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Campania and cancer mortality: An inseparable pair? The role of environmental quality and socio-economic deprivation

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ABSTRACT

The region of Campania in Southern Italy features high levels of socio-economic deprivation and low levels of environmental quality. A vast strand of the scientific literature has tried to verify whether poor environmental quality and widespread socio-economic deprivation might explain the high cancer mortality rates (CMRs) observed, especially in the municipalities – infamously labelled as the 'Land of Fires' – that were hit most severely by the crisis. While some studies managed to identify links between these two *confounding factors* and cancer mortality, the evidence is overall mixed. Interesting information may be drawn from the observation of municipal data: in spite of previous claims, some municipalities featuring high environmental quality and low socio-economic deprivation also display high CMRs, while other Campanian municipalities facing disastrous environmental and socio-economic conditions are characterised by low CMRs. These figures, in contrast to common sentiment and previous studies, need to be investigated thoroughly in order to assess the exact role of the confounding factors. In this work, we aim to identify the municipalities where confounding factors act as driving forces in the determination of high CMRs through an original multi-step analysis based on frequentist and Bayesian analysis. Pinpointing these municipalities could allow policymakers to design targeted and effective policy measures aimed at reducing cancer mortality.

1. Introduction

Campania is the third poorest region of Italy in terms of GDP per capita (ISTAT, 2020a). High unemployment rates, lack of social services, poor infrastructural endowments, low institutional quality and a significant presence of criminal organisations are all structural problems that constrain the economic performance of the region (Greyl et al., 2013; Pinotti, 2015). National and European measures tackling these structural problems have proved to be inadequate (Crescenzi et al., 2017; Cerciello et al., 2019). As a result, the population of Campania has been suffering from persistent and widespread socio-economic deprivation (Barba et al., 2011; Marfe and Di Stefano, 2016), while the gap with the Centre and the North of Italy has been increasing progressively over the last 50 years (Daniele and Malanima, 2011). Socio-economic deprivation is a major cause of health outcomes, including life expectancy at birth (Woods et al., 2005), which at present in Campania is the lowest of the whole country (ISTAT, 2020b). This negative phenomenon may be explained by the diffusion of cancer, which is one of the main causes of death both in Italy and globally (Alicandro et al., 2018; Vos et al., 2020). While the availability of new treatments and the diffusion of prevention activities have decreased cancer mortality in all areas of Italy, indeed, the drop has been considerably less marked in Campania (Crispo et al., 2013).

Socio-economic deprivation contributes to determining the course of cancer cases, influencing lifestyles, diagnosis timing, screening procedures, access to treatment, and treatment accuracy (Walker et al., 2005; Padilla et al., 2014; Auluck et al., 2016; Lokar et al., 2019; Smith et al., 2019). A branch of the literature argues that the probability of diagnosing cancer at an early stage is significantly lower in economically deprived areas, since residents of these areas resort to screening procedures less frequently and are less willing to seek medical care in view of potential cancer symptoms (Catalano et al., 2003; Bennett et al., 2011). More broadly, many studies have focused on the relationship between deprivation (cultural, material, relational, etc.) and health (Regidor et al., 2003; Mackenbach, 2006; Ministry of Health, 2011), finding that more deprived areas generally feature more health-related

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problems. Among others, Azamjah et al. (2019) evaluated the trend of breast cancer mortality rate (CMR) during the 1990–2015 period in a cross-country perspective. The authors defined seven super regions,[1] showing that mortality increased everywhere except in the high-income super region. Concerning access to healthcare, Chu et al. (1996) analysed the relation between breast cancer and mammographic screening in the United States, Canada, England and Wales, finding that early detection treatments, which are less frequently available in deprived areas, are the main drivers of declines in cancer mortality. Godfray et al. (2018) analysed the relationship between meat consumptions and health, highlighting the fact that meat consumption, which is concentrated in low-income families (while the wealthiest consume more vegetables), increases the risk of cancer. Deprivation is more problematic in the presence of low environmental quality: Fazzo et al. (2008) considered a socio-economic deprivation index as a driver of the relation between cancer mortality and exposure to environmental degradation, identifying spatial clusters in the provinces of Naples and Caserta with significantly higher CMRs.

The combination of socio-economic deprivation and environmental degradation has been described as an explosive mix following the socio-environmental disaster that shook Campania in the 2000s. Besides lagging behind most of the country with regard to economic development indeed, the region is ill-famed for its bad waste management system, which had been problematic since the 1980s (Armiero and Fava, 2016). In 1994, the national government declared a state of ‘waste emergency’ in Campania, due to the saturation of most regional landfilling sites. In 2007, another waste crisis erupted in the metropolitan city of Naples, drawing much attention from the media (Dines, 2015). Citizens reacted by creating associations and grassroots movements advocating ‘environmental justice’ and contesting the unequal distribution of environmental risks[2] (Armiero and D’Alisa, 2012; De Biase, 2015). The main concerns of pro-environmental activists focused on the supposed relationship between environmental deterioration and health damage (Armiero and D’Alisa, 2012). In particular, many pointed to a relationship between low environmental quality and cancer. This relationship has been at the centre of the scientific debate during the last 15–20 years, generating heterogeneous results.

Specifically, some studies find a significant effect of environmental quality on cancer dynamics (Jagai et al., 2017; Jian et al., 2017). Poor waste management leads to the contamination of water, soil, and atmosphere, producing a major impact on public health through high levels of carcinogenic toxins. One of the first attempts to analyse the health effects of waste mismanagement in Campania was carried out by Senior and Mazza (2004), who concluded that inadequate waste control and illegal dumping are drivers of cancer mortality. Comba et al. (2006) analysed cancer mortality and congenital malformations in several Campanian municipalities, detecting an increase in mortality in the areas that were most affected by environmental degradation. Benedetti et al. (2015) investigated the health of residents by age groups (children, adolescents, and adults), finding a significant increase in gastrointestinal stromal cancer for men in the areas most affected by pollution. Other recent epidemiological studies, reviewed by Mazza et al. (2018), compared Campania with different Italian regions, unfolding a relation between environmental contamination – associated with waste incineration and landfilling – and risks for public health.

[1] Sub-Saharan Africa, North Africa and Middle East, South Asia, Southeast Asia and East Asia and Oceania, Latin America and Caribbean, Central Europe and Eastern Europe and Central Asia, and High-income countries.

