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Health-care demand and supply at municipal level: A spatial disaggregation approach

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ABSTRACT

Improving the performance of the health care system has become a key policy issue to reduce the tensions between increasing demands and limited resources. In this paper, we address an innovative methodology and application framework for measuring health sector performance at a highly disaggregated level, offering a perspective that has been pursued to a limited extent. Using a decentralised country such as Italy as a case study and micro-territorial information, a composite indicator of health demand at the provincial level is first proposed. Then, using a spatially disaggregated method derived from the well-established Chow-Lin techniques, a municipality-level indicator is estimated to identify health needs and territorial imbalances between local supply and demand. It is found that there are specific spatial patterns in both demand and supply that should be taken into account to avoid inequitable supply tied to a regional boundary, and that health risk increases with spatial distance to health facilities. These findings highlight the lower responsiveness of peripheral areas and the ability to maintain an effective network across the territory, due to the simultaneous dismantling and fragmentation of territorial primary health care over the last 20 years in Italy.

1. Introduction

Regional differences in health care outcomes and performance have attracted the attention of health economists and policy researchers interested in finding a set of measurable and reliable indicators to carefully select policies and identify system caveats (see *e.g.* Refs. [1,2]). However, although health systems performance assessment has become one of the most important health policy issues, there have been few attempts to measure health systems performance at a very decentralised level. Against this background, this paper contributes to the efforts to investigate how effectively health spending leads to better health in a decentralised country. Italy provides an interesting case study, as the country has undertaken extensive reforms over the past three decades, including the gradual shift of responsibility for health care from central government to local authorities.These administrative and organisational reforms, carried out without the prior establishment of an adequate monitoring system for local health needs, have moved the health system even further away from an optimal area design [3], that is, from an efficient allocation of resources and services that ensure a uniform level of care throughout the national territory. The new autonomy granted to the regions has led to different approaches to the planning and organisation of health care, so that today the Italian National Health Service (INHS) is characterised by 20 different regional systems [4]. Large differences in health outcomes in terms of accessibility and adequacy of care are observed between regions and within each region, which seems to indicate a mismatch between demand and supply of health care at the local level. This is precisely the aim of this work, namely to investigate the existence of a sub-regional imbalance in resources using an original indicator estimated at a new territorial level of detail.

The methodology used draws on two strands of literature: firstly, the theoretical and applied contributions to the determinants of health care provision (discussed in Section 3.1) and, secondly, the statistical and econometric methods used to solve the problem of disaggregated estimation at the local level in order to identify the areas where there is a mismatch between health care supply and demand (Section 3.2).

Indeed, the availability of regional data is of paramount importance for medium and large economies characterised by territorial dualism or decentralised fiscal systems. Again, the case of Italy is paradigmatic. As mentioned above, Italy is on the way to fiscal federalism, which in principle should require a complete set of regional and sub-regional statistics to support policy decisions.

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Despite this need, there is a lack of reliable and timely data characterised by different frequencies, different publication deadlines and, above all, different spatial coverage. To address this need, a first step was to estimate a composite indicator of demand for health services at the provincial level. Given the multidimensionality of national health systems, several techniques have been presented in recent years to develop appropriate data aggregation methods to ensure comparability, consistency and robustness of results (Sect. 3.2). The techniques selected for the construction of the above composite indicator are from the "*Benefit of the Doubt*" (BoD [5], which endogenously finds the optimal set of weights for the elementary indicators of each unit: a property that is particularly useful in the political domain, "*as policy makers cannot complain about unfair weighting*" [6].

In a second step, the spatially disaggregated municipal-level indicator is estimated to reconstruct a more accurate picture of health demand that is not biased by the presence of large provincial centres, and to identify territorial imbalances between local supply and demand using a spatial version of the Chow and Lin [7] framework; the Chow-Lin method also has the advantage over the standard Small Area Estimation methods of explicitly separating trend estimation from spatial prediction of the residuals, which allows the use of arbitrarily complex regressive specifications (see *e.g.* Ref. [8] instead of simple linear techniques).

The rest of the paper is organised as follows. Section 2 provides background information on the institutional setup of the Italian health care system; Section 3 frames the proposed work in the literature dealing with both health care demand and spatial estimation approaches; the methodological proposal for measuring the health care needs is presented in Section 4, while Section 5 provides an application to the INHS; the mismatch between demand and supply is discussed in Section 6, while Section 7 concludes.

2. Institutional setup

Italy has a tax-funded NHS, established in 1978, to ensure equal access to uniform health services regardless of income and place of residence. The original organisation of the health care services was profoundly reformed in the 1990s. This introduced managerialism, regionalization, and a quasi-market model, *i.e.*, a separation between purchasers (*i.e.*, local health authorities) and providers [9].

Nowadays, the system is organised and administered at three levels: national, regional, and local. The central government – in consultation with the regions – determines the main health benefits or "Essential Levels of Care" (Livelli Essenziali di Assistenza, LEA) to be granted uniformly throughout Italy and allocates to the regions the financial resources collected through general taxation. The regions are responsible for organising and providing health services and for prevention and health promotion measures. Taking into account the population's demand for health services, local health costs and the budget allocated by the national government, each regional health authority provides a "standard" package of health services to its residents. Each Local Health Unit (LHU) is responsible for the financial balance between the funds allocated by the regions and the expenditure on health care at the local level.

Since the early 2000s, the health budget has been allocated to the regions on the basis of the capitation rate, partially adjusted to the age distribution of the population, but without adequately taking into account overall differences in health care needs and geographical differences in local costs/prices. Then, despite a resource allocation mechanism that was supposed to ensure equitable distribution, Italian regional health systems differ from one another. Disparities can be found in almost any area of health care provision, in health policy-making, health care expenditure, quality of health care, public satisfaction, health care services organisation and supply [10,11].

Therefore, while ensuring adequate access to health care is a key concern in countries with universal health coverage, unmet need for health care remains widespread as "*a person's demand for health services is not limited by price, household considerations, or ability to pay*" [12], but primarily by the availability of public resources relative to a person's geographic origin.

In Italy,[1] where the public sector accounts for about 70% of total health expenditure, the existence of unmet medical needs has been exacerbated by the progressive decentralisation process that has been taking place since the 1990s, strengthening the powers of regional health authorities in both financing and delivering health services. Regions are now fully responsible for organising their health systems to provide the LEA to be guaranteed nationwide. As a result, there are significant organisational differences in the way regions fulfil their health mandate.

Precisely, there are 20 different regional systems, which can be divided into three macro-organisational types. Lombardy has opted for a *Competitive model* characterised by competition among subregional health care organisations, with LHUs planning and controlling spending via ceilings agreed with each provider. Here, citizen-patients are free to choose among a range of public and accredited private providers who compete with each other. Another macro type is the *Integrated model*, characterised by a high degree of negotiation and planning, as well as collaboration and integration among health care organisations, regardless of their ownership and typology. This model has been implemented in Tuscany, Emilia-Romagna and in north-eastern regions such as Veneto or Friuli-Venezia Giulia. In these regions, many services are concentrated in a few large facilities and the number of hospitals is limited according to the rationalisation principle in order to reduce costs and improve the quality of the services offered. The accreditation of new private facilities is strictly limited ex-ante and controlled ex-post. The third model is the so-called *Bureaucratic model*, in which bureaucrats strongly manage the health care system with limited planning or management control and contractual agreements. Hospitals receive direct funding from the region through agreements that set budget ceiling. This model has been adopted mainly in the southern Italian regions, particularly Campania, Calabria, and Basilicata.

These regional differences result in different access rates and barriers to health service utilisation in a country characterised by large geographic differences in the level of economic development, the size and age composition of the population, and the availability and utilisation of health services. This result is also consistent with the published literature on the subject. Although Costa-Font and Turati [13] found no evidence of an increase in regional inequalities in outcomes and performance after the decentralisation of the health system, Cavalieri and Ferrante [14] found that this process did not improve population health, and Di Novi et al. [15] observed that although fiscal decentralisation may help to curb inequalities between regions, there is no statistical difference in the models analysed. The results suggest that wealthier health regions tend to perform better with fiscal decentralisation, indicating a reduction in health inequalities. However, the underprivileged regions continue to rely on subsidies at the central level.

As a consequence, increasing decentralisation and reliance on regional sources have increased interregional mobility from southern to central and northern regions and widened interregional disparities in health care among Italian regions, which traditionally differ greatly in demography, culture, economic development, and per capita income [16].

Nowadays, equity remains a critical issue in Italy, which is now facing two major challenges: to contain health care spending without compromising the quality of health care and to ensure equity between regions where there are still disparities in the provision of services and the performance of the health care system. As a result, there is a growing

[1] The share of health spending financed by the public sector through regional governments is 70%, while private insurance companies account for about 11% of total spending, and out-of-pocket payments and deductibles make up the remaining part.

demand for better matching of needs and service activities, which has increased the call for more detailed information, for example via composite indicators [17], and for robust methodological statistical tools that can match supply and demand for local public goods and services.

This need is becoming increasingly important for LHUs to better understand, measure, and therefore – where necessary – change supply in the area to ensure consistency with key policies and identify areas for improvement [18].

