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Local mortality patterns in Italy at the beginning of the 21st century

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Abstract

We analysed mortality levels and trends at the municipal level in Italy between 2002 and 2018, covering approximately 8000 local administrative units. Detailed mortality data at this level are unavailable, and apparently only crude death rates can be calculated (deaths divided by the average, i.e. mid-year, population). To overcome this limitation, we calculated standardised mortality ratios (SMR), comparing observed deaths to expected deaths derived by applying national age-specific mortality rates to local population age structures. We validated this approach, examined its properties, and used it to investigate local mortality patterns across Italy. Our findings highlight limited territorial heterogeneity in SMR, although with a slight increase over time: the coefficient of variation rose from 12.5% to 15%. The between-region variance component also increased, while the within-region component remained predominant, accounting for approximately 80% of the total variance. Selected ecological factors, particularly an Istat-developed frailty index for municipalities, were found to correlate with small-scale mortality patterns. Global spatial regression models (spatial autoregressive—SAR and spatial error—SEM) further revealed strong spillover effects influencing local mortality.

Keywords: Mortality and longevity, Italy, Small-area estimation, Standardisation, Spatial demography

Introduction and purpose

Italy's "demographic exceptionalism" (Billari and Tomassini, 2021) is closely linked to its geographical heterogeneity, which significantly shapes its socio-economic and demographic landscape (Asso, 2020; Daniele & Malanima, 2017). Among the key factors is the historical North–South divide: the economically dynamic North contrasts with the South, characterised by higher poverty, unemployment, and occasionally inadequate housing conditions. Persistent internal migration from the South to the North underscores the ongoing imbalance (Benassi et al., 2019; Bonifazi et al., 2021).

Another challenge lies in remote and scarcely accessible areas, especially in the South. These municipalities, often situated inland in hilly or mountainous regions, face economic marginalisation, emigration, depopulation, and population ageing (Golini et al., 2000; Reynaud & Miccoli, 2018; Reynaud et al., 2020). While cities generally fare better than smaller towns or villages, significant disparities also exist within urban centres, particularly between central, peripheral, and suburban areas (Buonomo et al., 2024; OECD, 2018). These forms of heterogeneity can only be detected through highly localised analyses (Benassi et al., 2023; Fotheringham & Sachdeva, 2022). Granular studies are essential for understanding community dynamics and informing "place-based" policy design and implementation (Neumark & Simpson, 2015). Such localised approaches often result in more effective interventions (Willekens & Heide, 1985).

However, conducting research at small scales poses several challenges. Available data may lack reliability, consistency, or comparability. For instance, mortality—crucial in population studies and central to this research—is heavily influenced by local disparities and inequalities (Caselli et al., 2003; Fantini et al., 2006; Sauerberg et al., 2024). Although numerous studies have examined territorial mortality trends globally, data availability limitations often necessitate aggregation at higher levels, such as regions (NUTS2) or provinces (NUTS3) in Italy (e.g., Barbi et al., 2018; Bellini et al., 1992; Caselli et al., 1993; Istat, 2024). This intermediate level of aggregation may be adequate for broad assessments but lacks the granularity required to evaluate mortality in deprived or isolated local administrative units (LAUs).[1]

Generating unbiased mortality estimates at fine geographical scales requires innovative approaches, often contingent on data availability. When basic data are insufficient, researchers have employed complex methodologies, building on Swanson's foundational work (1989). These include contributions by Anson (2018), Congdon (2004, 2009, 2014), Eayres and Williams (2004), and Regidor et al. (2015). For Italy, Basile et al. (2024) have also explored such methods.

Previous studies on municipal-level mortality in Italy have often focused on specific "problematic" areas, thereby lacking a national perspective (Biggeri et al., 2006; Cervellera & Cusatelli, 2022; Gennaro et al., 2022; Lillini & Vercelli, 2018). Others, such as Guccio et al. (2024), have analysed changes in mortality trends related to specific events (e.g., recovery plans for indebted regions) using difference-in-difference techniques. Finally, it should be noted that, in relation to the COVID-19 pandemic in Italy, several local-scale mortality studies have been published recently, including works by Biggeri et al. (2020), Blangiardo et al. (2020), Cerqua et al. (2021), Gibertoni et al. (2021), and Scimone et al. (2022). In particular, Miccoli et al. (2025), using the National Strategy for Inner Areas (SNAI)[2] classification, investigate mortality disparities among different territorial settings in Italy, focusing on individuals aged 60 years and over. Their findings reveal substantial heterogeneity, with a U-shaped pattern in mortality rates (i.e. higher survival rates in ultra-peripheral areas) and, in the period 2011–2023, slower improvements in survival in the South.

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[1] To refer to territorial units in a comparable way across Europe—for conducting socio-economic analyses and framing EU regional policies—the EU developed a classification known as NUTS (Nomenclature of Territorial Units for Statistics). Each country is divided into NUTS 1 (major socio-economic regions), NUTS 2 (basic regions), and NUTS 3 (small regions). In the case of Italy, NUTS 2 corresponds to regions, while NUTS 3 corresponds to provinces. Moreover, to meet the demand for statistics at a local level, Eurostat maintains a system of Local Administrative Units (LAUs)—essentially municipalities and communes—compatible with NUTS, of which, in fact, LAUs constitute the building blocks (https://ec.europa.eu/eurostat/web/nuts).

[2] This initiative, promoted by the Agency for Territorial Cohesion and the former Minister for Territorial Cohesion, Fabrizio Barca, aims to revitalise the most disadvantaged areas of the country by implementing policies designed to remove obstacles to socio-economic development, thereby counteracting demographic decline and geographical marginalisation (Barca, 2009; Barca et al., 2012). (https://www.agenziacoesione.gov.it/strategia-nazionale-aree-interne/?lang=en).

These findings reinforce the idea that mortality patterns in Italy cannot be understood solely through the traditional North–South dichotomy. Rather, they require a multiscalar approach that encompasses both regional disparities and intra-regional differences across urban, peri-urban, and rural areas. A more granular understanding of these patterns is essential for designing effective, targeted public health policies aimed at reducing inequalities in health outcomes across Italy's diverse territorial landscape (Benassi et al., 2024).

For our analysis of small-scale mortality trends, we opted to use standardised mortality ratios (SMR). This widely adopted method for evaluating hospital performance (Roessler et al., 2021) employs indirect standardisation, popularised by the "Princeton Project" for studying fertility decline in Europe (Coale & Watkins, 1986). However, in mortality studies, its application remains relatively rare (Anson, 2003, 2018). Sánchez et al. (2020) applied this methodology to describe small-scale mortality in Italy (2012–2016), focusing on local unemployment as a primary variable. Our study expands on their approach in several ways:

1. Extending the analysis to a longer time series (2002–2018).
2. Examining the advantages and limitations of SMR at the municipal level.
3. Investigating mortality variability over time at both local (LAU) and regional (NUTS2) levels.
4. Including a broader set of socio-economic covariates beyond local unemployment.
5. Employing spatial regression models to account for spillover effects.

Point (3) is particularly significant for Italy. The National Health Service, introduced in 1978, aimed to ensure equal access to healthcare regardless of income or place of residence. However, fiscal constraints led to decentralisation efforts beginning in 1992, shifting responsibilities to regional administrations. While proponents argue that regions are better placed to address local needs, critics warn that this could exacerbate regional disparities in health outcomes (Cavalieri & Ferrante, 2020; Egidi & Demuru, 2018). These concerns have been amplified by various austerity measures and recovery plans implemented over the past 20 years, which have resulted in reduced numbers of hospital and healthcare personnel (Guccio et al., 2024; Salinari et al., 2023).

This study aims to address the following research questions:

1. How significant were survival inequalities at the municipal level in Italy between 2002 and 2018?
2. How did these inequalities evolve over time?
3. Were these trends associated with the decentralisation of health services initiated in 1992?
4. What contextual factors were most strongly linked to poor survival outcomes at the municipal level?

To address these questions, we employed the SMR introduced earlier (and further discussed below) and manipulated them in several ways to highlight their evolution over time, their absolute and relative variability, and their association with a number of municipal covariates. We hypothesise that variability was initially low, reflecting Italy's high living standards and the lingering effects of the 1978 health reforms. However, we expect inequality to have increased over the study period, driven by growing economic disparities[3] and the decentralisation of health services. We also anticipate that frailer municipalities[4]—those with weak economic performance, limited services, and poor accessibility—exhibited higher mortality rates.