[2] Income level, social class and education influence exposure to environmental hazards (for instance high-income and highly educated individuals are unlikely to live near landfills or incinerators and to be exposed to pesticides). Thus, the distribution of socioeconomic resources is central to understanding the fundamental causes of cancer distribution (Hiatt and Breen, 2008; Krieger, 2008).

While this strand of the literature highlights the role of the confounding factors as drivers of high CMRs, other works detect no significant relationship between environmental degradation and cancer dynamics. Ulaszewska et al. (2011), comparing the levels of carcinogens in the breast milk of mothers living in the Land of Fires with those of mothers living in Northern Italy, find no direct correlation between exposure to open-air waste combustion and cancer risk. Similarly, Esposito et al. (2014) analyse risk agents in blood serum, looking for differences between residents of the Land of Fires and residents of other (supposedly less risky) areas of Campania. They find no evidence in favour of the idea that exposure to environmental degradation increases cancer risk. Finally, Esposito et al. (2018) compare the risks related to dietary exposure for residents of the Land of Fires with those faced by residents of other areas of Campania, finding no significant difference.

Overall, the scientific literature is divided on the real effect of environmental quality on CMRs, and other analyses are necessary to add further elements and try to explain why mortality rates are higher in some municipalities of Campania than in others. Surely, the confounding factors identified by the literature – i.e., environmental quality and socio-economic deprivation – are key drivers of CMRs, but there seem to be other elements. The observation of municipal data reveals that in some Campania municipalities characterised by good (bad) environmental quality and low (high) socio-economic deprivation, high (low) CMRs are recorded. This leads us to believe that there are other – yet unexplored – factors influencing CMRs, to which greater weight must be associated.

Starting from this data, our goal is to identify clusters of Campanian municipalities in which the confounding factors are the main drivers of the high mortality rates. This allows the identification of homogeneous clusters of municipalities to which similar policy recipes may be directed in order to influence mortality rates. To do this, we perform a multi-step analysis in order to verify in which municipalities the weight of environmental quality and socio-economic deprivation acts as a driving force in the growth of CMRs.

The rest of this work is organised as follows: Section 2 outlines the methodological framework we use, providing details on the multistep procedure employed. Section 3 introduces our dataset, describing the variables in detail. Section 4 presents our results. Section 5 contextualises the results obtained, providing relevant discussions and policy implications, and offers our final considerations and concluding remarks.

2. Methods

In this section, we introduce the methods employed to answer our research question. We use a multi-step procedure. First, we calculate two composite indicators, for environmental quality and socio-economic deprivation respectively, using the Mazziotta-Pareto method (Section 2.1). Second, using frequentist and Bayesian methods, we test whether the confounding factors drive differences in CMRs among municipalities of Campania (Section 2.2). To do so, we analyse separately *raw* and *purified* CMRs. Robustness checks on the choice of model specification are provided in the Appendix.

2.1. The Mazziotta-Pareto index

Both environmental quality and socio-economic deprivation are multidimensional and nuanced phenomena. To measure them, we build two to composite indicators, obtained through the Mazziotta-Pareto method (see Mazziotta and Pareto, 2016). This procedure aggregates elementary variables into a single value, according to a non-linear function that rules out full substitutability across dimensions. From a computational point of view, the procedure starts calculating the matrix $Z = \{z_{ij}\}$ of the standardised observed values as follows:

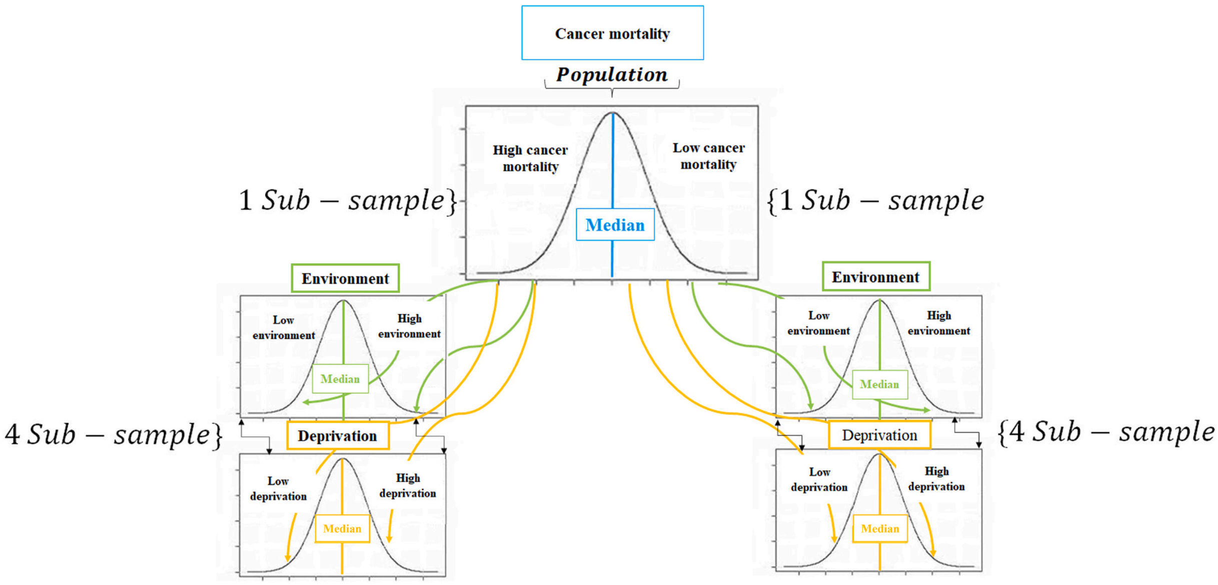

Fig. 1. Samples and sub-samples.

$$z_{ij} = 100 \pm \frac{(x_{ij} - M_{x_j})}{S_{x_j}} * 10 \tag{1}$$

where $M_{x_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$ and. $S_{x_j} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{ij} - M_{x_j})^2}$ are respectively the mean and the standard deviation of indicator j. The sign $\pm$ in equation (1) represents the polarity of elementary indicator j. In particular, if an indicator represents a positive dimension, the sign will be positive, and vice versa. Finally, n is the number of units involved in the analysis (i.e., the municipalities of Campania). The Mazziotta-Pareto index (MPI) also captures the variability within units (the so-called *horizontal variability* which, in our study consists in the variability observed within the municipalities of Campania). The procedure calculates the mean, the standard deviation, and the variation coefficient of the standardised values of unit i:

$$M_{z_i} = \frac{1}{m}\sum_{j=1}^{m} z_{ij}; \quad S_{z_i} = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(z_{ij} - M_{z_i})^2}; \quad cv_{z_i} = \frac{S_{z_i}}{M_{z_i}} \tag{2}$$