3. Related literature

3.1. Healthcare determinants and variable selection

Careful analysis of previous studies has shown that selected variables have emerged as the most important determinants of health care spending. Since the seminal work of Newhouse [19]; there has been a unanimous consensus that income is a clear determinant of health care spending [20]. Other subsequent studies first confirmed this result in a cross-sectional scenario, in time series and panel data sets, and found an income elasticity of demand close to one, implying that health care can be considered a normal good [21–23]. Specifically, Auteri and Costantini [24] find that the overall variation in the income elasticity of demand seems to be very large due to the different econometric techniques, ranging from slightly negative values (−0.082) to values well above one.

Together with the level of income, the ageing of the population has been identified as the main cause of the increase in health expenditure. Gruenberg [25] and Verbrugge [26] hypothesised that increasing life expectancy is associated with an increase in years spent in illness. This hypothesis was first challenged on methodological grounds in a seminal article by Zweifel et al. [27]; who claimed that only the last two years of life (eight quarters) matter, regardless of the age of the individual, as the probability of hospitalisation increases with proximity to death. Given these somehow contradictory hypotheses, the influence of proximity to death and treatment expenditure as a function of remaining life expectancy is still controversial among health economists (for a critical review of this literature, see Ref. [28]).

Other variables, such as the number of hospital beds, seem to indicate the presence of economies of scale at the regional level, as does the positive contribution to medical and non-medical staff expenditure per hospital. In addition, the influence of technology as an explanatory variable for the growth of health care spending is evident in Newhouse [29]. Years later, a major article by Okunade and Vasudeva [30] confirms technological progress as the main determinant of health spending in the United States during the period under consideration.

In the studies by Herwartz and Theilen [31] and by Koenig et al. [32]; health expenditures are explained by dependent variables classified into the following categories: demographic and general economic conditions, health status, payments to providers, health insurance, supply of physicians and specialists, market structure of providers, current costs, health care regulation and treatment guidelines, and technology. The main findings are that the demographic structure of the population is the driving element for health care spending. Other results show that a 10% increase in immigrant population is associated with a 91% increase in health care spending. Stearns and Norton [33] compare the future health care costs of the population aged 66–99 in England (1992–1998): the main results are that gender and geographic location cannot be considered as significant variables for health expenditure, while proximity to death increases the explanatory power of health expenditure. Conversely, Dormont et al. [34] analyse the determinants of health expenditure in France (1992–2000) and find that the impact of population ageing on expenditure is relatively small. Finally, the study by Mosca [35]; based on a sample of 20 OECD countries, shows that decentralisation has a positive impact on health expenditure.

3.2. Decoupling demand variables from supply in small area setting

It is important to note that the difficulty of decoupling legitimate demand variables from supply factors makes modelling the demand for health services in Italy a complex task. Mortality [36], socioeconomic status [37] and health service use [38] are most commonly used to capture health needs. These are often manipulated using indexing methods to combine them in different ways and/or to standardise age/sex. Earlier studies examined health needs using behavioural models that focused on specific individual characteristics, resources and needs, and the interaction between these determinants [39]. Later, health status (and satisfaction) outcomes were introduced to capture the dynamic and recursive nature of health [40]. More recently, scholars have emphasised the importance of organisational and institutional factors in individual health care decisions.

It should be noted that demand and utilisation are not necessarily complete measures of the need for health care services. Empirical studies have consistently shown that differences in utilisation are due to changes in demand (population, demographic, and socioeconomic differences) and supply (hospital size and physician availability and preferences) [41]. In particular, there is mixed evidence on the effects of distance between hospitals. Differences in utilisation may be partially explained by the availability of specialised or general medical care). In small geographic areas, spatial interaction models (SIMs) (mainly, gravity models) have been used to study and predict hospital utilisation flows between residents and hospitals. Empirical evidence has shown that differences in geographic accessibility, due to the location of health care facilities, affect utilisation [42], and that accessibility is worse in areas with lower economic status [43]. The empirical literature offers limited evidence on other factors that influence health care utilisation, such as the effects of the quality and reputation of health care facilities and the inappropriateness of utilisation [41].

The supply of health care facilities also influences the level of utilisation regardless of need. Moreover, in countries with centralised public health care, such as Italy, supply constraints would determine the level of spending on public health care. Nevertheless, supply effects can occur in several ways: first, when there is excess demand, supply constraints affect the care provided; second, some health services may serve as substitutes for some hospital care; and third, there is evidence that the local supply of health services (*e.g.*, doctors or hospitals) can stimulate demand [44]. It is therefore reasonable to assume that the level of take-up reflects the location, availability and general characteristics of health care provision, as well as patient preferences and needs, general practitioners' (GPs') preferences, primary care provision, and other costs associated with access to the system.

In this sense, small area variations in the use of inpatient health services are identified in order to match demand indicators with the supply of health services. As Royston et al. [45] noted, the use of larger areas can lead to spurious correlation of utilisation (ecological fallacy), and suitable data are not usually available at a smaller level of aggregation. However, modelling the uptake of health services by local populations can provide insight into the distribution of central resources across larger regions. Previous specification models (see *e.g.* Refs. [46–48]) have indeed been inadequate in three respects: in capturing the process of health demand, in modelling the interaction between health care utilisation and supply, and in dealing with geographic differences. Our goal is to overcome these difficulties, although relevant data on activities, provider characteristics, and demographic, morbidity, and socioeconomic characteristics are not always available for small geographic areas (municipalities). While the aggregate (*i.e.* regional) level can be misleading because it is largely driven by supply and estimates are highly biased by the presence of large metropolitan areas, the small-area level, where populations compete for services and their differential utilisation (after normalising of available factors), combined with spatial-geographic models, can better explain territorial variability in health needs and provide a true scenario analysis of accessibility and homogeneous catchment areas [49].

In order to answer the research questions, it is therefore crucial – after obtaining a synthetic measure of health demand – to use a method that allows estimates to be obtained at a finer territorial level than the original one.

Three main streams of methods can be found in the literature: *(i)* Small Area Estimation (SAE) methods [50] – especially model-based methods – commonly used for small area estimates, *i.e.* for areas with small or no sample size, in sample surveys originally designed for national estimates; *(ii)* geostatistical (or kriging) methods for spatial disaggregation, introduced in the 1950s by Krige [51] and refined, in a more complete form, by Matheron [52]; where kriging can be seen as a more general case of inverse distance interpolation, where the key question is how much importance to attach to each neighbour, to reflect the true spatial autocorrelation structure, and *(iii)* spatial methods derived from the time series approach of Chow and Lin [7]; where the disaggregated measure is the result of a spatially naïve deterministic part and an error term assigned to the lower level units on a neighbourhood basis.

The three groups of approaches presented here start from a common empirical basis, use additional information at a disaggregated level, and then model the error in a parametric or nonparametric way. The main difference between the SAE methods and the Kriging and Chow-Lin methods is that the latter two approaches have the advantage of explicitly separating the trend estimation from the spatial prediction of the residuals, which allows the use of arbitrarily complex regressions (see *e.g.* Ref. [8] instead of the simple linear techniques). Emphasising the regressive part is also important because the deterministic part is often more beneficial for the quality of the interpolation than the stochastic part (residuals) - especially when the *reliable indicators* hypothesis is satisfied (see below).

On the other hand, by including the local sampling variability in the disaggregated coefficients of the deterministic part, it is clear that the SAE-type model-based methods allow us to solve the local estimation problem in a single step.

4. Methodology and estimation

Demand at a detailed territorial level is estimated in a two-step procedure. In the first step, an aggregate measure of demand is estimated via a composite indicator, while in the second step this measure is disaggregated to a finer territorial level.

Composite indicators (aggregation of simple indicators that always have the same territorial level, see Refs. [53,54] for a short introduction) can indeed help to get the "*big picture*" [6] of a socio-economic phenomenon (or linked to social or medical stakeholders [55], at a given territorial level, but they are necessarily insufficient to provide information at a finer resolution. A real challenge in evaluation models, at least from a statistical and econometric point of view, is the *multidimensionality* of national health systems (Sect. 3.2); the nature of the object of evaluation, from an application point of view, is closely related to the development and use of robust and reliable techniques that measure complex measures in a synthetic way; in order to compare and improve performance, quality and level of service, it is crucial to know something about it: *i)* a set of reliable and comparable indicators built on a solid information system, and *ii)* robust and reliable methods aimed at integrating the specific information into a composite measure.

Aggregate measures of health care supply and demand may lack "*precision and combine uncertain weighting systems, imprecision arising from the potential non-comparability of component measures, and misleading reliability in the form of whole-population averages that mask distribution issues*" [56].

Therefore weighting these indicators is far from straightforward, as Barclay et al. [57] point out, noting the problems that can arise at each stage of developing a composite measure; more specifically, Smith, Peter [58] highlights four methodologically critical features of composite indicators in health sector evaluation: *i)* the calculation of the weighting set [6,59], *ii)* the normalisation of the external contextual factors on the performances [60,61], *iii)* the assumptions underlying the aggregative method [62] and *iv)* the potential supplementary restriction [63,64].