The remainder of this paper is structured as follows: after describing the data and the mortality indicator (SMR) that we use, we present our results and discuss our findings. In the final section, we offer our conclusions, outline the policy implications, and suggest some possible directions for future research.

Data and method

Italy is geographically and administratively divided into 20 regions (NUTS2), 107 provinces (NUTS3), and approximately 8000 municipalities, or local administrative units (LAUs). These municipalities vary significantly in size, with an average population of 7500, though extremes range from 30 residents to over 2.6 million. Moreover, the number of municipalities changes almost yearly due to mergers and splits, complicating temporal comparisons. In 2018, there were 7914 municipalities—a figure used by Istat (the Italian National Institute of Statistics) to compile a harmonised demographic series for 2002–2018, which served as the basis for our analysis.

We excluded two municipalities, collectively housing around 18,000 residents, due to missing key data. For the spatial regression analysis, we further excluded 30 municipalities—16 (with approximately 14,000 residents) lacking the frailty index, and 14 isolated ones that could not be used for spatial modelling (home to about 67,000 residents). Consequently, our analysis encompasses 7,882 municipalities, representing the vast majority of Italy's population during the study period.

To focus on Italian nationals, we excluded foreigners from our dataset. This choice was driven by their distinct demographic characteristics—primarily a younger age structure and lower mortality rates—and their uneven geographical distribution, predominantly concentrated in Northern and Central Italy. Thus, our analysis includes between 55 and 56 million Italians, a declining population over the study period, out of a total of 57–60 million residents.

Our data: deaths, population, and ecological indicators

National, regional, and provincial mortality levels and trends in Italy are well-documented, with official life tables readily available. However, at the municipal level, the data are limited to total deaths per year by gender, with no age breakdowns. This permits the calculation of crude death rates, d, as follows:

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[3] With reference to income, for instance, the Gini index increased from 34.7% to 35.2% between 2002 and 2018 (Source: World Bank; https://data.worldbank.org/indicator/SI.POV.GINI?end=2018&locations=it&start=2002). The Gini index ranges from 0 (indicating perfect equality) to 1 (indicating maximum inequality, with one unit having all of the variable under consideration, in this case, income).

[4] We refer to the classification of municipalities based on the municipality frailty index recently proposed by the Italian National Institute of Statistics (Istat). More information is available at the following link: https://www.istat.it/comunicato-stampa/indice-di-fragilita-comunale-ifc/.

$$d_{\mathrm{gst}} = D_{\mathrm{gst}}/P_{\mathrm{gst}}, \tag{1}$$

where D represents deaths and P the population of a given gender s, in a given geographical area g, and year t (dataset "Population", in Table 1).

Unfortunately, crude death rates can be misleading as a measure of survival conditions due to variations in local age structures. To overcome this limitation, we employed an indirect standardisation technique to derive standardised mortality ratios (SMR):

$$\mathrm{SMR}_{\mathrm{gst}} = D_{\mathrm{gst}}/E_{\mathrm{gst}}, \tag{2}$$

where E_{gst} represents expected deaths, calculated by applying national age-specific mortality rates (m_x) to the population's age structure (P_{gstx}):

$$E_{\mathrm{gst}} = \Sigma_x P_{\mathrm{gstx}} \cdot m_x. \tag{3}$$

Here, m_x corresponds to the national mortality rates for 2018, chosen as the standard for this study because it aligns with Istat's harmonised series and the indicators presented in Table 1.

In some cases, however, to limit random variability—particularly pronounced in small municipalities, as we shall see shortly—our SMR summarise the entire 17-year period, as we computed the ratio:

$$\mathrm{SMR}_{\mathrm{gsT}} = D_{\mathrm{gsT}}/E_{\mathrm{gsT}}, \tag{4}$$

where T (total) indicates the sum of all observed (D) and expected (E) deaths between 2002 and 2018.

Table 1 Data used for the empirical analysis

Label	Territorial level	Description	Link
Deaths	Municipality (LAU)	Population/demographic balance estimates 2001–2018 (intercensal reconstruction)	(a)
Population	Municipality (LAU)	Population estimates 2002–2019 by age and gender as of Jan 1st (intercensal reconstruction)	(b)
Life tables	Province (NUTS 3)	Life tables	(c)
Indicators	Municipality (LAU)	- Main geographical statistics on municipalities and classifications and size of municipalities as of 12/31/2019 - Municipality frailty index and its components - Income per capita (from tax return data)[a]	(d) (e) (f)

Notes. All official data, taken from Istat or, with regard to income, from the Revenue Agency. Territorial level is the finest available

(a) https://demo.istat.it/app/?i=RBD&l=it; (b) https://demo.istat.it/app/?i=RIC&a=2002&l=en; (c) https://demo.istat.it/app/?i=TVM&l=it; (d) https://www.istat.it/it/archivio/156224; (e) https://www.istat.it/it/archivio/292468; (f) https://asc.istat.it/ASC/

Deaths: data are detailed by gender, municipality, nationality, and year (we used the years 2002–2018)

Population: data are detailed by age (single year, up to "100 and over"), gender, municipality, nationality, and year (we used the years 2002–2018)

Life tables: data are detailed by age (single year), gender, province, and year. In this case, we used the m_x series (age-specific mortality rates) for the year 2018 (Italy, both genders) to derive our *E* series (expected deaths; see text), and the entire set (by province, 2002–2018) to test the performance of our indicator, SMR, by comparing it with official mortality data (e_0)

[a] For more details on the calculation of this indicator, please refer to Sect. 2.5

Adjustments and variability control

There are more than 400,000 possible SMR (our dependent variable), a figure obtained by combining:

- 8043 (or 8045) geographical units: 7912 municipalities, clustered into 107 provinces, which in turn are grouped into 20 regions that form three (or five) macro-regions (e.g., North—possibly distinguishing between NW and NE—Centre, and Mezzogiorno, with the South and, sometimes separately, the two main Islands of Sicily and Sardinia). In addition, Italy as a whole is considered;
- 18 years/periods: from 2002 to 2018, plus their average;
- 3 gender groups: males, females, and the total population.

Of course, we analysed only a selection of these combinations—those we deemed most interesting. The SMR are informative in themselves, as they provide an unbiased, synthetic measure of mortality for all the possible subpopulations defined by year, geographical area, and gender. While life expectancy at birth (e_0) is already known at the national, regional, and provincial levels, the SMR are not redundant; indeed, we used these geographical units to assess the reliability of our indicator. As the SMR turned out to be highly correlated with the corresponding e_0 at all observable levels, we inferred that they would also provide good mortality estimates for cases where the corresponding e_0 is unavailable, such as at the municipal level.

While it may be unwise to assume that the SMR provide fully reliable measures of mortality for every combination of gender, year, and municipality—due to potentially strong random variations (see below)—data can be aggregated to confidently assess mortality for several interesting cases: for example, a given municipality over the entire 17-year period, or municipalities with specific characteristics (e.g., small, or "frail", meaning lacking certain basic services; see Table 1). All of the analyses presented below refer to years not affected by the Covid-19 pandemic, which impacted Italy—and the rest of the world—only from 2020.

Reliability and variability of SMR

The reliability of standardised mortality ratios as indicators of mortality depends on several factors. SMR work perfectly only under two theoretical scenarios:

- When all observed units (e.g., municipalities) have identical age structures, rendering standardisation unnecessary.
- When local age-specific mortality rates, d_{gsx}, are proportional to the standard mortality rates, (m_x), such that $d_{gsx} = k \cdot m_{gsx}$, where $k > 0$ is a constant scaling factor. This would be the case in a municipality where mortality rates were, for example, 20% higher than the national standard (in which case $k = 1.2$).

In practice, neither condition is plausible. Consequently, SMR may introduce biases, particularly when there are significant differences in the shape between local and standard age-specific mortality rates (d_{gsx} and m_x, respectively). These biases have been extensively discussed in the literature (Roessler et al., 2021).

In our case, as the standard mortality rates, m_x, represent the national average for 2018, it is reasonable to assume that the shape of local age-specific mortality rates, d_{gx}, closely resembles the national standard. Therefore, any distortions introduced by deviations from this assumption are expected to be minimal (see also Appendix A).