where m represents the number of elementary indicators. The MPI is defined as

$$MPI_i = M_{z_i} \mp S_{z_i} cv_{z_i} \tag{3}$$

So, it is composed by two parts: *i)* mean level (M_{z_i}); *ii)* penalty ($S_{z_i} cv_{z_i}$). The penalty component penalises the units featuring high variability among the elementary indicators and rewards the units with greater balance (Mazziotta and Pareto, 2016; Agovino et al., 2018a). Concerning the sign in equation (3), it depends on the nature of the phenomenon measured. If the MPI is a positive outcome (i.e., positive variations in the phenomenon are associated with positive variations in index) then the negative sign is used, because the penalty component smooths the value of the indicator, pushing it downwards. Conversely, the positive sign is used with when the MPI is a negative phenomenon (i.e., the index varies negatively for negative variations of the phenomenon). This strategy allows to calculate the Environmental Indicator (EI) and the Deprivation Indicator (DI).

2.2. Frequentist and Bayesian methods

The municipalities of Campania are characterised by an uneven distribution of CMRs, indicating that this phenomenon is not random and may be driven by various underlying factors. As argued earlier on, the literature identifies environmental quality and also socio-economic deprivation as the main factors that determine the distribution of CMRs. In order to verify the relevance of these factors, we propose an empirical strategy consisting of four steps.

- In the ***first step***, we adopt the median[3] as a useful statistic to divide the distribution of CMRs across Campanian municipalities in two samples: a sample containing municipalities with high rates (above the median), and a sample containing municipalities with a low rate (below the median).
- In the ***second step***, the same procedure is applied to the two driving factors of CMRs (i.e., EI and DI). In this case, the two distributions of EI and DI are associated with the two samples of CMRs in order to generate sub-samples of municipalities. Sub-samples share a high (or low) EI and a high (or low) DI. This allows us to create eight one-by-one comparable sub-samples. Since the pairs of comparable sub-samples feature the same EI and DI (above or below the median) they will differ *ceteris paribus* only in terms of mortality rates (above and below the median). The practical objective is to verify whether, under the same conditions (same EI and DI), the differences in terms of CMRs in the two sub-samples of municipalities are due to chance or are mainly due to EI and DI. In this regard, Fig. 1 shows the procedure employed to partition the population into samples and sub-samples. Fig. 2 shows the sub-samples obtained. In particular, the following eight sub-samples emerge from the implementation of the second step:
  - *Sub-sample 1a,* which includes all the municipalities that feature high EI and low DI.
  - *Sub-sample 1b,* which includes all the municipalities that feature low EI and high DI.

[3] Although the average is the most used and best understood centrality index, the median is also a common centrality measure. The average and the median can be the same or nearly the same in some cases, but they are different if some observations are clustered towards one end of the data range and/or if there are few extreme values. In statistical jargon, this is called skewness. In this case, the average can be significantly influenced by few values, making it poorly representative of the majority of the values in the data set. Under these circumstances, the median provides a better representation of central tendency than the average.

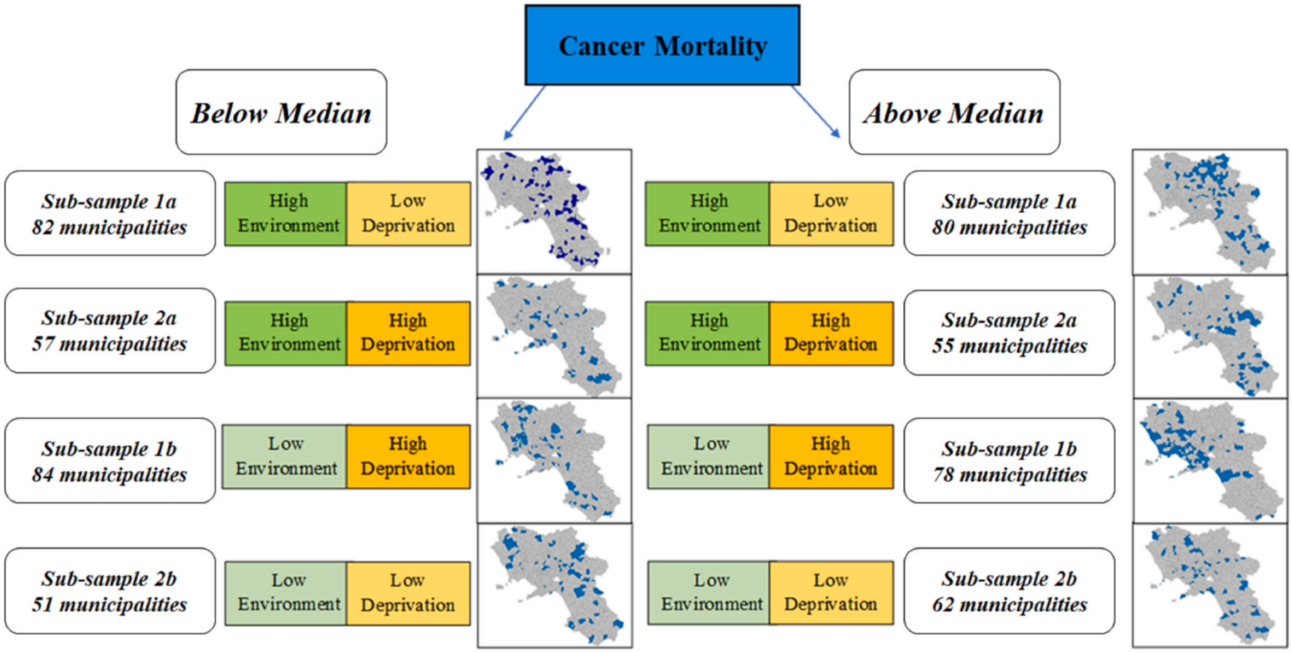

Fig. 2. Graphical representation of the empirical strategy.

- *Sub-sample 2a,* which includes all the municipalities that feature high EI and high DI.
- *Sum-sample 2b,* which includes all the municipalities that feature low EI and low DI.

The municipalities in sub-sample 1*a* face the best possible scenario, those in sub-sample 1*b* face the worst possible scenario and those in sub-samples 2*a* and 2*b* face mixed contexts.