To overcome these problems, several techniques have been presented in recent years (see *e.g.* multi-criteria [65] or BoD-DEA [66]; although "*there is no broad consensus or common methodology mainly on the method to identify an optimal set of weights to be used to form the composite index*" [58], more advanced methods share common properties (weight endogeneity, robustness to outliers), but differ in other ones (non-compensability).

These techniques, derived from the "*Benefit of the Doubt*" (BoD [5], approach, are used by several authors (*e.g.* Refs. [67–69]) as the most promising technique developed in the last two decades, mainly due to its theoretical properties (especially in avoiding subjective decisions).

Unlike other weighting methods based on mean measures, BoD makes it possible to find the optimal set of weights for the elementary indicators of each unit *endogenously*. In this way, the resulting indicator is the highest possible for each unit: a property that is particularly "*useful in the policy arena, since policy-makers could not complain about unfair weighting: any other weighting scheme would have generated lower composite scores*" [6].

The application of production efficiency techniques to the CIs field is relatively straightforward, as suggested by Witte and Rogge [70]; because "*the Benefit of the Doubt approach is formally tantamount to the original input-oriented CCR-DEA model of Charnes* et al. [71]*; with all questionnaire items considered as outputs and a dummy input equal to one for all observations*".

Indeed, the basic productive efficiency framework denotes a production technology in which the activity of each decision-making unit is characterised by a set of inputs $x \in \mathbb{R}^p_+$ that are used to produce a set of outputs $y \in \mathbb{R}^q_+$. The production set is the set of technically feasible combinations of (x, y):

$$\Psi = \{(x, y) \in \mathbb{R}^{p+q}_+ | x \text{ can produce } y\} \tag{1}$$

where Ψ is the so-called support of $H(x, y)$.

Given this premise, the Farrell-Debreu efficiency scores (input oriented) for a given production scenario $(x, y) \in \Psi$ when x is constant and equal to 1 for each unit (as in CIs), can be written as follows:

$$\theta(x, y) = \inf\{\theta | (\theta, y) \in \Psi\} \tag{2}$$

and consequently, hypothesising the convexity of Ψ, the convex hull - in accordance with Cherchye and Kuosmanen [72] - can be named $\widehat{\Psi}_{BoD}$:

$$\widehat{\Psi}_{BoD} = \left\{ \left(\mathbb{1}, y\right) \in \mathbb{R}^{1+q} | y < \sum\nolimits_{i=1}^{n} \gamma_i y_i \text{ for } (\gamma_1, .\gamma_n) \right. \\ \left. \text{such that } \sum\nolimits_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, \ldots, n \right\}. \tag{3}$$

The most important BoD properties can be summarised as: *(i)* the set of weights is determined *endogenously* through the observed performance of each unit and the benchmark is not based on constraints or on theoretical choices, but is the linear combination of observed performances; *(ii)* the *CI* is *weak monotone* and *scale invariant* and *(iii)*, as already mentioned, the set of weights is *the highest possible* for the single unit; in the face of these properties, the BoD models suffer from some drawbacks among which the lack of robustness respect to out-of-scale data.

Recently, Vidoli et al. [73] have proposed to bypass the robustness drawback following Daraio and Simar [74]'s proposal; considering a sample of m random variables with replacement $S_m = \{\mathbf{Y_i}\}_{i=1}^m$ drawn from the density of $\mathbf{Y}$, the random set $\widetilde{\Psi}_m$ can be defined as:

$$\widetilde{\Psi}_m = \bigcup\nolimits_{j=1}^{m} \{(\mathbb{1}, \mathbf{y}) \in \mathbb{R}^{1+Q}_+ | X \equiv \mathbb{1}, \mathbf{Y_j} \geq \mathbf{y}\}. \tag{4}$$

Therefore, the effect of a single outlier is mitigated by the fact that a single unit is not compared with all the others, but with a sub-set of samples of size m.

This generalisation enables an iterative calculation of the subset of samples of size m (for $b = 1, \dots, B$ times) and, for each b iteration, the distance from the frontier can be defined as follows:

$$\widetilde{\theta}_m(\mathbb{1}, y) = \inf\{\theta | (\theta, y) \in \widetilde{\Psi}_m\} \tag{5}$$

and the order-m composite indicator (named Robust BoD, RBoD) may be estimated as the mean of $\widetilde{\theta}_m(\mathbb{1}, y)$ over B:

$$D_m(\mathbb{1}, \mathbf{y}) = E(\widetilde{\theta}_m(\mathbb{1}, y)). \tag{6}$$

In order to derive composite measures at a more disaggregated level starting from aggregated indicators (indicators referring to an aggregated territorial measure (*i.e.* the average value at the provincial level) of a disaggregated indicator (*i.e.* at the municipal level), Chow and Lin [7] proposed a disaggregation method based on three main hypotheses:

1. *Structural similarity*: the aggregate model is structurally similar to the disaggregate one; that is, the relationships between the observed variables at the aggregate level are equivalent to the disaggregate ones, *i.e.*, the regression parameters are the same in both models.
2. *Error similarity*: the (spatially) correlated errors have the same structure at both the aggregate and disaggregate levels; that is, the (spatial) correlation is not significantly different.
3. *Reliable indicators*: the covariates have sufficiently large predictive power at both the aggregate and disaggregate levels; that is, R^2, or other regression fitting measures, are significantly different from zero.

Note that hypothesis violation (1) leads to systematically biased estimates; hypothesis violation (2) instead involves misperceptions about possible spillover effects that contribute strongly to the estimates, while hypothesis violation (3) means that the disaggregated estimates reflect only the simple proportion of the aggregate estimates.

The basic model is characterised both by an econometric relationship between y (in our case, the composite health indicator) and the explanatory covariates observable at the disaggregate level (and, of course, at the aggregate level), and by a methodology that allows us to derive the unknown parameters. The model is based on the assumption that there is a linear econometric relationship at the disaggregated level (which is not directly estimable since y_d is not known a priori):

$$y_d = X_d\beta_d + \varepsilon_d \tag{7}$$

where the subscript d stands for `disaggregated` (Municipalities in the application, Sect. 5).

Let denote as C the matrix of dimension $n*N$ (with n the number of Italian Municipalities and N the number of provinces in the application, Sect. 5), which allows the disaggregated observations to be converted into aggregated ones and the index a to be used for the `aggregated` terms; given the above, the aggregated linear equation can be written as follows:

$$y_a = CX_d\beta_a + \varepsilon_a \tag{8}$$

In particular, when addition is chosen as the aggregation operator, provincial estimates can be obtained by aggregating the corresponding municipal values ($y_a = \sum y_d$); in this case, the generic element C_{ij} is constructed as follows:

$$C_{ij} = \begin{cases} 1, & \text{if Municipality } i \in \text{Province } j, \\ 0, & \text{elsewhere.} \end{cases} \tag{9}$$

If the arithmetic mean is chosen as the aggregative operator instead, C must be built as follows:

$$C_{ij} = \begin{cases} 1/k, & \text{if Municipality } i \in \text{Province } j, \\ 0, & \text{elsewhere.} \end{cases} \tag{10}$$

where k is the number of municipalities belonging to province j; in which case, the provincial estimates are reconstructed by the average of the municipal estimates ($y_a = E(y_d)$).

Under these premises, and taking into account the constraint $y_a = Cy_d$, the *structural similarity* ($\beta_d = \widehat{\beta}_a$) and the *error similarity* assumptions ($\sigma_a^2 = \widehat{\sigma}_d^2$), the optimal forecast [75] of y_d can be written as follows:

$$\widehat{y}_d = X_a\widehat{\beta}_a + GU \tag{11}$$

where:

$$G = \widehat{\sigma}_a^2 C' (C\widehat{\sigma}_a^2 C')^{-1} \text{ and } U = (y_a - X_a\widehat{\beta}_a) \tag{12}$$

Polasek and Sellner [76,77] propose a very interesting generalisation of the model (and a `Matlab` routine) outlined in equations (11) and (12) by introducing a spatial autocorrelation term into a classical multivariate equation (7). From an application perspective, this means that the value of the dependent variable for a given area depends not only on its independent variables, but also on the level of variables in neighbouring areas (equation (7)). If spatial correlation effects in competition between municipalities, but also, and especially, within very similar provinces, are assumed then, given a matrix of spatial weights W_N and a spatial lag parameter $\rho \in [0, 1]$ at the disaggregate level, a "*mixed regressive spatial autoregressive*" [78] specification (not yet directly estimable) can be assumed:

$$y_d = \rho_d W_n y_d + X_d\beta_d + \varepsilon_d,\ \ \varepsilon_d \sim N(0, \sigma_d I_N) \tag{13}$$

Accounting for spatial effects in a health demand analysis means considering the many *omitted* spatial factors that determine that demand: the limited and incomplete nature of basic health data, in fact, may lead to a systematic underestimation of the level of demand in some areas, and this is even more true in contexts that are highly disaggregated from a territorial perspective.