Empirical validation of SMR

To empirically validate SMR as a mortality indicator, we compared them with life expectancy at birth (e_0) wherever possible. The correlation between SMR and e_0 was found to be extremely high, with R^2 values of approximately 99%, 96%, and 92% at the national, regional, and provincial levels, respectively (only the latter statistic is shown in the figures below).

Let us begin with Fig. 1a, which displays life expectancy at birth in Italy (for both genders), its evolution over the period 2002–2018, and illustrates the variability at the regional and provincial levels by showing the lines corresponding to the best and worst cases (which are not always the same). The overall impression is one of limited and approximately constant variability over time, consistent with the claim that the process of mortality convergence—detectable in the final 20 years of the twentieth century—ceased in the twenty-first century (Carboni et al., 2024).

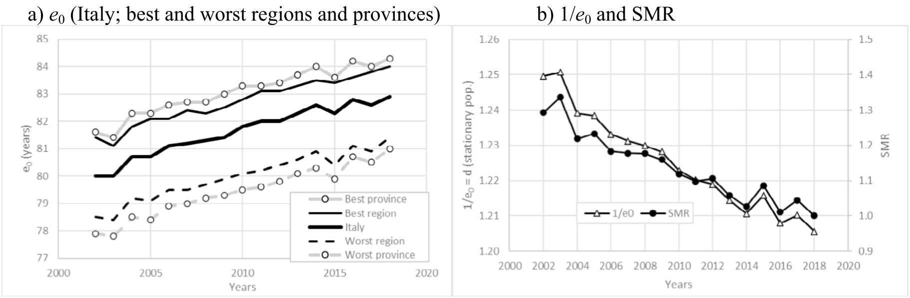
Instead of e_0, it is also possible to use its reciprocal, $1/e_0$, which, incidentally, represents the mortality rate of the stationary population associated with that life table and is more consistent with our mortality indicator, SMR. Indeed, the two variables ($1/e_0$ and SMR) exhibit very similar trends, as shown in Fig. 1b.

Figure 2, on the other hand, refers to provinces. The right panels demonstrate that our indicator (SMR) correlates very closely with life expectancy at birth for both females (top) and males (bottom). In contrast, crude death rates (d) show very poor correlation with e_0 (left panels of Fig. 2), as they are heavily influenced by age structure.

Keeping variability under control

Two main factors influence the variability of SMR:

1. *Survival.* As e_0 increases, SMR decrease, leading to reduced absolute variability.



a) e_0 (Italy; best and worst regions and provinces)

b) $1/e_0$ and SMR

Fig. 1 Life expectancy at birth e_0 and standardised mortality ratio SMR, Italy 2002–2018 (both genders). In the right panel, there are 680 points (17 years, 2 genders, 20 regions). Source: Own calculations on Istat data (see Table 1)

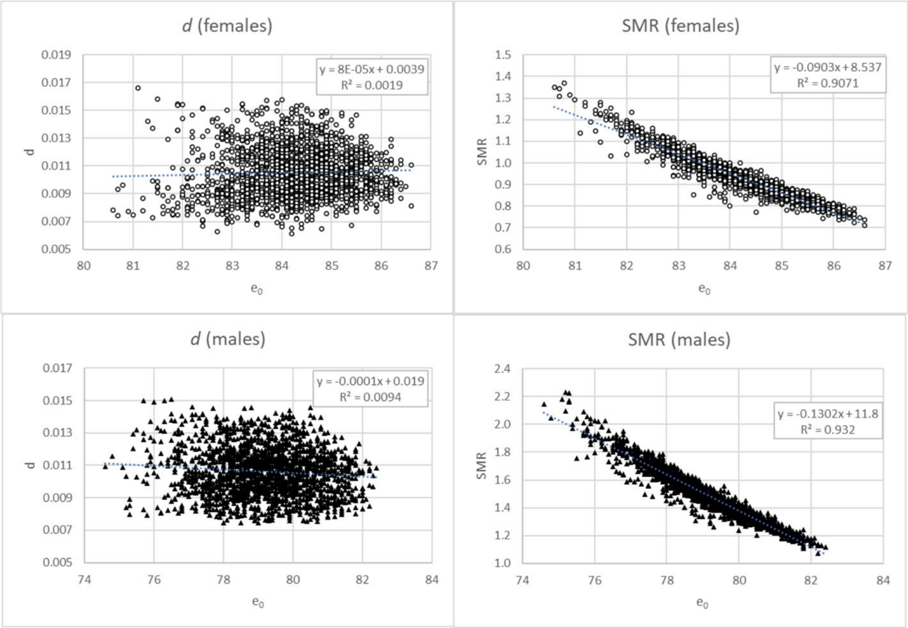


Fig. 2 Left panels: correlation between e_0 and d; right panels: correlation between e_0 and SMR. Italy 2002–2018 at provincial level, for females (top) and males (bottom). e_0 = life expectancy at birth; d = crude death rate; SMR = standardised mortality ratio. Source: Own calculations on Istat data (see Table 1)

2. *Population size effects*. Municipalities with small populations have low or very low expected death counts (E), resulting in higher intrinsic variability in SMR. For instance, in almost 3300 cases, $E < 1$, combining year, gender, and municipality.

To address these issues, we employed two adjustments. First, we scaled the SMR—thus obtaining a set of ${}_{s}$SMR—by forcing their (weighted) average to be 1 in each year, as follows:

$$ {}_{s}\mathrm{SMR}_{\mathrm{gst}} = \mathrm{SMR}_{\mathrm{gst}}/\mathrm{SMR}_{t}. \tag{5}$$

A brief discussion of the weights to be used in this case—specifically, E_{gst} (i.e. expected deaths)—is provided in Appendix B. Next, we computed their period average (denoted by A):

$$ {}_{s}\mathrm{SMR}_{\mathrm{gsA}} = \frac{\sum_{t=2002}^{2018} {}_{s}\mathrm{SMR}_{\mathrm{gst}}}{17}. \tag{6}$$

Then we estimated the standard deviation of each ${}_{s}\mathrm{SMR}_{gs}$, our measure of variability, with the formula:

$$ \hat{\sigma}_{\mathrm{gs}} = \sqrt{\frac{\sum_{t=2002}^{2018} \left({}_{s}\mathrm{SMR}_{\mathrm{gst}} -_{s} \mathrm{SMR}_{\mathrm{gsA}}\right)^{2}}{16}}, \tag{7}$$

dividing by (t–1), where t (equal to 17) is the number of our annual observations per municipality.

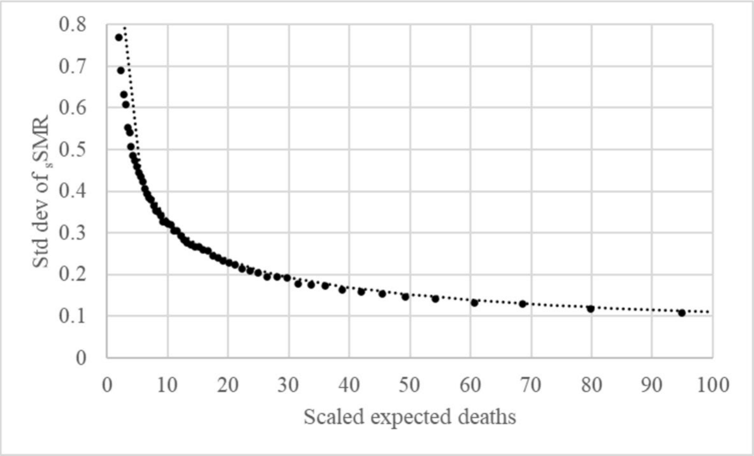


Fig. 3 Variability of scaled $_s\text{SMR}_{\text{gsA}}$ by number of (scaled) expected deaths $_s$E. Italy 2002–2018, by municipality g and gender s. Variability = standard deviation (formula 7). $_s\text{SMR}_{\text{gsA}}$ = Scaled SMR, by area and gender, average of the period (formula 6). For graphical reasons, municipalities, which were treated separately by gender, resulting in (7912·2 =) 15,824 observations, are here grouped in blocks of 250 (municipalities/genders with roughly the same E). Source: Own calculations on Istat data (see Table 1)

Finally, we estimated the relationship between variability in the set of scaled $_s$SMR and scaled expected deaths ($_sE$) using a power-law distribution[5]:

$$\hat{\sigma}_{\text{gst}} = \underset{(4.55)\,(363.4)}{0.98234 \cdot \text{sE}_{\text{gst}}^{-0.48908}} \left(R^2 = 0.893;\, t \text{ values in parentheses}\right). \tag{8}$$

Figure 3 illustrates this relationship, highlighting how variability decreases as $_sE$ increases.