- In the ***third step***, for each sub-sample we proceed to purify CMRs from the effects of EI and DI (for more details see Fazio and Lavecchia, 2013; Ferraro et al., 2021). In particular, we use OLS to regress the CMR on the two covariates (i.e., EI and DI). Next, we extract residuals that we use as a proxy to capture cancer mortality net of the confounding factors. The estimated equation for each sub-sample is the following:

$$Mortality = \beta_0 + \beta_1\ EI + \beta_2\ DI + \varepsilon \tag{4}$$

where *Mortality* is an $N \times 1$ column-vector, *EI* and *DI* are both $N\times 1$ vectors of observations on environmental quality and socio-economic deprivation respectively, β_0, β_1, and β_2 are the scalar parameters of interest and ε is an $N \times 1$ vector of well-behaved disturbances.

-In the ***last step***, we use t-tests for mean comparisons on the two halves of each sub-sample (above and below the median), investigating whether the difference in CMRs is significant. We implement this procedure for both the raw and the purified version of CMR. When dealing with purified CMR, *non*-significance, i.e. failure to reject the null, would imply that, net of environmental quality and economic deprivation, the observed mean difference in CMRs in two halves of a sub-sample is due to EI and DI. On the contrary, significance, i.e. rejection of the null, implies that net of EI and DI, the observed mean difference in CMRs in two comparable sub-samples is due to factors other than EI and DI. In practice, we apply the following *t*-test to the one-by-one comparable halves of the sub-samples identified in the second step (see Fig. 2):

$$H_0 : \varepsilon_H = \varepsilon_L \quad H_1 : \varepsilon_H \neq \varepsilon_L$$

where ε_H and ε_L represent respectively high and low purified mean mortality in the comparable sub-samples.

Both frequentist and Bayesian methods may be used to run the third step of analysis and then to implement hypothesis tests described in the last step. Equation (4), in other words, remains the model we aim to estimate under both frameworks. The main difference between these two approaches consists in the role they assign to observational data: frequentist statistics is completely based on data, whereas Bayesian statistics uses both data and prior knowledge – summed up by a set of *prior probability distributions* assigned to the parameters under investigation before the experiment actually takes place. In our experimental design, the Bayesian approach allows for the incorporation of previous knowledge on cancer mortality, thus drawing empirical strength from earlier research (Neuenschwander et al., 2008; Schmidli et al., 2014). In order to implement Bayesian estimation, it is necessary to postulate prior distributions for parameters, β_0, β_1, and β_2. To do so, we reviewed several studies on cancer mortalities and selected the most relevant sets of results. The studies and coefficients estimated using frequentist estimation techniques are summed up in Table 1.

The coefficient associated with socio-economic deprivation is positive in all the studies considered, whereas the coefficient reported for environmental quality is negative.[4] In other words, increases in socio-economic deprivation increase cancer mortality, whereas increases in environmental quality reduce cancer mortality *ceteris paribus.* In absolute values, the smallest estimates are reported by Jian et al. (2017), while the largest estimates are reported by Martuzzi et al. (2009). Both studies however obtain coefficients significant at the 1% level.

[4] These studies adopt different techniques and methods: Martuzzi et al. (2009), and Fazzo et al. (2011) use Poisson Regression, Mazza et al. (2015), and Chiang et al. (2014) report the estimates of relative risk (obtained through OLS regression), Jian et al. (2017) use multilevel regression, Porta et al. (2009) uses standard and Seifi et al. (2019) report the odds ratio obtained by running a logistic regression.

Table 1
Estimates produced in the previous Literature.

Authors	Environmental Quality	Socio-economic Deprivation
Martuzzi et al. (2009)	−1.25***	3.9***
Fazzo et al. (2011)	−1.14**	n/a
Mazza et al. (2015)	−1.02**	n/a
Jian et al. (2017)	−0.271***	0.60***
Chiang et al. (2014)	−1.2*	n/a
Porta et al. (2009)	−1.035*	n/a
Seifi et al. (2019)	−1.008**	n/a

Consequently, we use these two extreme sets of values as a basis for our priors. In order to impose as few restrictions as possible on our posterior distributions, we assume the priors for β_1 and β_2 to be uniform.[5] We estimate Equation (4) for each sub-sample. Subsequently, we implement the tests related to Fig. 2. With respect to frequentist tests, Bayesian two-sample tests return a lower type I error at the cost of a slightly higher type II error (Kelter, 2020). A synthetic measure that sums up the results of Bayesian tests is the Bayes Factor, which represents the change in the relative beliefs about the null and the alternative hypothesis, given the data available.

$$BF_{01} = \frac{P(H_0|x)}{P(H_1|x)}$$

A Bayes Factor much lower than 1 (for instance $BF_{01} < 0.1$) constitutes a strong evidence in favour of the null (Stefan et al., 2019).

3. Data

This work is based on data drawn from the official records of the Italian National Institute of Statistics (ISTAT) and of the Institute for Environmental Protection and Research (ISPRA). The data cover 549 of the 551 municipalities of Campania[6] and refer to 2012. Municipal-level data (LAU-2) offer important advantages (see Fazzo et al., 2008; Monge-Corella et al., 2008), since municipalities are the smallest administrative units for which mortality rates are available. Municipal data allow to control for the spatial distribution of cancer mortality, highlighting the presence of clusters of municipalities with similar characteristics (e.g., high or low mortality rates). Moreover, they overcome the *ecological fallacy* problem that arises with higher levels of territorial aggregation (Stoker, 1993; Agovino et al., 2018b, 2019, 2019).

The outcome variable of our analysis is CMR, obtained as the count of cancer-related deceases per 100,000 inhabitants. The covariates of our study are the EI and the DI, both constructed using the Mazziotta-Pareto method. To measure environmental quality, the EI aggregates three elementary dimensions: *i)* per capita unsorted waste, *ii)* per capita separated waste, and *iii)* per capita cost of waste management. We relate environmental quality to waste management on the basis of the strong relationship highlighted in the literature between health problems and waste-related environmental exposure (Porta et al., 2009; Musmeci et al., 2010; Kah et al., 2012; Mattiello et al., 2013; Triassi et al., 2015). Due to the lack of municipal data, we use per capita unsorted waste as a proxy for landfilling. This proxy is not perfect: landfills are located close to a few municipalities and a significant share of the unsorted waste might be disposed of in landfills outside Campania. Despite these limitations, per capita unsorted waste represents the best proxy available. Per capita sorted waste is a measure of virtuous waste management, while per capita costs represent the economic resources needed to manage waste properly. Information on illegal waste management is unfortunately unavailable. The EI thus allows to control for good management (separate waste collection, and management costs) and mismanagement (unsorted share) of waste.