The reduced form allows a better assessment of the spatial component affecting the contribution of X_d:

$$y_d = (I - \rho_d W_n)^{-1} X_d\beta_d + (I - \rho_d W_n)^{-1}\varepsilon_d \tag{14}$$

So it is possible to rewrite the reduced form of equation (14) with $R_n = (I - \rho_d W_n)$.

$$y_d = R_n^{-1} X_d\beta_d + R_n^{-1}\varepsilon_d,\ \ \varepsilon_d \sim N(0, \Sigma_d) \tag{15}$$

with the Σ_d covariance matrix equal to:

$$\Sigma_d = \sigma_d (R_n' R_n)^{-1} \tag{16}$$

The unknown terms of the models at the disaggregated level are ρ_d, β_d and the covariance σ_d. To estimate these unknown terms, according to the basic hypotheses, the mixed autoregressive relationship between y and X at the aggregate level can be considered:

$$y_a = \rho_a W_N y_a + CX_d\beta_a + \varepsilon_a \tag{17}$$

with the aim to obtain $\widehat{\rho}_a$ and $\widehat{\sigma}_a$.

Given the structural similarity ($\rho_d = \widehat{\rho}, \beta_d = \widehat{\beta}_a$) and error similarity ($\sigma_d = \widehat{\sigma}_a$) hypotheses, even in this case, it is possible to substitute the estimated parameters in equations (15) and (16). The β_a estimate can be obtained as follows, similar to the Chow-Lin basic method:

$$\widehat{\beta}_{a,GLS} = (X_a'(C\widehat{\Sigma}_d C')^{-1} X_a)^{-1} X_a'(C\widehat{\Sigma}_d C')^{-1} y_a \tag{18}$$

and the estimate of y_d at the disaggregate level can be constructed as:

Table 1
Provincial demand composite indicator: PCA analysis.

Diseases	Factor1		Factor2		Factor3		Factor4	
Cancers	89	*						
Pneumonia	86	*						
Digestive apparatus cancers	81	*						
Infective	74	*						
Breast cancers	74	*						
Respiratory	74	*	43					
Mental disorders	67	*						
Colon cancers	66	*	47					
Nervous system	58							
Muscular system	55							
HIV/AIDS	53							
Skin and tissue	45							
Circulatory system			84	*				
Endocrine glands, nutrition and metabolism			81	*				
Brain circulatory disorders			79	*				
Diabetes	−50		75	*				
Genitourinary system			68	*				
Chronic obstructive pulmonary			64	*				
Ischaemic heart disease			56					
Road accidents					80	*		
External causes of injury and poisonings					71	*		
Suicide and self injuries	47				51			
Cirrhosis and other chronic liver							77	*
Digestive system	40						76	*
Blood, blood-forming organs and immune disorders			42				50	

Note: The printed values are multiplied by 100 and rounded to the nearest integer. Values greater than 60 are marked with an '*'. Values less than 40 are not printed; Rotation method: Varimax with Kaiser normalisation.

$$\widehat{y}_d = \underset{(1^{st}\ \text{term})}{\widehat{R}_n^{-1} X_d \widehat{\beta}_a} + \underset{(2^{nd}\ \text{term})}{\widehat{\Sigma}_d C^{'} (C \widehat{\Sigma}_d C^{'})^{-1}} \underset{(3^{rd}\ \text{term})}{(y_a - C \widehat{R}_N^{-1} C^{'} X_a \widehat{\beta}_a)} \tag{19}$$

Thus, the first term of equation (19) represents the naïve estimate of the unknown vector y_d, while the third term of the equation represents the estimated error at the aggregate level multiplied by the second term, the "*gain projection matrix*" [79].

This amount depends crucially on the spatial lag parameter $\widehat{\rho}_a$ on the aggregate level; note that when $\widehat{\rho}_a = 0$, the $\widehat{\Sigma}_d$ matrix is equal to the matrix identity, and it is reduced to the projection matrix transpose: $G = C^{'}(CC^{'})^{-1}$ as in the baseline model; therefore, given ρ_d and W_N matrix, the residuals at the aggregate level are no longer assigned equally to all municipalities (of the same province), but are filtered by the spatial weight matrix.

5. Empirical application

5.1. Variables selection, data availability and model specification

Italy has been a strong advocate for the achievement of Universal Health Coverage (UHC), and regions have taken different paths in prioritising health care under UHC. As a result, the country offers a wealth of lessons for other countries, particularly those where differences in health care utilisation across geographic areas are well documented. The empirical evidence on whether the demand side or the supply side is the driving force behind regional differences in health care is conflicting (Section 3.2). If differences across territorial area cannot be explained by differences in medical need, this may be a sign of inefficiency or a misallocation of health care resources.

In the context of a public, universal health care system, several of the more recent studies conclude that supply-side factors, such as physician preferences, practise styles, and incentives play a key role than demand-side factors in explaining geographic differences in health care [44]. However, this finding is not clearly shared by all applied analyses: while some researchers indeed claim that demand factors play an important role in explaining regional differences, others (see *e.g.* Refs. [80,81]) affirm that not all territorial differences in health care provision can be explained by observable characteristics of demography, employment, health status and infrastructural factors.

This relates to whether geographic differences can be justified by underlying demand factors or whether they should be viewed as a misallocation of common supply-side resources. To this end, the determinants of `population by age` are included in our empirical specification as proxies for overall health status. To adjust for health status (medical need), demographic covariates include the proportion of elderly citizens aged 55 to 64, the proportion of seniors aged 65 to 80, and the proportion of seniors aged 80 and older.

Socioeconomic structure covariates include `education level`, `average income`, and `unemployment`. These covariates are added because they are likely to influence individual health behaviours and the efficiency of health self-care, and thus the motivation and ability to use health services.

In addition, we take into account that the Italian territory is characterised by geographical differences that affect the opportunity cost of seeking health services (*i.e.*, travel time and travel costs may interact with the affordability of transportation). As primary care centres, which are supposed to represent access to the health system, are unevenly distributed, the possibility to choose an acceptable and effective access may be partly limited by the geographical characteristics of the Italian territory.

In estimating the physical accessibility of the health network, as suggested by Perucca et al. [82]; we take into account that people have to reach the health facility through different topographic variations and landscape features. Therefore, `elevation` was also considered, as areas may be vulnerable to adverse weather conditions with snow cover in winter. In addition, limited road networks, poor road quality, and difficult terrain may characterise different travel scenarios, leading us to control for `traffic accidents`, which have been shown to be an important public health problem.

5.2. Potential demand composite indicator at the provincial level

The health demand CI at the provincial level is estimated using the

Table 2
Robust BoD CI and demand characteristics at provincial level: comparing models.

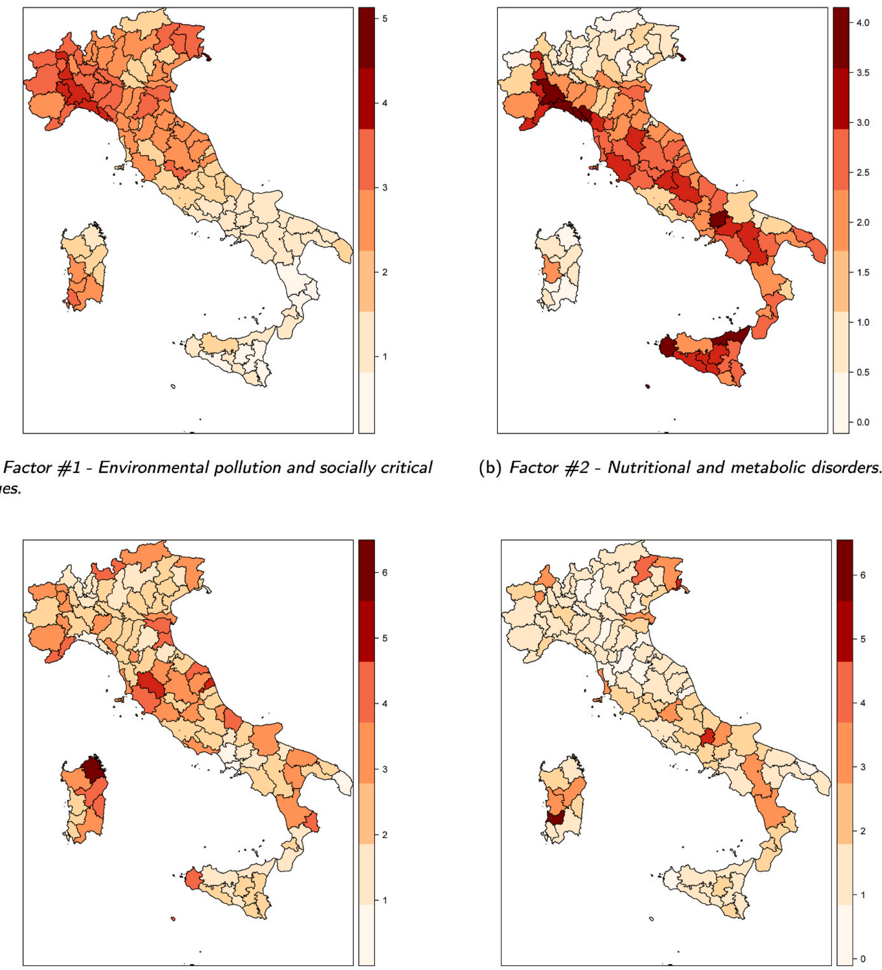
	Dependent variable: Robust BoD CI					
	(1)	(2)	(3)	(4)	(5)	(6)
Population (55–64 year)	− 0.019	− 0.018	− 0.076***	− 0.085***	−5.606	−0.074***
Population (65–80 year)	− 0.011	− 0.011	0.033*	0.037**	3.206	0.036**
Population (>80 year)	0.059**	0.060**	0.058**	0.057**	2.008	0.042*
Altitude		0.014*	0.011*	0.011*	0.148	0.003
Average income			− 0.001**	− 0.001**	−0.275	−0.001
Graduates			− 0.009*	− 0.014**	−0.871	−0.010**
People seeking employment			0.022*	0.027**	0.869	0.023***
Injured in road accidents				0.168**	0.523	0.034
Constant	80.763***	74.696***	100.110***	99.701***	0.000	72.859***
R^2	0.230	0.260	0.489	0.515	–	–
Adjusted R^2	0.205	0.227	0.448	0.471	–	–
ρ	–	–	–	–	–	0.2714**
AIC	764.17	762.33	732.8	729.68	–	859.09
BIC	776.99	777.71	755.88	755.32	–	892.99
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3
Descriptive statistics (year 2018).