Introducing $_{\text{adj}}$SMR

To further control for variability, we introduced the adjusted scaled standardised mortality ratio ($_{\text{adj}}$SMR):

$$_{\text{adi}}\text{SMR}_{\text{gst}} = \frac{_s\text{SMR}_{\text{gst}} - {}_s\,\text{SMR}_{\text{Ast}}}{\hat{\sigma}_{\text{gst}}}, \tag{9}$$

where $\hat{\sigma}_{gst}$ is estimated with formula (8) and where

$$_s\text{SMR}_{\text{Ast}} = \frac{D_{\text{Ast}}}{\text{sE}_{\text{Ast}}} = \frac{\sum_{g=1}^{7912} D_{\text{gst}}}{\sum_{g=1}^{7912} \text{sE}_{\text{gst}}}. \tag{10}$$

This adjustment is in essence a standardisation, except that the standard error σ is not constant, but context-specific (so σ_g), and it is estimated (so $\hat{\sigma}_g$), as a function of the number of expected deaths. This apparent complication ensures that small municipalities, with low expected death counts, do not disproportionately skew the results.

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[5] The power law is a functional relationship between two variables, whereby the latter varies as a power of the former. This relationship can be represented by the formula $y = kx^a$, where y and x are the two variables, k is a constant, and a is the exponent. For more information on the use of power law distributions in population-based studies, and in particular in the study of mortality, see Bohk et al. (2015), Cohen et al. (2018), and Yang et al. (2022).

For example, if the $_{s}$SMR is 3 in a specific case—indicating "three times as many deaths as expected"—this number may reveal a serious mortality issue in a large municipality. However, in a small municipality, such a value might simply be the result of random effects (e.g., one death observed instead of the 0.33 theoretically expected). Our adjusted mortality measures, $_{\text{adj}}$SMR, keep this potential source of bias under control by taking into account whether the expected number of deaths is large or small.

Non-spatial and spatial regression analysis: theory

In this section, we explore the relationship between the adjusted standardised mortality ratio ($_{\text{adj}}$SMR), our dependent variable (y), and a set of socio-demographic variables (x_p, covariates). The analysis is conducted at the municipality level, or LAUs (local administrative units).

We ran three statistical global regression models. By global regression models, we refer to models that assume a single set of parameters applies uniformly across all observations in the dataset, meaning that the estimated relationships between the dependent variable and the covariates are spatially invariant. This contrasts with local regression models, which allow for parameter variation across space and capture potential spatial heterogeneities in the relationships under study. Global models can be either non-spatial, such as the ordinary least squares (OLS) model, or spatial, like the spatial autoregressive model (SAR) and the spatial error model (SEM).

The classical ordinary least squares (OLS) regression model,[6] which serves as our baseline, can be expressed as follows:

$$y_g = \beta_0 + \sum_{p=1}^{P} \beta_p x_p + \varepsilon_g, \tag{11}$$

where y_g represents the dependent variable ($_{\text{adj}}\text{SMR}_g$) for geographical area g (in our case, a generic Italian municipality), x_p denotes the pth covariates, varying from 1 to P, β_0 is the intercept, β_p are the coefficients of each covariate (both β_0 and β_p to be estimated), and ε is the error term.

In addition to OLS, we employed two spatial global regression models: the spatial autoregressive model (SAR) and the spatial error model (SEM) (Anselin, 2001; LeSage & Pace, 2009). Both models are particularly suited to handling data from small-scale territorial units (such as municipalities), as they account for spatial dependencies across units, thereby enhancing the accuracy of estimates (Benassi et al., 2022; Golgher & Voss, 2016).

OLS models rely on the assumption that observations are independent and identically distributed. However, this assumption is rarely, if ever, valid in spatial analysis, where geographical proximity creates spillover effects that lead to dependencies across observations. In other words, the value of a variable in a given municipality is often influenced by the values observed in neighbouring municipalities. The advantage is that these effects can be observed and controlled more accurately at smaller scales (e.g.,

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[6] This can be also defined as Global non-spatial regression model or, in the words of Golgher and Voss (2016), standard linear model.

municipalities) than when larger units (such as provinces or regions) are used, where spatial heterogeneity tends to be higher and more difficult to account for.

To explicitly model spatial dependence, we employ two spatial global regression models: the spatial autoregressive model (SAR) and the spatial error model (SEM). A fundamental component of spatial econometric models is the spatial weights matrix, denoted as W. This matrix encodes the spatial structure of the data by defining the relationships between geographical units. Each element $w_{g,j}$ of the matrix represents the spatial connection between location g and location j. The general properties of W are as follows:

i. it is an ($N·N$) square matrix, where N is the number of spatial units (municipalities, in our case),
ii. it is typically row-standardised, meaning that the sum of each row equals one $\left(\sum_{j=1}^{N} w_{g,j} = 1, \forall g\right)$;
iii. if g and j are neighbours, then $w_{g,j} > 0$, otherwise, $w_{g,j} = 0$.

In our study, we define neighbourhood relations using a first-order Queen contiguity criterion: two municipalities are considered neighbours if they share either a border or a vertex. This method ensures that spatial interactions are captured in a flexible and realistic manner. This spatial weights matrix has been adopted for the estimation of the two spatial regression models (formulas 12 and 13) as well as for computing the global Moran's I index of spatial autocorrelation (formula 14).

The SAR model explicitly incorporates spatial dependence by including a spatial lag term in the dependent variable. The SAR equation is:

$$y_g = \beta_0 + \sum_{p=1}^{P} \beta_p x_p + \rho \underbrace{\mathrm{Wy}}_{\text{spatial lag component}} + \varepsilon_g, \tag{12}$$

where Wy represents the spatially lagged dependent variable, capturing how local $_{\text{adj}}$SMR are influenced by those of neighbouring municipalities, and ρ (rho) is the spatial autoregressive coefficient, measuring the strength and direction of spatial dependence. The extra parameter in SAR models compared to OLS is ρ, which quantifies the extent of spatial dependence among the dependent variable values in neighbouring municipalities. In our case, the positive values of ρ (see further in the text) indicate that neighbouring municipalities tend to exhibit similar $_{\text{adj}}$SMR values, whereas negative values would suggest that high $_{\text{adj}}$SMR are typically associated with low $_{\text{adj}}$SMR in adjacent areas. Finally, a value of ρ close to zero indicates little or no spatial dependence across municipalities (Benassi et al., 2022; Sun et al., 2020).

The SEM model, on the other hand, does not assume a direct spatial interaction in the dependent variable; instead, it accounts for spatial dependence in the error terms. The SEM equation is:

$$y_g = \beta_0 + \sum_{p=1}^{P} \beta_p x_p + \lambda \underbrace{\mathrm{Wu}}_{\text{spatial lag error}} + \varepsilon_g, \tag{13}$$

where u represents spatially correlated errors, λ (lambda) is the spatial error coefficient, and Wu captures the spatial structure of the unobserved errors. In other words, SEM models incorporate a spatial error term to address spatial dependencies arising from variables not included in the model (or "unobserved"). This allows researchers to correct for any residual spatial autocorrelation that might otherwise bias the results (Sun et al., 2020). The characterising parameter of SEM models is therefore λ: it measures the spatial correlation of model errors, or in other words, reveals if, how, and to what extent unobserved variables—captured in the model errors—are spatially correlated across municipalities. A positive (negative) value of λ indicates that model errors in one municipality tend to be similar to (different from) those in neighbouring municipalities, in both cases suggesting that there are spatially correlated factors not included in the model that influence the dependent variable ($_{\text{adj}}$SMR, in our case). A value of λ close to zero indicates that there is no significant spatial correlation in the model's errors, implying that spatial dependencies have been effectively captured by the observed variables.

To summarise, ρ can be considered a measure of the "contagion effect" between neighbouring municipalities in terms of mortality (as measured by the $_{\text{adj}}$SMR), whereas λ represents a "hidden correlation" in the factors that, although not directly observed or included in the model, influence the dependent variable and are manifested in the errors. Ultimately, the aim is to estimate the association of certain explanatory variables with the $_{\text{adj}}$SMR while taking spatial dependency into consideration. By controlling for spatial autocorrelation, more accurate and reliable estimates of the relationships between the variables of interest can be obtained.