To quantify deprivation in Campanian municipalities, we resort to the composite indicator proposed by Cadum et al. (1999). This indicator – the DI – is based on five elementary dimensions: *i)* the share of people who have completed primary school, *ii)* the share of households living in rented accommodations, *iii)* the share of dwellings without toilets, *iv)* the unemployment rate, *v)* the share of single-parent households. The first variable represents the cultural dimension of deprivation, the second and third variables measure the material dimension, while the last two variables contain the three dimensions of deprivation: material, cultural, and relational. Table 2 provides a more detailed description of the data and their sources.

Fig. 3 maps the territorial distribution of CMR, environmental quality and socio-economic deprivation in the municipalities of Campania. Concerning CMR, a high extent of spatial heterogeneity emerges, yielding no municipal clusters. This point is not in line with the previous literature, which highlighted the existence of clusters, including the Land of Fires. The spatial distribution of the confounding factors, however, highlights the presence of a spatial cluster composed by the municipalities of the provinces of Caserta and Naples, featuring low environmental quality and high deprivation. Conversely, a virtuous spatial cluster emerges in the provinces of Avellino and Benevento.

4. Results

After creating the sub-samples of municipalities (first and second step), in this section we run the third step of the analysis, consisting in estimating equation (4) for each subsample. With OLS regressions, although the coefficients estimated feature the expected signs, no significant effect is unfolded. As a result, confidence intervals contain both positive and negative values. Conversely, with Bayesian estimation, the credibility intervals obtained contain either positive values only or negative values only. In other words, we find a univocally negative effect of environmental quality and a univocally positive effect of deprivation when the findings of the previous literature are incorporated in the analysis. This result holds with priors based both on Jian et al. (2017), and on Martuzzi et al. (2009). Unsurprisingly, the coefficients obtained using priors based on Martuzzi et al. (2009) are consistently higher. We show the Bayesian results for sub-sample regressions[7] in Table 3.

In the last step of the analysis, to verify whether the differences in CMRs are primarily due to the confounding factors, we run tests on the means of the two halves within each sub-sample. Concerning sub-sample

Table 2
Descriptive statistics and data sources.

Variable	Observations	Mean	Std. Dev.	Min	Max	Source
CMR	549	15.99	11.25	0	122.65	ISTAT
Environment	549	100.74	4.93	72.061	119.22	ISPRA
Deprivation	549	99.29	5.09	76.32	116.43	ISTAT

[5] Uniform priors represent a half-way solution between non-informative priors and strong restrictions. Concerning β_0, we assume that is normally distributed, as standard in the literature (see Lemoine, 2019).

[6] Two municipalities were excluded from the analysis due to the lack of data. Namely they are Montoro Inferiore and Montoro Superiore, which merged in December 2013 into the new municipality of Montoro, in the province of Avellino.

[7] We refrain from showing the OLS regressions, which return almost all non-significant coefficients. The sole exception is the coefficient associated to DI, which is positive and significant at 10% in the low-mortality half of sub-sample *2b*.

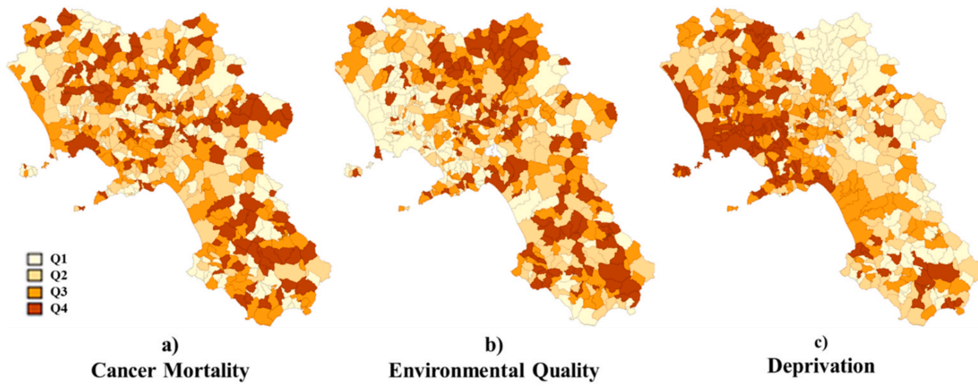

Fig. 3. CMR (a), Environmental Quality (b), and Deprivation (c) in Campania, Quartiles (year: 2012). Source: Authors' elaborations based on data provided by ISTAT and ISPRA. Note: 549 municipalities of Campania were considered in the analysis.

1a for instance, among the municipalities featuring high environmental quality and low deprivation, i.e. municipalities in the best possible conditions, we compare those displaying high mortality with those displaying low mortality. T-tests are implemented first on raw mortality and subsequently on purified mortality. Concerning raw mortality, Table 4 shows frequentist t-tests, while Table 5 displays Bayesian t-tests.

When using frequentist t-tests, we consistently find significant differences across the sub-samples, suggesting that the confounding factors are not the main drivers of mortality. In other words, traditional estimation techniques point to the lack of explanatory power in our model.

When using Bayesian tests on the other hand, the role of the confounding factors turns out to be paramount in two sub-samples out of four. In particular, sub-samples *1a* and *2b*, roughly corresponding to the province of Benevento and a large portion of the province of Salerno, exhibit low values of the Bayes Factor, implying that mortality differences between the two halves are not significant. Thus, the confounding factors emerge as the main drivers of the differences in cancer mortality reported in these areas. Conversely, sub-samples *1b* and *2a* display high values of the Bayes Factor, meaning that the evidence points to the alternative hypothesis, under which factors other than environmental quality and socio-economic deprivation drive municipal differences in cancer mortality. The Land of Fires*,* contained in sub-sample *1b*, thus remains somewhat of a puzzle, since the role of the confounding factors does not appear to be paramount in the area.

Variable purification may shed more light on the problem. The Bayesian tests on the purified variable are shown in Table 6.[8]

Bearing in mind that purified CMR may be interpreted as CMR net of the confounding factors, the significant differences reported for two sub-samples when using raw CMR fade away[9] if purified CMR is used instead. In other words, we find evidence of the primary role of the confounding factors in explaining municipal gaps in cancer mortality in all sub-samples. Thus, the differentials in mortality are driven by environmental quality and socio-economic deprivation. The relative weight associated to these factors is even larger in sub-samples *1a* and *2b*.