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Cancers	110	29.658	4.323	21.110	26.560	32.420	41.290
Pneumonia	110	1.590	0.775	0.230	0.945	2.040	5.010
Digestive apparatus cancers	110	9.899	1.488	6.660	8.805	10.883	13.130
Infective	110	2.100	0.781	1	1.5	2.6	5
Breast cancers	110	3.854	0.794	2.390	3.288	4.383	6.090
Respiratory	110	7.253	1.550	3.990	5.982	8.362	11.940
Mental disorders	110	3.105	1.047	1.480	2.288	3.820	6.490
Colon cancers	110	3.178	0.537	1.650	2.810	3.480	5.050
Nervous system	110	4.203	1.060	2.400	3.428	4.850	7.760
Muscular system	110	0.581	0.223	0.000	0.430	0.730	1.410
HIV/AIDS	110	0.103	0.074	0.000	0.050	0.150	0.350
Skin and tissue	110	0.188	0.105	0.000	0.110	0.230	0.570
Circulatory system	110	39.071	6.786	25.790	33.655	42.855	55.170
Endocrine glands, nutrition and metabolism	110	4.584	1.201	1.170	3.658	5.492	7.250
Brain circulatory disorders	110	10.406	2.656	5.760	8.160	12.173	20.070
Diabetes	110	3.544	1.120	1.110	2.580	4.263	6.730
Genitourinary system	110	2.022	0.474	1.090	1.647	2.322	3.490
Chronic obstructive pulmonary	110	3.592	0.808	2.030	3.090	4.125	5.940
Ischaemic heart disease	110	12.368	2.686	6.960	10.238	13.915	19.730
Road accidents	110	0.612	0.185	0.240	0.470	0.740	1.080
External causes of injury and poisonings	110	4.050	0.745	2.260	3.490	4.505	6.620
Suicide and self injuries	110	0.772	0.275	0.110	0.595	0.910	1.650
Cirrhosis and other chronic liver	110	1.034	0.312	0.540	0.790	1.232	1.990
Digestive system	110	4.000	0.841	2.850	3.348	4.450	6.420
Blood, blood-forming organs and immune disorders	110	0.521	0.164	0.230	0.408	0.605	0.990
Population (55–64 year)	110	1,125.077	926.557	223.446	496.596	1,371.098	5,201.000
Population (65–80 year)	110	1,431.217	1,231.759	260.673	622.702	1,785.823	7,818.333
Population (>80 year)	110	589.659	500.015	111.878	268.861	744.803	3,329.833
Altitude	110	338.165	192.131	7.040	198.253	421.508	951.284
Average income	110	16,509.930	2,844.502	12,116.250	13,865.060	18,806.060	23,313.920
Graduates	110	888.823	878.401	136	363.5	1,065.2	5,314
People seeking employment	110	447.993	458.648	44.778	172.259	495.848	2,864.800
Injured in road accidents	110	46.918	43.748	8.933	17.431	55.810	253.817

ISTAT "*Health for All*" database for 2018, the latest year available for all indicators (Table 3 contains the descriptive statistics of the variables used in the different steps of the application). This source of information contains a wide range of indicators on the health system and health in Italy, mainly at the regional administrative unit level, but in some cases also at the provincial level. Information from previous years is also available: this issue can certainly be the subject of a future methodological deepening by including also panel characterisation in the proposed spatial disaggregation framework.

On the other hand, the source of information for the determinants of health demand (see Table 2) is ISTAT for `population`, `altitude`, `injured in road accidents`, and `job seekers`, the Italian Internal Revenue Service for `average income`, and the Ministry of Education for the `number of university graduates`. The choice of the analysis dimension is clearly constrained by the availability of statistical data on health demand at a very detailed level: in this application, only standardised (per 10,000 population) mortality rates - disjoint separated by cause of death - were available at the provincial level. Under these



(a) *Factor #1 - Environmental pollution and socially critical issues.* (b) *Factor #2 - Nutritional and metabolic disorders.*

(c) *Factor #3 - Non-sanitary causes of death.* (d) *Factor #4 - Alcohol abuse.*

Fig. 1. Provincial demand composite indicator: PCA analysis.

premises, the composite indicator can be considered an indicator of "*health risk*" rather than an indicator of "*health demand*".

In the BoD framework, CIs are formed by a weighted linear aggregation applied to simple indicators. However, the linearity of the aggregation can only be positively accepted only following the Krantz et al. [83]'s theorem [6]; p. 103), which suggests that, given variables ($I_1, I_2, \ldots, I_n$), there is an additive aggregation function if and only if these variables are mutually preferentially independent.

From an operational point of view, the theorem implies that an additive aggregation function allows the marginal contribution of each variable to be evaluated separately, and that the marginal contribution of each variable can then be summed to obtain an overall value; this implies, then, that linear aggregation is fully appropriate only in cases where each simple indicator is not only collinear but also independent. In other words, since the method is additive, the use of simple correlated indicators would have favored the main dimensions that had more indicators, regardless of their informative nature.

Given these premises, from a statistical point of view, this implies that it is necessary to move from simple indicators to principal components (PCA, see Ref. [84] for recent advances in this standard technique), especially when the simple indicators are highly correlated.

Table 1 shows the PCA-rotated factor pattern related to provincial mortality rates by disease. Four main factors are significant (explaining 64% of the total variance): factor 1 can be interpreted as related to environmental pollution and to socially critical issues; factor 2 to nutritional and metabolic disorders; factor 3 to non-sanitary causes of death (car accidents and self-inflicted injuries), while factor 4 is related to alcohol abuse.

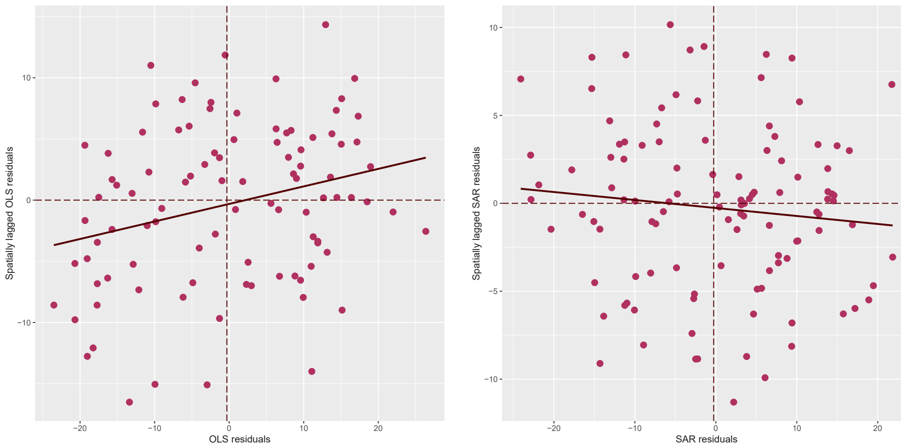
Table 4
Provincial demand composite indicator: comparing methods.

	BoD	Robust BoD	MPI
BoD	1.00	0.93	0.70
Robust BoD	0.93	1.00	0.72
MPI	0.70	0.72	1.00

Fig. 1 highlights an obvious spatial regularity in North-South direction, especially in the northwestern area between Liguria and Piedmont also for factor 2; the other two factors do not seem to be related to specific regional factors, but rather to specific characteristics of each area.

Once the uncorrelated factors were identified, the composite indicator was estimated using BoD, Robust BoD and MPI methods [85]. Spearman's rank correlation coefficient (Table 4) shows good stability despite the different underlying properties of the methods.

The Robust BoD method was therefore chosen for its robustness properties and because of the endogenous weights (see Ref. [73]). The territorial distribution of the RBoD indicator does not seem to show a clear north-south regularity (Fig. 4), although some local - cross-regional regularities can be easily identified (Liguria - Piedmont, Tuscany, the Apennines, and the area near Venice - Porto Marghera petrochemical site).