To assess the degree of spatial dependence on the dependent variable ($_{\text{adj}}$SMR), and also to measure the level of spatial autocorrelation in the distribution of the residuals obtained from non-spatial and spatial regression models (see Table 2 in "Results" section), we used Moran's I index (Moran, 1948):

$$I = \frac{N}{W} \frac{\sum_{g=1}^{N} \sum_{j=1}^{N} w_{\text{gj}} z_g z_j}{\sum_{g=1}^{N} z_g^2}, \tag{14}$$

where $z_g = y_g - \bar{y}$. Statistical inference was derived using random permutation testing, with a significance level of $\alpha = 0.05$. This statistic measures the extent to which similar values of a variable cluster together in space. Moran's I ranges from -1 to 1. A positive value indicates positive spatial autocorrelation, meaning that municipalities with similar $_{\text{adj}}$SMR values tend to be clustered together. A negative value indicates negative spatial autocorrelation, meaning that high and low $_{\text{adj}}$SMR values are spatially dispersed. A value close to zero suggests a random spatial pattern, indicating little to no spatial dependence. In the analysis of local residuals (i.e. the differences between observed and expected $_{\text{adj}}$SMR for each municipality), a significant Moran's I would indicate that spatial dependence has not been fully accounted for, and that model specification could be improved.

To conclude, by explicitly incorporating spatial dependence into our regression models, we can obtain more accurate and reliable estimates of the relationships between $_{\text{adj}}$SMR and socio-demographic factors. The SAR model captures direct spatial interactions in $_{\text{adj}}$SMR values, while the SEM model accounts for unobserved spatially correlated factors. Together with Moran's *I* analysis, both models enable us to evaluate the role of space in shaping mortality patterns at the municipal level.

Socio-demographic variables used in the regression analysis

We conducted our regression analysis separately by gender to highlight gender differences in mortality characteristics, including associations with covariates and spatial correlation. Although we expect the effects of our ecological covariates to be similar across genders, the data suggest that this may not be the case. The dependent variable is always the adjusted and scaled standardised mortality ratio ($_{\mathrm{adj}}$SMR), as defined in formula (10).

With regard to the covariates, following a series of preliminary investigations on the available data (Table 1), we ultimately decided to retain five, selected to capture the most relevant socio-economic and demographic aspects of Italian municipalities while minimising collinearity.[7] These five variables can be classified according to the conceptual dimension they represent. To mitigate bias arising from regressors with different orders of magnitude, we standardised all covariates except for the frailty index, which, due to the peculiar way in which Istat presents it (in deciles), was transformed into a dummy variable.

Population

Resident population (log-transformed and subsequently standardised). This variable serves as a proxy for the municipality's relevance and its position within the spatial hierarchy of the territorial system. The decision to apply a logarithmic transformation is driven by the distribution of municipal populations, which is highly skewed—ranging from a few municipalities with a large number of residents (up to 2.6 million in the case of Rome, the capital) to many municipalities with very small populations, in some cases as few as 30. The logarithmic transformation mitigates these disparities and enhances model performance during estimation. The expectation is that, all else being equal, smaller municipalities—typically characterised by fewer basic services and lower accessibility—should experience higher mortality rates.

Share of the population aged 70 years and over (standardised). This variable provides a simplified measure of the population's age structure, specifically indicating the extent of the ageing process. Although, in principle, our mortality measure ($_{\mathrm{adj}}$SMR) is standardised and thus independent of the local age structure, it may not be entirely insulated from it. Moreover, older municipalities tend to be those that are otherwise less attractive (e.g., where emigration exceeds immigration) and, once again, those where higher mortality rates are expected.

Territory

Altitude (metres above sea level; standardised). This time-invariant variable has proven useful in modelling population change, particularly depopulation, in Italy in recent

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[7] A few additional variables, though theoretically relevant, were ultimately discarded as they proved to be non-significant, with their effects absorbed by other variables in the model. The dummy for urbanisation, for instance, was among the casualties of this "trimming" process. Unfortunately, not everything that may potentially affect mortality can be measured or is available in our dataset—this limitation is discussed further in the text.

years (Reynaud et al., 2020). It can be regarded as a proxy for the degree of isolation of a municipality, with the expectation that mortality should increase with altitude.

Vulnerability

Municipality frailty index (dummy, equal to 1 if the frailty index, originally ranging from 1 to 10, is 6 or above). This composite index, recently introduced by Istat (see Table 1), provides a synthetic measure of municipal vulnerability by considering exposure to natural and anthropogenic hazards, alongside critical demographic, social, and economic conditions. It integrates 12 elementary indicators: landslide hazard, land consumption, accessibility to essential services, motorisation rate, waste collection, extent of protected natural areas, population dependency, education levels, employment rate, population growth, density of local industry and service units, and labour productivity. Although the original index ranges from 1 to 10 (with 10 indicating maximum vulnerability), we transformed it into a dummy variable, assigning a value of 1 (vulnerable) if the municipality's index exceeds the median, and 0 otherwise. Our expectation is that mortality should be higher in more fragile municipalities.

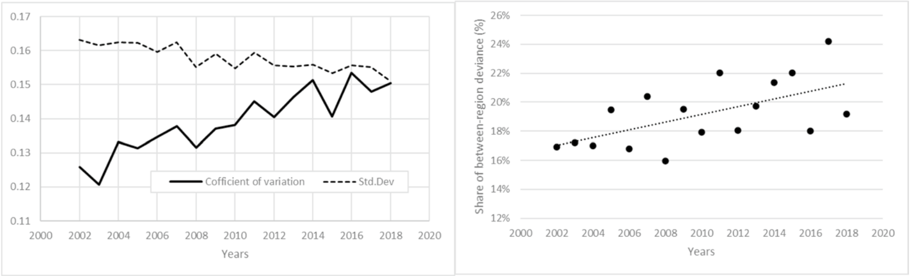
Income per capita (standardised). This variable, derived from individual tax return data (IRPEF, Imposta sul Reddito delle Persone Fisiche), is calculated as the total declared income divided by the number of residents in each municipality (see Table 1). To ensure comparability and avoid issues associated with variables of markedly different scales, we standardised this measure before including it in our regression models. It is important to acknowledge the limitations of tax-based income data. The presence of a significant underground economy in Italy—estimated at around 10% of the official national GDP—means that actual income levels may be underreported in tax declarations. This underreporting is likely to be spatially heterogeneous, affecting some municipalities or socio-economic groups more than others. Despite these limitations, official income per capita remains a relevant indicator of economic well-being at the local level. We expect mortality to be higher in municipalities where officially declared income per capita is lower, as lower income levels are generally associated with poorer living conditions, limited access to healthcare, and other socio-economic disadvantages that negatively impact health outcomes.

Results

Descriptive results

Between 2002 and 2018, life expectancy in Italy increased from approximately 80–83 years (with a shrinking female advantage, from 5.8 years at the beginning of the period to 4.3 years at the end), while the SMR declined correspondingly from 1.3 to 1.0 (Fig. 1a). The use of SMR_g (specific to geographical units, regions, provinces, and municipalities) enables us to address our research questions, starting with #1 and #2. Figure 4, left panel, shows that heterogeneity (and therefore inequality) was low at the start of the period. Over time, it declined slightly in absolute terms (the standard deviation of SMR_g decreased from approximately 0.16 to around 0.15), but increased in relative terms, as the coefficient of variation rose from 12.5 to 15%.

To address our research question #3, we can refer to Fig. 4, Panel b. It shows that the between-region component of the total variance increased from approximately 17% to



a. Standard deviation and coefficient of variation of SMR at the municipal level

b. Share of total variance attributable to between-region differences

Fig. 4 Evolution of survival heterogeneity in Italy 2002–2018, both genders combined (SMR measured at municipality level, across 7912 such units, or LAUs). Source: Own calculations on Istat data (see Table 1)

21%. In other words, regional disparities in mortality became slightly more pronounced over time, although the within-region component still dominated (~ 80% of the total variance). This aligns with our hypothesis that regions are gradually "drifting apart" in terms of survival; although, admittedly, it does not prove that this drift is due to the regionalisation of the health service. In any case, despite these indications of rising inequality, it is important to note that disparities were relatively small at the beginning of the period and remained so throughout the 17 years under examination. Furthermore, these findings must be viewed within the broader context of improving survival conditions nationwide.