Overall, our analysis shows a mismatch between frequentist and Bayesian results: when the raw version of mortality rate is considered, frequentist tests detect significant differences within all municipal sub-samples sharing similar characteristics, while Bayesian tests find significant differences only for two out of four sub-samples. When the purified version of CMR is used as the dependent variable instead, the significant differences within sub-samples disappear. These conflicting indications point to the complexity of the problem. The more conventional frequentist approach is less computationally intensive, but it is also less solid theoretically and epistemologically. Frequentist methods are strictly related to sampling and the results they produce are only asymptotically valid, i.e. they manage to identify the ontological parameters investigated only for sample sizes approaching infinity and for endless repetitions of the experiment in question. One critique to this approach is that experiments may not be reproduced identically several times (Samaniego, 2010). Bayesian methods instead do not rely on sample sizes and limiting distributions, and they are based on the theoretical notion of probability. For this reason, the Bayesian results may be considered as more solid, in spite of their reliance on the (subjective) choice of prior distributions. In our case, since the priors have been defined based on the established literature on mortality rates in Campania, the degree of subjectivity is minimal. In line with the previous literature thus, Bayesian estimates point to the relevance of environmental quality and socio-economic deprivation as driving forces of the differences in cancer mortality across municipalities in Campania, and especially in certain disadvantaged areas, including the Land of Fires.

Although the results of this work do provide relevant insights, it is necessary to highlight the limitations of this work, which have partly influenced our results with the hope that they will be addressed in the future. One important limitation that emerged during our research relates to the lack of updated information on cancer mortality at the municipal level. Frequent updates on epidemiological data with fine-grained information at the local level (including for instance district-level observations) need to be provided by national institutions in order to identify spatial clusters and contagion effects as a basis for the design of adequate policy measures. In addition, CMR captures only in part the broader picture of cancer dynamics. In particular, we lack observations on cancer incidence, which is certainly a relevant dimension. Incidence is based on epidemiological data and is not affected by differential survival patterns, reflecting differences in access to appropriate diagnostic and therapeutic procedures (Fazzo et al., 2011). The lack of data on the mobility history of residents represents another a problem. We have no information on how long residents have dwelled in a certain municipality, where they have lived before, and how often they have moved. It is impossible in this situation to disentangle short-term from long-term exposure to toxic environments or to deprivation conditions. As a consequence, the CMRs we consider may be biased. Third, the available data do not distinguish between male and female mortality rates, nor do they provide information on different age groups. These characteristics are often considered as relevant in most – though not all – medical studies (Goli et al., 2013; Askarian et al., 2014; Jeong et al.,

[8] Due to space constraints, we refrain from showing the results of the frequentist tests implemented after the variable purification procedure. The overall picture however remains very similar to the case of the raw variable. All details will be made available for interested readers upon request.

[9] All the results of the tests, including plots, graphs and detailed tables, obtained using JASP, are available should the reader be interested.

Table 3
Bayesian Regressions by sub-sample.

	Jian et al. (2017)		Martuzzi et al. (2009)	
Sub-sample 1a	Mortality (H)	Mortality (L)	Mortality (H)	Mortality (L)
EI	−0.14986	−0.15091	−0.63418	−0.64299
	(0.076212)	(0.074969)	(0.344495)	(0.352093)
	[-0.26428;	[-0.26428;	[-1.21329;	[-1.21319;
	−0.00869]	−0.01087]	−0.05432]	−0.06765]
DI	0.215501	0.208146	0.696422	0.70614
	(0.133428)	(0.12703)	(0.396043)	(0.40412)
	[0.010323;	[0.01323;	[0.047774;	[0.050445;
	0.494359]	0.485309]	1.40356]	1.450533]
_cons	−2.15874	−1.52329	0.366657	0.119228
	(9.343866)	(9.161824)	(9.610991)	(9.518935)
	[-19.606;	[-19.989	[-18.7843;	[-18.6067;
	15.80126]	15.9074]	18.79304]	17.94928]
N	80	82	80	82
Sub-sample 1b	Mortality (H)	Mortality (L)	Mortality (H)	Mortality (L)
EI	−0.1513	−0.1521	−0.63136	−0.63418
	(0.073719)	(0.074689)	(0.346432)	(0.343765)
	[-0.26502;	[-0.26428;	[-1.20179;	[-1.22493;
	−0.01436]	−0.01087]	−0.04069]	−0.05771]
DI	0.188801	0.188462	0.598023	0.594135
	(0.117639)	(0.11917)	(0.340122)	(0.332379)
	[0.011119;	[0.011218;	[0.051033;	[0.055151;
	0.454669]	0.448245]	1.244853]	1.221383]
_cons	−2.13436	−1.80165	0.127743	−0.14318
	(9.069755)	(9.0113)	(10.12386)	(9.546985)
	[-20.6436;	[-19.3271;	[-19.0589;	[-19.107;
	15.83228]	14.79399]	19.61428]	18.507]
N	78	84	78	84
Sub-sample 2a	Mortality (H)	Mortality (L)	Mortality (H)	Mortality (L)
EI	−0.15665	−0.1471	−0.64215	−0.65776
	(0.0744436)	(0.074663)	(0.0744436)	(0.350051)
	[-0.265515;	[-0.2627;	[-1.21348;	[-1.22495;
	−0.0158353]	−0.00806]	−0.0502]	−0.0542]
DI	0.2052696	0.204648	0.663288	0.679086
	(0.1320084)	(0.130457)	(0.367209)	(0.379254)
	[0.0125203;	[0.012888;	[0.048278;	[0.052834;
	0.5009711]	0.496584]	1.333038]	1.349492]
_cons	−1.144198	−1.94959	−0.21305	−0.25234
	(8.897942)	(9.366815)	(9.690706)	(10.08538)
	[-20.07522;	[-19.7492;	[-19.819;	[-20.0072;
	16.18287]	16.22045]	17.91473]	18.97541]
N	55	57	55	57
Sub-sample 2b	Mortality (H)	Mortality (L)	Mortality (H)	Mortality (L)
EI	−0.14926	−0.1519494	−0.65023	−0.6507
	(0.075781)	(0.0750303)	(0.350484)	(0.343072)
	[-0.26375;	[-0.26551;	[-1.22457;	[-1.22069;
	−0.008]	−0.012562]	−0.0518]	−0.05685]
DI	0.207401	0.2133883	0.677194	0.683251
	(0.1307)	(0.1319131)	(0.383954)	(0.373941)
	[0.010275;	[0.009416;	[0.051847;	[0.058587;
	0.500373]	0.506463]	1.390354]	1.404082]
_cons	−2.10575	−2.005619	0.449909	−0.37403
	(9.064131)	(9.144929)	(9.665422)	(10.00024)
	[-19.6646;	[-20.27354;	[-19.1307;	[-21.2491;
	14.80484]	16.30878]	18.88877]	18.03617]
N	62	51	62	51

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4
Frequentist t-tests for sub-sample Comparisons.