(a) *OLS residuals* (b) *SAR residuals*

Fig. 2. Moran plot for residuals.

It is therefore necessary to disaggregate the provincial indicator to the municipal level in order to identify the existence of homogeneous local areas and to analyse the determinants that affect them.

5.3. Demand identification and model selection at provincial level

As highlighted in section 4, the Chow-Lin framework puts a special emphasis on the deterministic part of the model, while the stochastic error part is allocated among the territories through ρ and W.

Table 2 reports the OLS and SAR estimates of the relationship between Robust BoD CI and provincial-level demand characteristics: in particular, columns (1) to (4) report the OLS estimates, column (5) reports the standardised regression coefficients according to the full OLS model, and column (6) reports the estimates of the spatial autoregressive lag model.

As highlighted in section 4, the `population` characteristics, the physical and social characteristics of the area (`Altitude`, `Income`, `Graduates`, and `Job seekers`), and the local risk factors (`Injured in road accidents`) must be available at both the provincial and municipal levels in order to estimate the composite indicator at the disaggregated level as well. All covariates are provincial averages of the corresponding variables at the municipality-level.

Please note, in particular, the coefficient estimates for the full model given in column (4): *(i)* the `population` coefficient is negative for the younger age group, while it is positive and increases with age; *(ii)* `income` and `university graduates` (substitution effect, public/private costs, and culture effect on preventive care) have negative coefficients, while in the poorest areas of the country (`job seekers`) health demand increases; *(iii)* greater exposure to road infrastructure (`people injured in road accidents`) directly increases health demand.

The OLS estimation method is recognised to be correct if the known error properties are satisfied: in particular, if the residuals are spatially autocorrelated, this assumption is not satisfied; in other terms, if OLS residuals are spatially autocorrelated, OLS estimates are biased and inconsistent. This is the case for the OLS estimates (column 4) in Table 2 with a significant Moran test of 0.144 ($p-value=0.004\,3$), while it is not more significant for the SAR specification (column 6) (-0.045 with $p-value=0.74$). Fig. 2 shows the positive correlation between residuals and spatially lagged residuals for the OLS model, while this evidence is no longer significant for SAR specification.

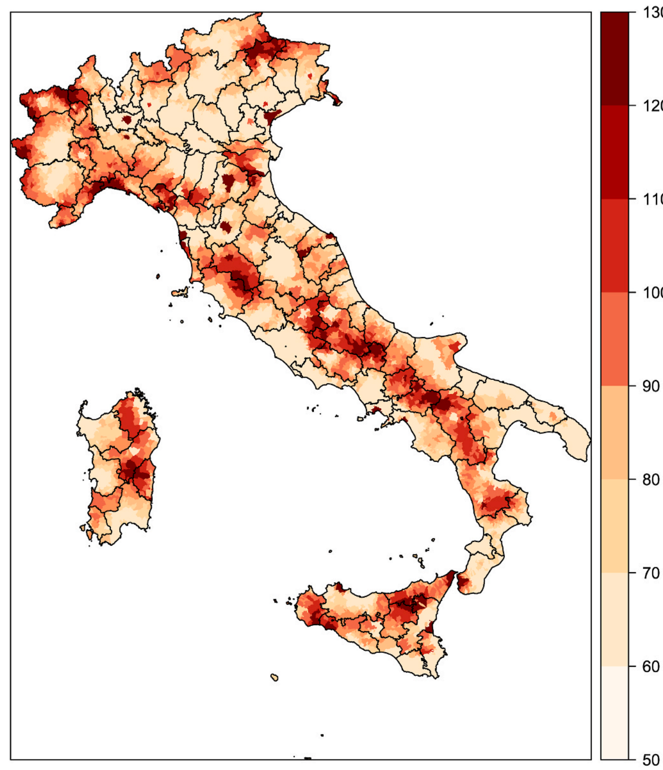


Fig. 3. Estimated demand RBoD composite indicator at municipal level: spatial Chow-Lin method.

The SAR estimates (column 6, ρ positive and significant) confirm – once again – the need to include spatial effects in the disaggregation model and, ultimately, the need to use a disaggregation framework that also, adequately, accounts for territorial demand factors.

Finally, the neighbourhood matrices used in the estimations were derived for both provinces (W_N) and municipalities (W_n)[2] using Delaunay triangulation of the points, where the neighbourhood relations are defined by the triangulation extending outward to the convex

[2] Different specifications of the proximity matrices have been used to test the robustness of the specification, and no significant differences have been found in the results obtained. Further results are available on request from the authors.

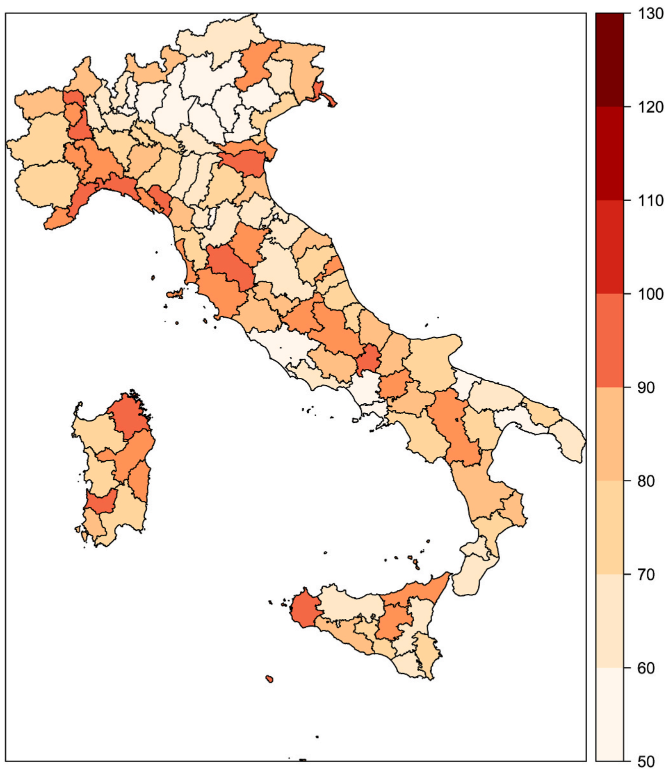


Fig. 4. Provincial demand RBoD composite indicator.

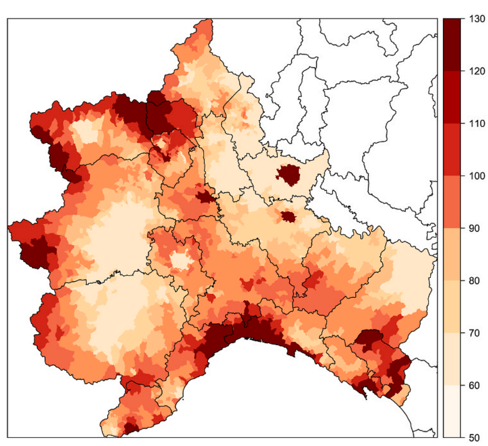


Fig. 5. Estimated demand RBoD composite indicator at municipal level: Italian North-Western regions.

hull of the points (function tri2nb, package R spdep).

5.4. Spatial disaggregation at municipal level: Chow-Lin approach

Based on the estimated relationship between the Robust BoD CI and the provincial-level demand characteristics, the Chow-Lin method can be usefully employed to estimate the municipal-level health demand indicator using the model outlined in equation (19). According to the previously estimated model – where the covariates were formed as province averages – matrix C has been set according to equation (10).

Fig. 3 shows significant heterogeneity within each province, highlighting - once again - the need to reach a greater level of detail to better understand the spatial regularity of health demand.

Fig. 5 maps the estimated demand RBoD composite indicator specifically for the Italian North-Western regions: it is easy to observe how, besides obvious cross-regional regularities, specific needs related to, for example, industrial factors (near Genoa area) emerge.

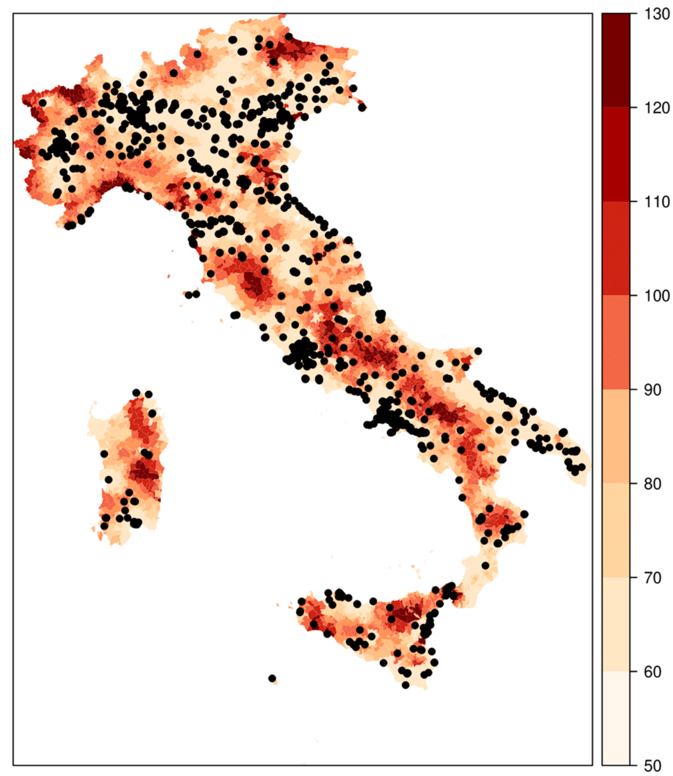


Fig. 6. Supply and estimated Chow-Lin demand at municipal level.

