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Does regional belonging explain the similarities in the expenditure determinants of Italian healthcare deliveries? An approach based on Artificial Neural Networks



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ABSTRACT

The investigation of the determinants of public health expenditure is the focus of a vivid debate among health economists whereas the actual crisis of the welfare systems calls for the adoption of innovative tools to inform rational decisions, in the light of stringent budget constraints.

The purpose of this paper is to show the potentialities of Artificial Neural Networks (ANNs) in investigating whether healthcare providers belonging to the same jurisdiction show similarities in their health care expenditure determinants.

Similarities are reproduced in terms of fuzzy dependencies between health budgetary data of the healthcare providers belonging to five Italian regions. The analysis carried out sees the application of Auto Contractive Maps (AutoCM) model.

The methodology is effective in illustrating regional patterns of expenditure and similarities across Local Health Units (Aziende Sanitarie Locali—ASLs).

The results give interesting insights on the presence of notable regional models for health expenditure.

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1. Introduction

The investigation of the determinants of public health expenditure is the focus of a vivid debate among health economists. The actual crisis of the welfare systems calls for the adoption of innovative tools to inform rational decisions in the light of stringent budget constraints (Le Grand, 2003, 2007) as well as epidemiological, organizational and institutional factors (Moorin and Holman, 2006a).

In OECD countries, healthcare is predominantly publicly funded and its progressive growth, led by technological and demographic drivers, currently constitutes a major challenge. For this reason, national policy makers, typically the Ministry

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of Economics and Finance in cooperation with the Ministry of Health, have set a series of measures aimed at dealing with the situation. These range from raising the budget for health to improving the efficiency of health spending to reassessing the boundaries between private and public spending (OECD, 2015; Braithwaite et al., 2015).

As far as Italy is concerned, OECD estimates predict that public healthcare spending, which accounted for 3.3% of the GDP in the period 2006–2010, will raise to 7.0% by 2030 and to 8.7% by 2060. Such a trend constitutes a challenge for Italian policy makers who, in the past two decades, have been committed to reform the system by introducing measures aimed at reducing public deficit and enhancing efficiency.

The Italian health care system is a regionally-based National Health Service (*Servizio Sanitario Nazionale*—SSN), operating at three levels: national, regional and local.

The national level is responsible for the general objectives and fundamental principles of the SSN and for the definition of the essential levels of assistance (*Livelli Essenziali di Assistenza*—LEA)—the basic package of healthcare services which must be available to all citizens throughout the country. Regional governments are responsible for the delivery of a benefits package through a network of population-based Local Health Authorities (*Aziende Sanitarie Locali*—ASLs) and public and private accredited hospitals.

The devolution of healthcare provision to regional Health Ministries was established with the reforms of the '90s. Since then, regional responsibilities in healthcare financing and delivery have been progressively strengthened: ASLs and public hospitals (*Aziende Ospedaliere*—AOs) have gained financial independence and have become fully responsible for their budgets, financing, management and technical functioning (Lo Scalzo et al., 2009).

Even if regional ASLs and AOs enjoy a certain degree of autonomy in the management of resources, they have to comply with regional planning which, in turn, is developed within the framework of national strategies (Muraro and Rebba, 2010). There is a considerable difference in the extent to which the various ASLs implement regional policies. For example, those belonging to the Lombardy region, in Northern Italy, follow region-specific policies concerning the outsourcing of non-health goods and services (Francese and Romanelli, 2011). The ASLs located in other regions, on the other hand, experience a high variability in some expenditure items (such as personnel), as a result of different work practices or skill mixes (Francese and Romanelli, 2011). Moreover, extra-region similarities in the expenditure determinants may be observed as a result of an imitative process which may not be strictly dependent on regional belonging.

Hence, determining to what extent the adherence to region-specific health policies can explain similarities in the expenditure determinants of ASLs still remains a partially unsolved question.

The specialized literature provides a wide range of methods and applications potentially useful to address this issues (Aigner et al., 1977; Charnes et al., 1978; Manning et al., 1987; Newhouse, 1996; Gerdtham et al., 1998; Gerdtham and Jönsson, 2000; Bordignon and Turati, 2009; Francese and Romanelli, 2011). However, they rely on traditional inferential frameworks and exhibit a number of potentialities and limitations widely discussed among scholars (see, for example, Linna, 1998; Moorin and Holman, 2006b).