Sub-sample	Observations	Mean Difference	Standard Error	*t*	p-value
1a	162	0.001585	0.0001345	11.7825	0.000
1b	162	0.0012027	0.0000934	12.8706	0.000
2a	112	0.0015372	0.0001554	9.8931	0.000
2b	113	0.0015157	0.0002159	7.0197	0.000

Note: the null hypothesis states that mortality is equal between the two halves of each sub-sample.

2016; Ayubi et al., 2017). Finally, the cost of using municipal data is the lack of observations for multiple years. In particular, the only year for which information is available is 2012.

5. Discussions and conclusions

This work evaluates the role of environmental quality and economic deprivation – the main *confounding factors* considered in the medical literature – in explaining CMRs in Campania. Using Bayesian estimation methods, we find that these confounding factors play a major role in driving differences in CMRs across Campanian municipalities.

In light of our results, governmental programmes aiming to reduce social and economic disparities and policies in support of the environment are relevant instruments in the fight against cancer mortality. Both types of policies however need to be implemented more incisively in Campania, especially in municipalities that suffer from both low environmental quality and high socio-economic deprivation (sub-sample *1b)*, roughly corresponding to the Land of Fires. Targeted economic policy interventions need to reduce social, economic, and environmental inequalities. The high extent of socio-economic deprivation observed in many Campanian municipalities contributes to cancer mortality through several channels. Half of the cases bladder cancer, for instance, have been estimated to be caused by smoking (Freedman et al., 2011), which is a typical habit displayed by residents of deprived areas. Data from Istituto Superiore di Sanità (i.e., Superior Institute of Health) indicate that smoking is more widespread in Campania than the rest of the country, with significant differences within the region. The more deprived province of Naples, in particular, features higher rates of smokers, while the more affluent province of Salerno is in line with the national average (Di Lorenzo et al., 2015). Similarly, obesity – a disease that largely affects the poor (Zukiewicz-Sobczak et al., 2014) – has been long recognised as a driver of cancer mortality (Akinyemiju et al., 2018). High unemployment, low education, and lack of money to spend on physical activities prevent citizens in the deprived areas of Campania from staying fit, which increases the incidence of obesity and diabetes. With 37.4% overweight residents and 14.1% obese residents, in 2018, Campania is the Italian region that suffers from weight-related problems the most (Istituto Superiore di Sanità, 2019).

While some criticists gave into the tempting claim that these problems originate from cultural traits, the root of negative lifestyles is largely economic, leaving much room for economic policy measures. Anti-poverty policies in Campania have mostly proved ineffective over the last decades, and they have often been hindered by high levels of inequality in service provision and access. This demonstrates why the struggle against poverty should be paralleled by efforts to reduce inequality in Campania. Up to present, social policy instruments have largely consisted in passive welfare measures, such as the recent basic income scheme. These measures, rather than favouring employment, are often aimed to gather political consensus. More specific, means-based and targeted programmes must be devised to affect lifestyles and ultimately contribute to reducing cancer mortality.

Furthermore, it is necessary to maintain a high degree of attention on the Campanian municipalities characterised by high CMRs associated with high environmental degradation and marked economic

Table 5
Bayesian tests for sub-sample Comparisons.

Sub-sample	Mean	Standard Deviation	Bayes Factor	Lower Bound	Upper Bound
1a	0.0011235	0.0030114	0.128	-0.0047376	0.0074209
1b	0.006797	0.008720	3.41	0.003792	0.006797
2a	0.07529	0.0076496	5.267	0.0653847	0.0875955
2b	.000492	.0026643	0.053	-0.0038152	0.004371

Note: the tests were implemented using priors based on Jian et al. (2017). The picture remains unchanged if priors based on Martuzzi et a. (2009) are used instead. Grey lines indicate sub-samples for which the null is not reiected.

Table 6
Bayesian tests for sub-sample comparisons on the Purified Variable.

Sub-sample	Mean	Standard Deviation	Bayes Factor	Lower Bound	Upper Bound
1a	0.015	0.000652	0.079	-0.292	0.322
1b	0.020	0.000441	0.069	-0.287	0.326
2a	-0.112	0.000514	0.112	-0.481	0.257
2b	-0.036	0.000791	0.096	-0.404	0.333

Note: the tests were implemented using a prior based on Jian et al. (2017). The picture remains the same if a prior based on Martuzzi et a. (2009) is used instead. Grey lines indicate sub-samples for which the null is not rejected.

deprivation. This will be possible through continuous updates of the cancer database, and the provision of increasingly finer data in order to identify spatial clusters characterised by contagion phenomena (e.g., neighbourhood-level data). Therefore, accurate collection of data will need to be associated with studies aimed at understanding, with increasingly sophisticated empirical tools, the causes of the concentration of high CMRs in some areas of Campania relative to others. The constant focus on this problem finds its foundation on the right to health, constitutionally protected and guaranteed, which must be guaranteed to all citizens. The achievement of substantial equality entails, as expressly provided for by art. 3 of the Constitution, the duty of the state to remove obstacles that prevent the full development of the human person and effective participation in the social organisation of the country.

In this regard, attention to environmental problems in Campania, and mainly in the municipalities of the Land of Fires, was guaranteed by the active participation of citizens through the establishment of neighbourhood committees. In particular, in the last 15 years, rather than an effective collaboration between institutions and citizen associations on the issue of waste disposal, several clashes have been reported (Armiero and D'Alisa, 2012; De Biase, 2015; Armiero and Fava, 2016). Citizen associations have developed many alternative waste disposal proposals over the years. Despite their efforts to involve authorities and public sector officials in these processes, governmental action rejected alternative waste management proposals, marginalising organised civil society. Citizen associations criticise the existing waste cycle and aim at energy recovery, through two key strategies that translate the zero-waste principle into concrete form: first of all, the reduction of waste production and the implementation of door-to-door collection; second, the transformation of existing waste disposal plants into recycling centres using new technologies. This approach would reduce the need for incinerators and increase the recycling of materials (Movimento Campano per Rifiuti Zero, 2009). The national government and local administration, however, tackled the environmental crisis with an authoritarian stance, suppressing civil protests and failing to involve residents in the decision-making process (Armiero and D'Alisa, 2012; De Biase, 2015). Nonetheless, citizens mobilised, advocating environmental justice, demanding proper management of landfills and incinerators, and ultimately producing a bottom-up response that stimulated environmental awareness (Agovino et al., 2019). The positive response on part of the citizenship suggests that policymaking in Campania should take advantage of grassroots associationism, channelling its proposals and instances towards a regional strategy for environmental regeneration, rather than delegitimising and fighting it.

