.0171	0.0107	0.00515
	(0.0121)	(0.0210)	(0.0227)	(0.0158)
70-80°F × Q1	0.0360*	-0.0169	0.0127	-0.00688
	(0.0137)	(0.0199)	(0.0246)	(0.0151)
80-90°F × Q1	-0.0328	-0.00812	-0.0629*	-0.0444*
	(0.0166)	(0.0267)	(0.0247)	(0.0181)
⩾90°F × Q1	0.0747	0.00181	0.140	0.169
	(0.0721)	(0.0905)	(0.165)	(0.0949)
Q1	-0.204	-0.285	-0.00601	-0.00317
	(0.249)	(0.277)	(0.444)	(0.302)
<30°F × Q5	-0.0260	0.0383	0.0435	-0.0336
	(0.0279)	(0.0373)	(0.0427)	(0.0287)
30-40°F × Q5	0.0141	0.0253	-0.0206	-0.0307*
	(0.0126)	(0.0136)	(0.0191)	(0.0144)
40-50°F × Q5	-0.00392	-0.00507	-0.0323*	-0.0254**
	(0.00538)	(0.0102)	(0.0144)	(0.00917)
50-60°F × Q5	0.0233*	-0.0338	-0.0177	-0.0291**
	(0.0111)	(0.0186)	(0.0167)	(0.00967)
70-80°F × Q5	0.00401	0.000829	0.00452	-0.0135
	(0.00983)	(0.00969)	(0.0174)	(0.00876)
80-90°F × Q5	0.0376***	0.00492	0.0248	0.0526***
	(0.0107)	(0.0120)	(0.0182)	(0.0115)
⩾90°F × Q5	0.0187	0.103	-0.121	-0.0167
	(0.102)	(0.219)	(0.198)	(0.130)

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Table C.14 – continued from previous page

	(1)	(2)	(3)	(4)
		Children	Elderly	
	Mortality	Resp.	Cardio.	Resp.
Q5	-0.122	-0.158	0.0904	0.351
	(0.297)	(0.313)	(0.432)	(0.227)
Municipality fixed effects	Yes	Yes	Yes	Yes
Year × month fixed effects	Yes	Yes	Yes	Yes
Province × month fixed effects	Yes	Yes	Yes	Yes
Province-specific time-trends	Yes	Yes	Yes	Yes
Pollution and weather conditions	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Mean of dep. var.	93.02	18.73	62.16	26.03
Obs.	1306487	1304955	1306487	1306487
R^2	0.842	0.253	0.200	0.185

Notes - The table reports regression results of monthly mortality rates per 10,000 individuals for the period 2003-2015 (column 1) and of emergency hospital admission rates of children (0-5 years; column 2) and the elderly (over 75 years; columns 3-4). Columns 2 and 4 report results for respiratory diseases, and column 3 reports results for cardiovascular diseases. Temperature bins measure the number of days per month with average temperature falling within 10°F bins, with the baseline being the number of days with temperatures between 60°F and 70°F. In columns 2-4, current temperature bins are used, and in column 1 temperature bins are 2-month moving averages. *Q1* and *Q5* are dummy variables equal to one for municipalities belonging to the first of fifth quintile of the per capita local government social expenditure distribution lagged by one year, respectively. All models control for the average monthly precipitation rate and humidity, the natural logarithm of the yearly personal income, the cumulative regional health care expenditure for the past 5 years, municipality, month×year and province×month fixed effects, province-specific time trends and pollution. The model in column 1 further controls for population age structure. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the the age-group-specific population.