The Artificial Neural Network (ANN) is a pioneering approach (Buscema, 2007; Buscema et al., 2008a,b; Buscema and Grossi, 2009; Buscema and Sacco, 2010, 2016) that allows to detect the “fuzzy” dependencies, explaining similarities within a dataset and outlining some information related to the characteristics of the observed units and their correlations, which would, otherwise, remain hidden for not being fully specified by functional dependencies. In fact, inferential statistics might sometimes miss the subtle associations constituting the framework of any database. Every linear multivariate analysis links data through simplified relations, but most socio-economic phenomena often do not follow plain linear “cause–effect” relationships; this means that, in many databases, non-significant linear relationships may conceal the keystone of the entire system.

In this paper, we test the possible use of the ANN to detect dependencies that, in turn, explain the similarities in the determinants of expenditures made by ASLs. Data employed are related to the year 2010 and concern the budgets of 66 ASLs located in 5 Italian regions.

In particular, our aim is to test whether, by observing the detected fuzzy dependencies, it is possible to identify which units, among all the ASLs, are characterized by the same behavior concerning health expenditure decisions. If the ASLs that may be grouped together according to their similarities are located within the same Region, this would confirm how similarities in the determinants of health expenditure relate to regional peculiarities; this could help to understand the extent to which the Italian SSN complies with a Regional governance model (Le Grand, 2003, 2007).

2. Methods

2.1. Background information

Investigating the pattern of correlations among a huge number of variables in large databases is a demanding task in terms of both computational time and capacity.

The statistically-oriented literature has developed a variety of methods with different power and usability. All such methods present a few basic problems, one of which is the difficulty of organizing the output in an easily grasped, ready-to-access format for the non-technical analyst.

As a result, the traditional methods may be unreliable or not applicable at all to the analysis of poorly understood problems characterized by heterogeneous sets of potentially relevant variables. Moreover, even in cases where traditional

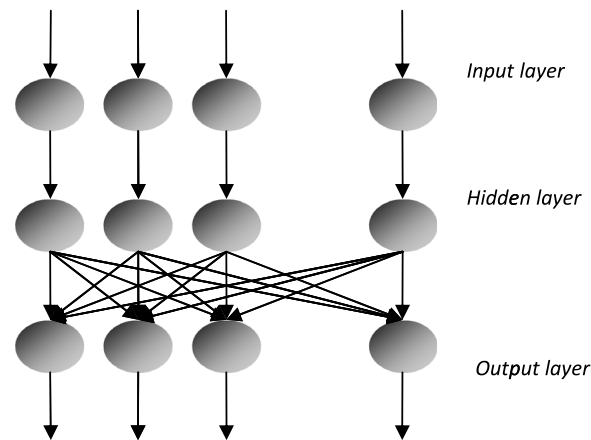


Fig. 1. Architecture of the AutoCM.

methods manage to provide a sensible output, its statement and implications may not be useful or, even worse, may be easily misunderstood.

2.2. The Auto Contractive Map (AutoCM)

In this paper, we introduce a new methodology based on an ANN architecture, the Auto Contractive Map (AutoCM), which allows for basic improvements in robustness of use in computationally demanding problems (Buscema and Sacco, 2010; Buscema and Grossi, 2009; Buscema and Sacco, 2016).

In particular, AutoCM highlights the correlation among variables by constructing a suitable embedding space where a cognitively notion such as ‘closeness’ among variables reflects their associations.

Through optimization techniques, such ‘closeness’ can be converted into a graph-theoretic representation that picks all and only the relevant correlations and then organizes them into a coherent picture. This graphical representation is likely to show the whole pattern of variation: the paths connecting nodes, that result from the interaction of all the variables considered in the analysis are interdependent and can, therefore, explain the variability of the whole dataset (Zuo, 2004).

Overall, the AutoCM architecture is based on three layers of nodes: the input layer captures the signal from the environment (collected data); the “hidden” layer modulates the initial signal within the network; the “output” layer returns a response to the environment on the basis of the “learning process” occurred (Fig. 1).

In this context, the budget data of each ASL represent the input nodes, whilst the hidden layers explain the similarities in terms of fuzzy dependencies among health expenditure determinants. The output layers express the detected dependencies in terms of closeness. By observing the output layers, it is possible to identify the hidden information of the dataset.

The three layers have the same number N (in the present case, the ASLs) of nodes. Each connection between the layers is assigned a weight: v_i represents the connections between the i th input node and the corresponding hidden node, w_{ij} is the weight for the connections existing between the generic j th node of the hidden layer and the i th node of the output layer.

The AutoCM mathematical specification is illustrated in Appendix A.

3. Data

As it has been described earlier, since 1992 ASLs have gained economic and financial autonomy and have become responsible for providing and delivering healthcare at a local level.