The waste crises experienced in Campania from the 2000s onwards are an archetypical example of poor management of basic public services, resulting in an impressive case of environmental injustice. The continuous exclusion and repression of neighbourhood committees, and of civil society in general on part of governmental authorities, has been constituting a denial of the right to self-determination and has been hindering the process of popular participation. The role of criminal organisations has become evident, as have the limits of policies and regulations and the lack of power of the communities. In this context, change must spur from policy action. National and local governmental authorities must review their stances with respect to civil society and embrace the bottom-up push produced by the citizenship, aiming to build a shared final solution to the long-standing problem of waste management in Campania. Up to now, the wind of change has not seemed to be blowing.

Appendix

Geographical data may feature spatial persistency patterns[10] in the form of spatial autocorrelation in the dependent variable, significant effects produced by the spatial lags of the covariates, or both phenomena occurring jointly. In order to check the robustness of our results, first we compute the Moran's I statistic for the dependent variable (i.e., mortality rate), and then we run the bivariate Moran's I between mortality indicator and both environmental and socio-economic deprivation indicators. The Moran's I provides a measure that quantifies the spatial autocorrelation. In other words, it allows to analyse the existence of global spatial autocorrelation in CMRs across municipalities of Campania. The bivariate Moran's I checks the linear association between the cancer mortality in a municipality and the environmental quality, and socio-economic deprivation in nearby municipalities. According to Anselin (2002), equations (A.1) and (A.2) define the univariate and bivariate Moran's I, respectively:

$$I_U = \frac{N\sum_i\sum_{j\neq i}W_{i,j}\left(X_i-\overline{X}\right)\left(X_j-\overline{X}\right)}{\left(\sum_i\sum_{j\neq i}W_{i,j}\right)\sum_i\left(X_i-\overline{X}\right)^2} \tag{A.1}$$

$$I_B = \frac{N\sum_i\sum_{j\neq i}W_{i,j}\left(X_i-\overline{X}\right)\left(Y_j-\overline{Y}\right)}{\left(\sum_i\sum_{j\neq i}W_{i,j}\right)\sum_i\left(X_i-\overline{X}\right)^2} \tag{A.2}$$

Table A1 shows the results of univariate and bivariate Moran's I based on the Queen (binary) contiguity Matrix for each sub-sample of our analysis. A general absence of spatial autocorrelation emerges for both univariate and bivariate measures except for three cases, where the index values are still very close to zero. While some unexpected signs of Moran's I are reported, the estimates are not statistically significant, allowing to exclude the existence of spatial relations. In sum, the Moran Indices are not significantly different from zero when using the Queen contiguity matrix. As a robustness check, we also computed the Moran's I using the *k-nearest neighbours* contiguity matrices with different number of nearby, i.e., $k = 5$, $k = 10$, and $k = 15$. The results are confirmed also using these matrices.[11]

Table A1

		Univariate Moran's I	Bivariate Moran's I (EI)	Bivariate Moran's I (DI)
Below Median	Sub-sample 1a	−0.013	−0.068	−0.003
		(0.060)	(0.056)	(0.047)
	Sub-sample 2a	0.045	0.064	−0.041
		(0.085)	(0.081)	(0.089)
	Sub-sample 1b	0.119*	0.035	−0.074
		(0.067)	(0.043)	(0.055)
	Sub-sample 2b	0.080	−0.021	−0.046
		(0.092)	(0.085)	(0.071)
Above Median	Sub-sample 1a	0.017	0.066	−0.047
		(0.033)	(0.042)	(0.038)
	Sub-sample 2a	−0.056	−0.003	−0.042
		(0.038)	(0.097)	(0.082)
	Sub-sample 1b	−0.030	0.071***	−0.044
		(0.050)	(0.026)	(0.033)
	Sub-sample 2b	0.004	−0.016	−0.020
		(0.040)	(0.062)	(0.049)

In order to ensure the robustness of our results and to check whether a spatial model should be preferred to OLS, we also compute three additional specifications, namely Spatial Autoregressive (SAR), Spatial Lag of X (SLX) and Spatial Durbin Model (SDM), using the Queen contiguity matrix to compute spatial lags.[12] Table A2 shows the BIC information criterion[13] computed for sub-samples in order to select the most appropriate model specification.

Table A2
BIC in sub-samples

		OLS	SAR	SLX	SDM
Below Median	Sub-sample 1a	−1001.837	−997.4312	−993.1387	−991.628
	Sub-sample 2a	−702.4977	−697.8383	−702.3454	−699.9133
	Sub-sample 1b	−639.7449	−635.8156	−632.7602	−628.98
	Sub-sample 2b	−1050.005	−1053.456	−1049.027	−1046.407
Above Median	Sub-sample 1a	−850.2582	−848.3599	−844.0786	−839.9056

(*continued on next page*)

[10] Wet thank our anonymous referee for raising the point.

[11] The univariate and bivariate Moran's I based on *k-nearest neighbours* matrix are not reported for sake of concision, but they are available upon request on part of interested readers.

[12] As in the case of the Moran's I indices, we also ran the SAR, SLX, and SDM models by using several *k-nearest neighbours* matrices (i.e., k = 5, k = 10, and k = 15). Again, the results are not reported for sake of concision, but they are available upon request on part of interested readers.

[13] We have also computed the AIC criterion. While in most applications the two criteria indicate the same model, in our case they produce conflicting results. In particular, in some sub-samples AIC suggests SAR is the most appropriate specification, while BIC suggests using OLS. However, the general consensus in the literature is that in case of conflicting indications, BIC should be preferred (Kuha, 2004; Yang, 2005).

Table A2 (*continued*)

	OLS	SAR	SLX	SDM
Sub-sample 2a	−596.691	−593.7842	−590.3404	−586.3596
Sub-sample 1b	−621.5785	−618.4306	−614.3431	−613.964
Sub-sample 2b	−899.9558	−895.748	−896.998	−892.6427

The model specification featuring the lowest values for BIC is to be preferred. Overall, OLS is consistently preferable to all other specifications, indicating the lack of relevant spatial persistency patterns.

Credit author statement

All authors have contributed equally to the research development and writing process.

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