Let us now turn to our fourth research question: the contextual factors most strongly associated with poor survival outcomes at the municipal level. Figure 5 maps the adjusted SMR (or ${}_{\mathrm{adj}}$SMR) averaged across the period 2002–2018 for 7882 municipalities, separately for males and females.

Lower mortality, particularly for females, is generally observed in the eastern parts of Italy (Trentino–Alto Adige, the southern part of Veneto, Emilia Romagna, Marche), along with Umbria, Tuscany, and the southern part of Sardinia. This latter area has recently been identified as one of the so-called "blue zones" of the world, known for exceptionally high longevity (https://longevitybluezone.com/the-5-blue-zones/). However, this exceptionality does not stand out in our data and does not appear to apply to the period covered by this study.

Conversely, poorer survival conditions are found in the southwestern part of Italy (particularly the area around Naples), the municipalities surrounding the capital city Rome (although not Rome itself), and, somewhat surprisingly, numerous municipalities in the "affluent" North-West (Liguria, Valle d'Aosta, Piedmont, and parts of Lombardy), as well as most municipalities along the river Po (running eastwards, from Turin to just below Venice). Another concerning area lies in the North-East, covering parts of Friuli–Venezia Giulia and the northern municipalities of Veneto.

Territorial variability is greater for males than for females (standard deviation = 1.25 and 0.87, respectively), but Moran's I index is higher for females (0.45 vs. 0.32), indicating that the spatial distribution of their mortality is more strongly correlated across municipalities. In other words, municipalities with high or low SMR tend to cluster more closely for females than for males. As it turns out, for both genders, spatial correlation is positive and high, which must be taken into account in the regression design.

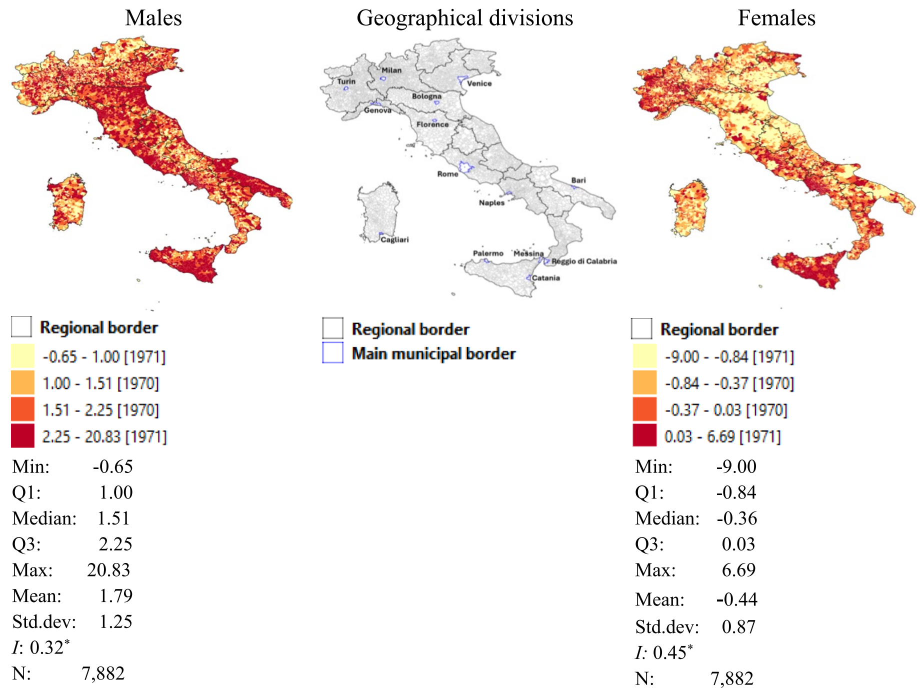


Fig. 5 Map of municipalities by mortality level (Italy, ${}_{adj}$SMR average in 2002–2018, Males and Females). I = Moran's I index; ${}^{*}p<=0.05$. The numbers in square brackets represent the number of municipalities belonging to each quartile. Source: Own calculations on Istat data (see Table 1)

Non-spatial and spatial regression analysis: results

Table 2 presents the results of the three regression models for the ${}_{adj}$SMR, run separately by gender: OLS, SAR, and SEM. Model performance, as measured by R^2, the Akaike information criterion (AIC), and the Bayesian or Schwarz information criterion (BIC), improves with the use of spatial models, especially for females, whose mortality, as briefly discussed in the comments to Fig. 5, shows greater spatial autocorrelation. Moran's I, which is high and statistically significant in non-spatial regressions (0.36 and 0.21 for females and males, respectively), declines significantly with the use of SAR or SEM models. In other words, spatial models are necessary to account for spillover effects. However, caution is needed when interpreting and comparing the estimation results, given the particular nature of the regression coefficients, especially in the case of the SAR model (Golgher & Voss, 2016). For this reason, we do not interpret the coefficients of the SAR model; instead, we compare the general performance of the models and the signs of the coefficients (Crisci et al., 2022).

As Table 2 shows, of our five regressors, two behave consistently across genders, while three do not. These three, displayed at the bottom of the table, are likely easier to interpret when considered together. For instance, among females, mortality is lower in larger municipalities (i.e. cities), but also higher when altitude and the share of older population are greater, which is typically seen in smaller and more rural communities. However, the opposite holds for males. The most plausible explanation we can offer, though admittedly tentative, is that these three parameters, considered together, control for background conditions, and that these conditions—contrary to what might be expected at first glance—are not fundamentally different between genders.

Table 2 Regression results (dependent variable: ${}_{\text{adj}}$SMR, municipal mortality, Italy, 2002–2018)

	OLS		SAR		SEM	
	Females	Males	Females	Males	Females	Males
Rho/Lambda	-	-	0.4723 ***	0.0940 ***	0.5220 ***	0.3596 ***
Fragility	0.1919 ***	0.1828 ***	0.0737 ***	0.1601 ***	0.0239	0.1357 ***
Income2018pc	-0.1946 ***	-0.0649 ***	-0.1122 ***	-0.0584 ***	-0.1915 ***	-0.0726 ***
Log population	-0.3373 ***	1.0752 ***	-0.2765 ***	1.0356 ***	-0.3303 ***	1.1489 ***
Altitude	-0.0159	0.0411 ***	-0.0292 ***	0.0544 ***	-0.0222 .	0.0797 ***
% 70+	-0.2049 ***	0.2602 ***	-0.1747 ***	0.2618 ***	-0.1905 ***	0.2762 ***
R2	0.2156	0.5614	0.3869	0.5662	0.4026	0.604
Log likelihood	-9163.6	-9692.4	-8365.3	-9655.9	-8307	-9386
Akaike info criterion	18339.3	19396.9	16744.5	19325.7	16625.9	18783.9
Schwarz criterion	18381.1	19438.7	16793.3	19374.5	16667.7	18825.8
Moran I on residuals	0.363	0.206	-0.015	0.139	-0.045	-0.027

$N = 7882$ Italian municipalities. Multicollinearity condition number 3.7. p-value: *** = 0.001; . = 0.1

Source: Own calculations on the data of Table 1

On the other hand, the remaining two covariates send an unambiguous and strong signal: communal frailty, a very comprehensive indicator of the presence of discomfort conditions, and communal affluence (per capita income) both affect mortality in the expected direction for both genders. The regression coefficients are always highly significant (with the exception of females in the SEM regression). This suggests that poor surrounding conditions, including but not limited to low income, negatively impact survival chances. While this is hardly surprising, it also highlights an area where policy intervention is possible and, as our analysis demonstrates, necessary: exposure to natural and anthropogenic risks, as well as poor socio-economic conditions, diminishes survival prospects (see, e.g., Barbi et al., 2018).

Discussion

The results of our study offer valuable insights into the patterns and determinants of small-area mortality in Italy between 2002 and 2018, highlighting both the strengths and limitations of the methodology employed. Life tables are not available for all municipalities: they exist only for the largest ones, are locally produced, difficult to access, and not fully comparable with each other. A systematic analysis of mortality at the municipal level therefore requires a different approach, and standardised mortality ratios (SMR) provide a possible solution. Unfortunately, although generally recognised as robust tools for indirect standardisation, SMR are not free from bias, particularly in small populations or in areas with highly atypical age structures. However, by carefully adjusting for expected death counts and introducing the adjusted SMR (${}_{\text{adj}}$SMR), we were able to reduce much of the variability typically associated with such analyses, facilitating meaningful comparisons across Italy's nearly 8000 municipalities.