The ratio between the naïve and the total estimate (see equation (19)) can be a good measure of the disaggregated estimates; the more it approaches 1, the more the hypothesis (3) (*Reliable indicators*) is satisfied, and the less the disaggregated estimate is affected by the unexplained spatial error. In this application, the ratio is never less than 0.85 - for any municipality - showing that the disaggregated estimate is strongly influenced by the deterministic component model.

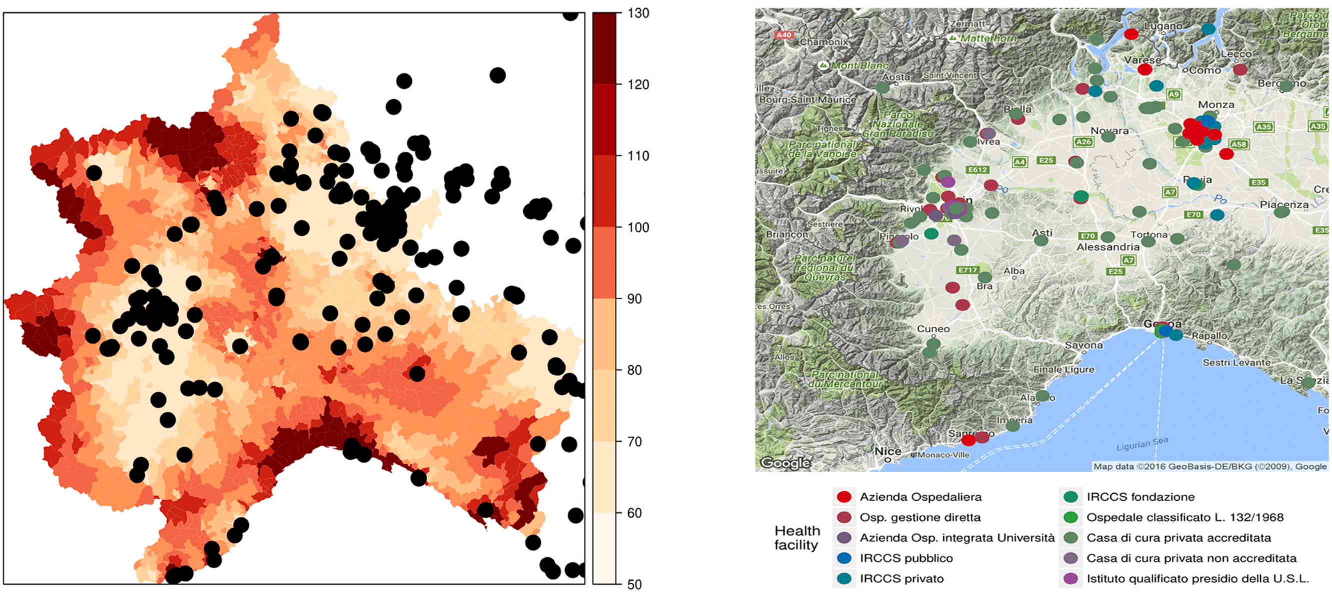
6. Matching supply and demand at municipal level

While several contributions to the literature have examined the role of competition in health care, spatial interactions, and feedback mechanisms among providers (see, inter alia [86–88]), or, conversely, spatial accessibility by the community [89,90], insufficient attention has been paid to mechanisms for spatial allocation of supply to meet demand levels for public decision makers.

The main objective of the health services demand indicator - estimated at the municipal level - is to allow policy makers (in the Italian case, at the regional level) to better know the characteristics of their own territory: this policy tool is definitely more useful when combined with the analysis of the relative supply in each territory.

Under these premises, the aim of this section is to examine the spatial correspondence between supply and demand at the municipal level. It is clear that inter-dependencies exist and that it is not possible – at least in a cross-section setting – to correctly analyse causality and convergence between supply and demand over time.

Conversely, it is useful to understand whether the location of hospital care structures is appropriate at time t and whether health care demand increases with distance to the same structures.



(a) *Demand and supply.* (b) *Supply and orography.*

Fig. 7. Supply and estimated Chow-Lin demand at municipal level: Italian North-Western regions.

Table 5
Codispersion between estimated Chow-Lin demand and distance by lag classes.

Lag classes	Upper Bounds	Cardinality	Coefficient
1	0,4012	470 651	0,2084
2	0,8024	1068 371	0,2166
3	1,2036	1353 979	0,2135
4	1,6048	13 110 710	0,1989
5	2,006	1319 460	0,1911
6	2,4072	1236 447	0,1751
7	2,8084	1154 419	0,1506
8	3,2096	1050 112	0,1331
9	3,6108	978 088	0,1282
10	4,012	904 622	0,1269
11	4,4132	827 775	0,1182
12	4,8144	735 889	0,1348
13	5,2156	4089 397	0,1817

The official data of the Ministry of Health[3] contains the complete list of local health and hospital facilities throughout the country, along with their address. The geo-referenced address – obtained through the Google Maps Geocoding API – allowed to map health supply directly to the territory (Fig. 6). Although Fig. 6 is still qualitative, it highlights a central theme of this study (which in turn was made possible by analysing supply and demand at a more detailed level): *health risk increases with physical distance from health facilities*.

Fig. 7 focuses on the territorial supply and estimated demand Chow-Lin demand for the northwestern regions of Italy. The mismatch between health risk and supply is illustrated by the fact that supply structures (black points) are located in orange areas (lower health risk) and risk increases with increasing distance from the structure (red areas). So what can be a first explanation for this result? One possible explanation could be – in our opinion – the higher private costs for the inhabitants of peripheral, mountainous and/or poorer areas [49], which make it more difficult to access health structures that reduce preventive medicine and screening.

In order, therefore, to obtain more accurate estimates of the relation between the location of the municipality and the composite indicator of demand, it was necessary to calculate the distance – by the ellipsoid method of Vincenty [91] – from the centroid of gravity of each municipality to every other health institution. Once all distances had been calculated, the shortest was chosen as the reference for each municipality.

A measure of the spatial relationship between two territorial variables can be obtained by the codispersion coefficient [92] for a given number of classes of lag distance. The computational procedure calculates the codispersion coefficient for two spatial sequences defined on general (non-rectangular) grids. First, a certain number of bins is created for the lag distance. Then, the codispersion for each bin is calculated. Finally, Table 5 shows that the coefficient of codispersion - independent of the lag classes - is significantly positive; in more remote areas (larger distance), this codispersion is higher (see Tables 6 and 7).

7. Final remarks

In recent years, the management of health care in Italy has undergone major changes, mainly due to the demands of budgetary control: regional local health units have become larger and lost the characteristics of territorial management, while health planning functions have been returned to the central administration, with the aim of distributing available health care resources so that people who are equally in need have equal access to care, regardless of where they live. To implement this principle, health care needs must be measured in different areas. However, in countries with centralised public health care, health care utilisation is assumed to be determined only by demand and supply, while the amount of public health care spending depends only on supply constraints, and those who distribute resources do not have sufficient information to measure health care needs directly.

This paper highlights the need to look at health demand at the lowest disaggregated level to rebalance relative supply, especially in a "*quasi-market*" where supply does not naturally adjust to demand in the short run. Under these conditions, supply and demand data at the municipal level are necessary for planning purposes, as provincial-level data often obscure important insights given the large provincial centres.

To obtain a demand indicator at the disaggregated municipal level, the spatial Chow-Lin method was proposed. The relevant variables used to spatially disaggregate the provincial index were considered at the municipality level and their contribution to the estimation was

[3] "*Elenco Aziende sanitarie locali e Strutture di ricovero*", source: Nuovo Sistema Informativo Sanitario (NSIS), Ministry of Health.

Table 6
Factor scores and BoD composite indicator by Province (1/2).

Code	Province	Factor #1	Factor #2	Factor #3	Factor #4	BoD CI
1	Torino	3.23	1.70	2.10	1.66	0.75
2	Vercelli	4.14	2.97	3.16	1.26	1.00
3	Novara	2.73	1.62	2.11	1.06	0.66
4	Cuneo	2.97	2.30	3.06	1.27	0.78
5	Asti	3.71	3.14	3.70	1.43	0.97
6	Alessandria	3.77	3.61	2.46	0.93	0.96
7	Aosta	2.98	0.47	2.96	2.69	0.82
8	Imperia	3.20	3.37	3.71	1.41	0.96
9	Savona	3.58	3.41	4.41	2.07	1.00
10	Genova	4.35	3.89	0.80	1.31	1.00
11	La Spezia	3.86	3.58	1.65	2.25	0.93
12	Varese	3.00	1.07	1.23	1.12	0.64
13	Como	2.73	0.92	1.42	1.30	0.61
14	Sondrio	2.74	0.53	4.10	1.05	0.87
15	Milano	3.00	0.90	1.22	0.96	0.64
16	Bergamo	2.27	0.41	2.26	0.75	0.59
17	Brescia	2.43	0.67	1.73	0.59	0.58
18	Pavia	3.41	2.23	2.18	2.17	0.79
19	Cremona	3.07	1.42	2.25	1.60	0.74
20	Mantova	2.10	1.98	2.78	1.07	0.62
21	Bolzano/Bozen	1.57	0.15	2.82	1.47	0.61
22	Trento	2.32	0.74	1.82	1.46	0.57
23	Verona	2.20	1.13	2.41	0.88	0.59
24	Vicenza	2.22	0.45	2.11	1.36	0.57
25	Belluno	3.68	1.50	2.16	3.78	0.91
26	Treviso	2.01	0.26	2.43	1.06	0.56
27	Venezia	2.74	1.18	2.35	2.13	0.71
28	Padova	2.31	1.09	2.27	0.74	0.60
29	Rovigo	2.59	1.98	3.13	3.34	0.90
30	Udine	3.23	1.00	3.12	2.98	0.89
31	Gorizia	3.67	1.11	2.38	5.07	1.00
32	Trieste	4.82	3.85	1.57	3.36	1.00
33	Piacenza	3.41	2.09	2.99	1.31	0.86
34	Parma	3.12	1.81	2.14	1.23	0.74
35	Reggio nell'Emilia	2.67	1.52	2.37	0.41	0.67
36	Modena	2.68	1.21	2.53	0.90	0.69
37	Bologna	3.40	2.13	1.85	1.42	0.76
38	Ferrara	3.05	2.84	4.55	2.20	1.00
39	Ravenna	2.93	2.24	3.95	0.82	0.87
40	Forli-Cesena	2.91	1.80	1.52	1.00	0.65
41	Pesaro e Urbino	2.43	2.30	2.54	1.26	0.66
42	Ancona	2.78	2.22	3.77	1.15	0.83
43	Macerata	2.75	2.81	3.13	1.06	0.80
44	Ascoli Pice	2.56	2.59	2.17	0.67	0.71
45	Massa-Carrara	3.33	3.74	2.95	1.35	1.00
46	Lucca	2.67	3.23	2.47	1.50	0.87
47	Pistoia	2.30	2.38	2.81	1.53	0.69
48	Firenze	2.77	2.22	2.49	0.65	0.70
49	Livorno	2.24	2.70	3.47	2.84	0.94
50	Pisa	2.66	2.70	2.53	0.84	0.74
51	Arezzo	2.44	3.34	3.19	0.36	0.92
52	Siena	2.22	2.60	4.97	1.73	1.00
53	Grosseto	2.42	3.33	4.15	1.81	0.97
54	Perugia	2.35	2.33	2.97	0.88	0.68
55	Terni	3.21	2.83	2.51	2.51	0.84

Table 7
Factor scores and BoD composite indicator by Province (2/2).

Code	Province	Factor #1	Factor #2	Factor #3	Factor #4	BoD CI
56	Viterbo	2.09	2.62	3.64	2.01	0.85
57	Rieti	1.87	3.13	2.80	2.83	0.94
58	Roma	2.15	1.67	2.01	1.09	0.55
59	Latina	1.18	1.32	3.21	0.97	0.62
60	Frosinone	1.26	2.90	2.50	2.45	0.84
61	Caserta	0.88	1.81	0.40	1.91	0.52
62	Benevento	1.10	3.79	0.98	2.32	0.98
63	Napoli	0.87	1.82	0.47	2.01	0.53
64	Avellino	1.09	3.45	1.16	1.61	0.89
65	Salerno	0.85	2.63	1.92	1.50	0.71
66	L'Aquila	2.02	3.03	2.78	2.65	0.90
67	Teramo	1.77	1.94	2.53	2.55	0.74
68	Pescara	1.99	1.81	3.48	2.01	0.79
69	Chieti	1.65	2.93	3.71	1.94	0.87
70	Campobasso	1.40	2.81	2.65	2.88	0.89
71	Foggia	0.93	1.55	3.22	2.21	0.76
72	Bari	0.91	1.32	3.02	1.55	0.65
73	Taranto	0.99	1.81	2.27	1.36	0.56
74	Brindisi	1.25	2.77	2.70	0.53	0.76
75	Lecce	1.87	2.38	0.92	1.23	0.62
76	Potenza	1.17	2.98	2.38	2.96	0.90
77	Matera	0.83	2.51	2.83	1.41	0.72
78	Cosenza	0.60	2.02	3.05	3.30	0.89
79	Catanzaro	0.68	2.52	1.64	2.35	0.72
80	Reggio di Calabria	0.85	2.50	1.74	1.90	0.68
81	Trapani	0.97	3.61	3.73	0.74	1.00
82	Palermo	1.54	2.30	1.25	1.17	0.60
83	Messina	1.10	3.60	1.43	1.12	0.93
84	Agrigento	0.66	3.23	1.91	1.50	0.85
85	Caltanissetta	1.07	3.01	1.70	1.58	0.79
86	Enna	0.73	3.25	2.70	2.65	0.92
87	Catania	0.71	2.49	2.56	0.98	0.69
88	Ragusa	0.89	1.89	2.57	2.04	0.68
89	Siracusa	0.49	2.75	2.77	1.35	0.77
90	Sassari	1.91	0.99	3.30	1.91	0.73
91	Nuoro	1.72	0.53	4.31	3.16	0.98
92	Cagliari	2.34	0.37	3.43	1.04	0.74
93	Pordenone	3.12	0.94	1.49	1.46	0.68
94	Isernia	1.39	2.25	1.50	5.03	1.00
95	Oristano	2.26	1.81	2.49	2.75	0.75
96	Biella	3.43	2.27	3.40	3.45	0.98
97	Lecco	2.42	0.64	1.71	1.42	0.57
98	Lodi	3.17	0.89	2.40	0.30	0.76
99	Rimini	2.64	1.09	2.15	0.87	0.65
100	Prato	2.23	1.77	1.81	0.35	0.55
101	Crotone	0.40	1.43	4.03	2.23	0.87
102	Vibo Valentia	1.08	1.99	1.98	1.89	0.62
103	Verbano-Cusio Ossola	3.65	1.47	1.32	3.09	0.81
104	Olbia-Tempio	0.96	0.18	6.10	1.29	1.00
105	Ogliastra	2.00	0.61	4.17	2.70	0.93
106	Medio Campidano	2.65	0.37	2.07	6.14	1.00
107	Carbonia-Iglesias	3.53	0.95	2.77	1.52	0.86
108	Monza e della Brianza	2.55	0.24	1.21	1.49	0.56
109	Fermo	1.82	2.10	4.83	1.11	0.94
110	Barletta-Andia-Trani	0.91	1.05	1.60	2.47	0.56

evaluated over a continuous spatial field. Therefore, the disaggregated estimation consists of a deterministic part associated with municipal factors and a stochastic part associated with provincial factors.

From a statistical point of view, the paper has shown that – in the absence of more reliable and disaggregated official data – spatial disaggregation techniques can be very useful to define more precisely spatial patterns of higher and lower demand, allowing optimal planning of supply by policymakers. It should be noted that spatial effects do not eliminate the effect of known and measurable determinants, but rather reduce the contribution of the residual error in the deterministic part.

Two important results emerge: *(i)* there are cross-regional regularities in both demand and supply (both for first level hospitals and for prevention and care facilities in the territories) and that these should then be taken into account to avoid unequal care tied to a regional boundary; *(ii)* health risk increases with the spatial distance from health facilities: higher private costs for residents of more peripheral, mountainous, and/or poorer regions can make access to health structures more difficult, reducing preventive medicine and screening. The concomitant dismantling and fragmentation of territorial primary health care over the last 20 years in parallel with the financial structural reforms has reduced both the responsiveness of peripheral territories (an example of this is the impact of the COVID -19 pandemic crisis in Italy, see *e.g.* Ref. [93]) as well as the ability to maintain an active network across the territory especially with regard to the secondary care (a similar effect with many European countries; see for example Portugal, [94]). This paper, therefore, represents an attempt to provide empirical evidence derived from disaggregative techniques to better address the allocation of public resources and physical health units in a sub-regional perspective.

Many questions remain to be discussed and two extensions, in particular, may be explored: the first one, more methodological, concerns the extension of spatial dependence also in the deterministic part of the disaggregation model and not only in the autocorrelated term of the dependent variable; the second one relates to the possibility of integrating information from several heterogeneous sources (education, income, wealth, epidemiological status) with the aim of combining the study of the impact of policy decisions always at a detailed level of resolution and the identification of homogeneous patterns of individuals along a given timeline [95].

CRediT authors contribution statement

Francesco Vidoli: Methodology, Software. **Monica Auteri:** Conceptualization of the study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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