Territorial inequalities in survival were low in 2002 and remained low throughout the observation period (2002–2018), which answers our research question #1. However, there was also a modest yet noticeable increase in mortality variability over the study period, which, in response to our research question #2, reflects an underlying trend of growing inequality. This is particularly evident in the rising share of variance attributable to regional disparities, which increased from 17 to 21%. While the within-region component continues to dominate, the regional drift—though slight—raises important questions about the effects of decentralising Italy's healthcare system (research question

#3). Introduced in the early 1990s, this shift in governance aimed to bring decision-making closer to citizens and improve the responsiveness of health services. However, our findings suggest that decentralisation may have inadvertently exacerbated regional disparities, potentially undermining the principles of equity and universality established by the 1978 National Health Service reforms. All of this must be contextualised, however: throughout the period under observation, Italy was a country with very high survival rates, and it remains so today. In 2024, according to the Population Division of the UN, Italy ranked 7th in the world in terms of life expectancy (second in Europe, after Switzerland).

The answer to our research question #4 is that frailty and socio-economic disadvantage emerge as key drivers of mortality disparities at the municipal level. Municipalities classified as "fragile" according to Istat's composite frailty index exhibited significantly higher mortality, independent of other covariates. This indicator synthesises a range of ecological vulnerabilities, including economic underperformance, poor accessibility to essential services, and exposure to natural and anthropogenic risks. The strong association between frailty and mortality highlights the need for targeted policy interventions to address these structural disadvantages. Similarly, per capita income was a powerful predictor of survival outcomes, with lower-income municipalities consistently showing higher mortality. These findings align with a broader body of literature documenting the adverse effects of poverty and social marginalisation on health outcomes, even within high-income countries like Italy.

The spatial dimension of mortality further enhances our understanding of these dynamics. Our analysis revealed significant spatial autocorrelation, with neighbouring municipalities tending to exhibit similar mortality patterns. This spatial clustering was more pronounced for females than for males, as evidenced by the higher Moran's I index. This finding suggests that women's mortality may be more sensitive to localised environmental or infrastructural conditions, potentially reflecting differences in healthcare utilisation, social networks, or exposure to risks. The spatial regression models (SAR and SEM) further confirmed the importance of accounting for spillover effects in mortality analyses. The significant spatial parameters (ρ and λ) highlight the interconnected nature of municipalities, where health outcomes in one area are often influenced by conditions in neighbouring regions.

An intriguing aspect of our findings concerns the gendered nature of mortality determinants. While frailty and income effects were consistent across genders, other covariates exhibited strikingly different associations. For instance, larger municipalities and higher altitudes were associated with lower female mortality but higher male mortality. These patterns may reflect complex interactions between socio-economic and behavioural factors, such as occupational risks, lifestyle choices, or gendered access to healthcare. Although the exact mechanisms remain speculative, these differences warrant further investigation, as they suggest that interventions aimed at reducing mortality may need to be tailored to account for gender-specific vulnerabilities.

Our study is not without limitations. The reliance on aggregate data raises the potential for ecological fallacy, where relationships observed at the municipal level may not hold at the individual level. However, the fine granularity of our analysis mitigates this risk compared to studies conducted at broader geographical scales. Data limitations also prevented us from exploring certain dimensions of interest, such as education levels, air pollution, or substance abuse. Additionally, the exclusion of foreigners, while necessary to reduce heterogeneity, leaves an important demographic group underexamined. Foreign residents, with their distinct mortality patterns and growing presence in Italy, represent a critical area for future research.

Despite these limitations, our findings contribute to a nuanced understanding of small-scale mortality in Italy. The modest increase in inequalities observed during the study period may signal the early stages of a broader divergence in health outcomes, particularly as regionalisation and fiscal austerity continue to reshape Italy's healthcare landscape. The persistence of higher mortality in fragile and impoverished municipalities underscores the enduring relevance of place-based policies. These findings emphasise the need for targeted investments in vulnerable areas, addressing not only health service provision but also the broader social and economic determinants of health.

In conclusion, our analysis highlights both the achievements and challenges of Italy's healthcare system. While mortality levels remain low by international standards, the emergence of localized inequalities calls for renewed attention to equity and universality. Future research, particularly in the context of the COVID-19 pandemic and its aftermath, will be essential to monitor these trends and ensure that Italy's healthcare system continues to serve as a model of inclusivity and resilience.

Conclusions

This study has illuminated the patterns and determinants of small-area mortality in Italy between 2002 and 2018, shedding light on the interplay between territorial disparities, socio-economic conditions, and spatial dynamics. While mortality levels in Italy remain low by international standards, the findings reveal subtle but significant increases in inequalities, particularly between regions. These disparities, though modest, underscore the persistent challenges in achieving equitable health outcomes across the country.

The rise in mortality variability and the growing share of variance attributable to regional differences suggest that decentralisation of healthcare services may have had unintended consequences. While regional autonomy can enhance responsiveness to local needs, it also risks reinforcing pre-existing inequalities, particularly in regions with fewer resources or weaker governance structures. These trends highlight the importance of monitoring the effects of policy changes on health outcomes and ensuring that equity remains a central pillar of healthcare governance.

The strong association between municipal frailty, low income, and higher mortality emphasises the need for targeted interventions in vulnerable areas. Improving access to healthcare and addressing broader determinants of health—such as education, employment, and environmental conditions—will be critical in reducing mortality disparities. These efforts must be accompanied by policies that promote inter-regional solidarity, ensuring that resource allocation reflects the needs of all communities, regardless of their economic or geographic circumstances.

Spatial dynamics emerged as a key factor in understanding mortality patterns. The significant spatial autocorrelation observed in this study suggests that health outcomes are not confined to individual municipalities but are shaped by the broader regional context. This finding underscores the importance of adopting a territorial perspective in health policy, recognising that interventions in one area may have ripple effects across neighbouring municipalities. Coordinated, place-based approaches that address both local and regional factors are likely to be more effective than isolated and decontextualised measures, as some recent studies clearly indicate (Miccoli et al., 2025; Monturano et al., 2025).

Gender differences in mortality determinants point to the need for more nuanced analyses of health disparities. The contrasting associations of variables such as municipal size and altitude with male and female mortality highlight the complex interplay of social, environmental, and behavioural factors. These differences call for gender-sensitive policies and further research to better understand the mechanisms driving these disparities.

The methodological contributions of this study, particularly the use of adjusted SMR or $_{\mathrm{adj}}$SMR, demonstrate the feasibility and utility of small-area mortality analyses even in data-scarce contexts. However, the limitations of the data—such as the absence of cause-specific mortality and the exclusion of foreign residents—highlight the need for more comprehensive datasets to support future research.

In conclusion, the findings of this study provide a critical foundation for understanding the spatial dimensions of health inequalities in Italy. They underscore the importance of maintaining a focus on equity in health policies and interventions, particularly as demographic, economic, and political pressures continue to reshape the country's healthcare landscape. By highlighting the interconnectedness of municipalities and the influence of localised vulnerabilities, this research contributes to a broader understanding of the socio-spatial determinants of health, offering valuable insights for policymakers and scholars alike.

Appendix A. A graphical representation of the potential sources of bias in direct and indirect standardisation

What follows is a visualisation of the issues that may arise with direct and indirect standardisation and bias results. The methodology has often been criticised (especially indirect standardisation; see, among others, Roessler et al (2021) but its shortcomings have often been exaggerated, and, in all cases, alternative procedures are rarely better.

Let us imagine that mortality must be compared in two different populations, 1 and 2. Both are characterised by their own series of age-specific mortality rates, which, for the sake of simplicity, can be imagined as linear on a logarithmic scale (Fig. 6).
Population 1 ($\mathbf{P}_{(1)}$, grey) has low mortality and an old age structure: the grey arrow points to the barycentre of the age distribution (i.e. its average age: about 60 years in this example). Population 2 ($\mathbf{P}_{(2)}$, black) has higher mortality, but a younger age structure, synthetically represented by the black/white arrow (average age: about 30 years in this example). In comparing mortality between the two cases, standardisation is needed to avoid the bias caused by the different age structures. What type? Whenever possible, direct standardisation is preferable, but it is not without problems.

In the best scenario (Panel A), the ratio between the two sets of age-specific mortality rates is a constant k $(= m_{(2,x)}/m_{(1,x)} = m_{(2)}/m_{(1)})$. In this case, regardless of the age distribution of the population adopted as the standard of reference (centred on the grey, black, or any other arrow), mortality in $P_{(2)}$ will always appear k times higher than mortality in

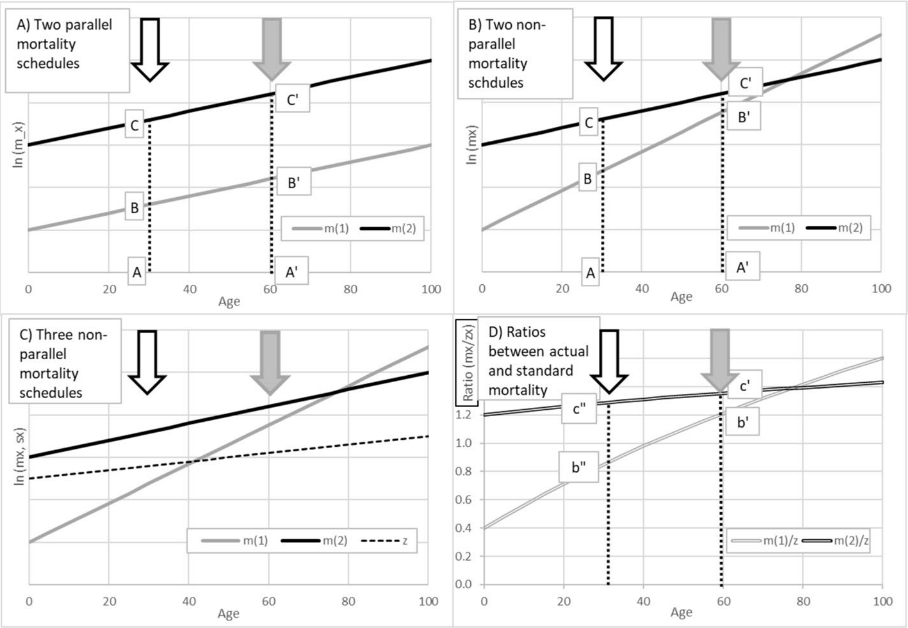


Fig. 6 Comparing mortality in two countries (1 and 2) with direct and indirect standardisation. Source: authors' simulation

$P_{(1)}$. Graphically, this happens because the ratio between segments (AC/AB = A'C'/A'B') is the constant k (= $m_{(2)}/m_{(1)}$), at all ages.

More frequent is the case when the ratio between age-specific mortality rates depends on age ($k_x = m_{(2,x)}/m_{(1,x)}$; panel B). In this case, the choice of the age structure of the population adopted as a standard matters. In the example of panel B, with a young standard (black arrow) mortality will appear much higher in $P_{(2)}$ than in $P_{(1)}$ (the ratio AC/AB is high), while with an old standard (grey arrow), mortality will appear just slightly higher in $P_{(2)}$ than in $P_{(1)}$ (the ratio A'C'/A'B' is close to one). In fact, almost any result is possible, depending on the age structure of the standard population (graphically, on where the "standard" arrow points), and, of course, on the actual shape of the mortality rates series of the two populations.

With indirect standardisation, a new age-specific mortality schedule is introduced: the standard z_x (panel C), which, ideally, should be intermediate between the two original schedules, although this is not always guaranteed, or possible. As each country is now compared to the standard, what researchers are left with can be conveniently represented by panel D: the ratio between that country's mortality and that of the standard. This ratio depends on age, but now the age structure adopted for the comparison is that of the *original* populations. In our example, the standardised mortality ratio of the first country (grey, point b') will be about $SMR_{(1)} \approx 1.21$ while that of the second country (black, point c") will be just slightly higher $SMR_{(2)} \approx 1.28$—each one calculated around the (average) age indicated by the arrow.

Even if the mortality schedules of the two countries were identical, but different from the standard, the fact that the ratios m_x/z_x depend on age reverberates in the final result. Imagine, for instance, that both countries share the same low mortality schedule of country 1 (grey line). As panel D shows, the two standardised mortality ratios would then be $\text{SMR}_{(1)}\approx 1.21$ (point b') and $\text{SMR}_{(2)}\approx 0.85$ (point b"), respectively. An apparently large, but in fact artificial, mortality difference. On the other hand, when the standard (age-specific) mortality schedule z_x is reasonably similar in shape to that of the population under scrutiny, results can be satisfactory. For instance, if both populations share the same high mortality schedule of country 2 (black line), results will be $\text{SMR}_1\approx 1.35$ (c') and $\text{SMR}_2\approx 1.27$ (c"): not identical, as they should be, but close.

In short, what emerges from this short (and to the best of our knowledge, original) presentation of the well-known issues surrounding the use of indirect standardisation (and SMR) is that:

1. indirect standardisation should be handled with care and adopted only when no valid alternative is available;
2. distortions are possible, but drastically reduced when the age-specific mortality schedules of the units under analysis are similar and the age-specific mortality schedule adopted as a standard conveniently represents all the groups under scrutiny (two countries in this example).

In this study, the units that we analyse are 7912 Italian municipalities, each observed 17 times (yearly, between 2002 and 2018), and the standard mortality schedule is that of Italy in 2018. There are reasons to believe that the group of 7912 municipalities is relatively homogeneous (same country, same period), and that the shape of mortality (i.e. the shape of the age-specific mortality schedules, not necessarily their level) is roughly comparable across the entire group, which makes indirect standardisation a relatively reliable methodology. Better than no standardisation, in all cases, as Fig. 2 (left panels) clearly indicates.

Appendix B. About SMR: weights and variability

In this paper we used SMR_{gst}, standardised mortality ratios by geographical area g, gender s and time t (although, to simplify the notation, we will omit indexes when they are not necessary). They are defined as $\text{SMR}=D/E$, where $D=$observed deaths and $E=$expected deaths, given that sub-population's age structure and a vector of standard mortality rates (formulae 2 and 3).

Independently of the level of geographical disaggregation (nation, regions, provinces, municipalities), it is always true that, using E_g as weights (expected deaths), the weighted average of the SMR_g at any smaller scale gives the average SMR of the block that contains all the G units considered (1, 2, … g, …, G): e.g., the weighted average of regional values gives the national value:

$$\text{SMR}_G = \frac{D_G}{E_G} = \frac{\sum_g D_g}{\sum_g E_g} = \frac{\sum_g \frac{D_g}{E_g} E_g}{\sum_g E_g} = \frac{\sum_g \text{SMR}_g E_g}{\sum_g E_g}. \tag{B.1}$$

Let us assume that the true value of E_g exists, but that an incorrect value E'_g is used instead, because of an incorrect choice of the vector of the standard mortality rates in formula (3). If $E'_g = k \cdot E_g$, all the resulting SMR'_g will be biased, because

$$\mathrm{SMR}'_g = \frac{1}{k}\mathrm{SMR}_g. \tag{B.2}$$

In this paper, the vector of standard mortality rates is that of 2018 (Italy, both genders). Using a unique standard has a few advantages, because trends emerge, and differences are preserved. For some applications, however, some limitations must be considered. Variability, for instance, will be affected, because $\sigma' = \sigma/k$, if σ is the unbiased standard error (of that subgroup and that year). The bias is easily eliminated by multiplying all the $\mathrm{SMR}_{g,t}$ by k, which in practice forces their average to 1. For instance, using 2018 as a standard, we calculated $\mathrm{SMR}_{2002} \approx 1.3$, which means that $k \approx 1/1.3 \approx 0.769$. All the communal SMR_g of 2002 ($\mathrm{SMR}_{g,2002}$) must therefore be multiplied by about 0.769 (or divided by about 1.3—thus obtaining their scaled equivalent, called $_s$SMR in this paper), to make their standard error comparable with that of 2018.

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Author contributions
GDS had the original idea and wrote the paper. MM collected all the data, harmonised them, and made all the calculations except for those that refer to spatial analysis. FB and GC are responsible for all that refers to spatial analysis, including spatial data acquisition and preprocessing, mapping, and quantitative spatial analysis. All authors read and approved the final manuscript.

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Data availability
The datasets analysed during the current study are publicly available. They were created (or made publicly accessible) by Istat, and are listed, with their URL, in Table 1 of this paper.

Declarations

Ethics approval and consent to participate
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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