Every financial year, ASLs and AOs must fill out two main accounting documents: (1) the income statement, which measures the net income, computed as the difference between revenues from the services delivered and the overall cost of resource utilized to produce that amount of output, and (2) the balance sheet, which measures the gross working capital (Assets – Liabilities + Equity) and the networking capital (Assets – Liabilities). Economic and financial data are then transmitted to the Regional Health Department and to the Ministry of Health.

Since 2001, data have been summarized by means of a specific form referred to as “Income statement form of ASLs and AOs”, formally introduced by the Ministerial Decree No. 16 of 2001. Data are reported in a worksheet organized into four sections for each Region: (i) decoding of each ASL and hospital of the region; (ii) decoding of chapters and items of the income statement; (iii) revenues; (iv) expenses.

The “Income statement of ASLs and AOs” is considered the most relevant form for the monitoring of healthcare expenditures. These are grouped in macro aggregates concerning purchase of goods (pharmaceuticals, medical devices, non-health goods, etc.), purchase of services (pharmaceutical care, in-hospital care, outpatient ambulatory care, rehabilitative care, remuneration of private practice within public facilities and training of health professionals, etc.), “wages and salaries”

(for healthcare staff, healthcare professionals, technical and administrative staff, etc.), other expenses such as subsidies, insurance premiums, legal expenses, depreciation of material assets. Overall, 401 expenditure determinants are considered in the income statement.

In this paper, the focus is on [Appendix B](#) of the income statement, labeled “B—Costs of production”; all the macro aggregates considered are listed in the [Appendix B](#).

For each observed unit (*i.e.* the ASLs located in five regions) the dataset employed takes into account the *per capita* expenditure determinants, weighted for the case-mix index; this expresses the complexity of the cases treated by a hospital in relation to the average complexity of a set of reference hospitals.

Budgetary data utilized in the current analysis refer to 2010 and were provided by 66 ASLs located in 5 Italian Regions, namely Lombardy, Veneto, Emilia–Romagna–Romagna, Lazio and Campania. Lombardy, Veneto and Emilia–Romagna are regions located in Northern Italy, while Lazio and Campania are located in Central and Southern Italy, respectively.

3.1. Data analysis

To investigate whether fuzzy dependencies explain similarities among expenditure determinants depending on regional belonging, we followed three steps.

First, we used the Minimum Spanning Tree (MST) to detect and to graphically represent the “minimal” fuzzy dependencies of the whole dataset as the necessary ones for maintaining a cohesive system, disregarding the belonging region. Within the MST framework each connection originating an internal cycle is eliminated through a process that minimizes a Hubness (H) function (for further technical and analytical details see [Buscema and Sacco, 2010](#)).

Then, within the MST, we identified a “reference” region as the one holding the highest number of within-region “minimal” fuzzy dependencies. With i and j being two nodes (ASLs) belonging to region R we defined the degree of closeness of node i as:

$$C_i = \sum_j^N l_{i,j} \quad (1)$$

where:

$l_{i,j}$ fuzzy dependency between the node i th and the j th

and

if $l_{i,j} \in R$ then $l_{i,j} = 1$

if $l_{i,j} \notin R$ then $l_{i,j} = 0$.

We defined the within-region strength of closeness (S) of node i belonging to Region R as:

$$S_i = \frac{C_i^2}{\sum_{j=1}^N C_j}; \quad S = 1(\text{baseline}) \quad (2)$$

S_R is the mean value of the S_i of ASLs belonging to the same region. The highest S_R value characterizes the reference region.

Finally, we performed a paired case-control analysis using the budgetary data of the ASLs belonging to the reference Region as a control and those of the other Regions as cases.

To do so, we used the Maximally Regular Graph (MRG), which allowed us to detect the whole pattern of fuzzy dependencies and to observe whether they showed within-region similarities.

Through an iterative process which maximizes the H function, the MRG adds to the original MST the most relevant fuzzy dependencies (*i.e.* the connections): the higher the value of the function H, the more significant is the cyclic microstructure predicted by its graph (for further technical and analytical details see [Buscema and Sacco, 2010](#)).

4. Results

[Fig. 2](#) shows the MST obtained for all the regions included in the dataset. Each region is identified by a different color.

The MST highlights how the ASLs belonging to Lombardy register the highest within-region S values and are therefore closely connected to each other.

The closeness of the ASLs belonging to Lombardy may be attributed to the regional model adopted, which has been recognized by the ANN that has been built. The regional healthcare model is based on a quasi-market structure of the healthcare delivery in Lombardy: compared to other regions, hospitals in Lombardy enjoy a wider managerial autonomy, which results in the strengthening of competition within the region.

The theoretical principle of the quasi-market model consists in introducing competition into the system, in order to improve the quality of services and to control the level of health care expenditure ([Le Grand, 2007](#)). The multiplicity of

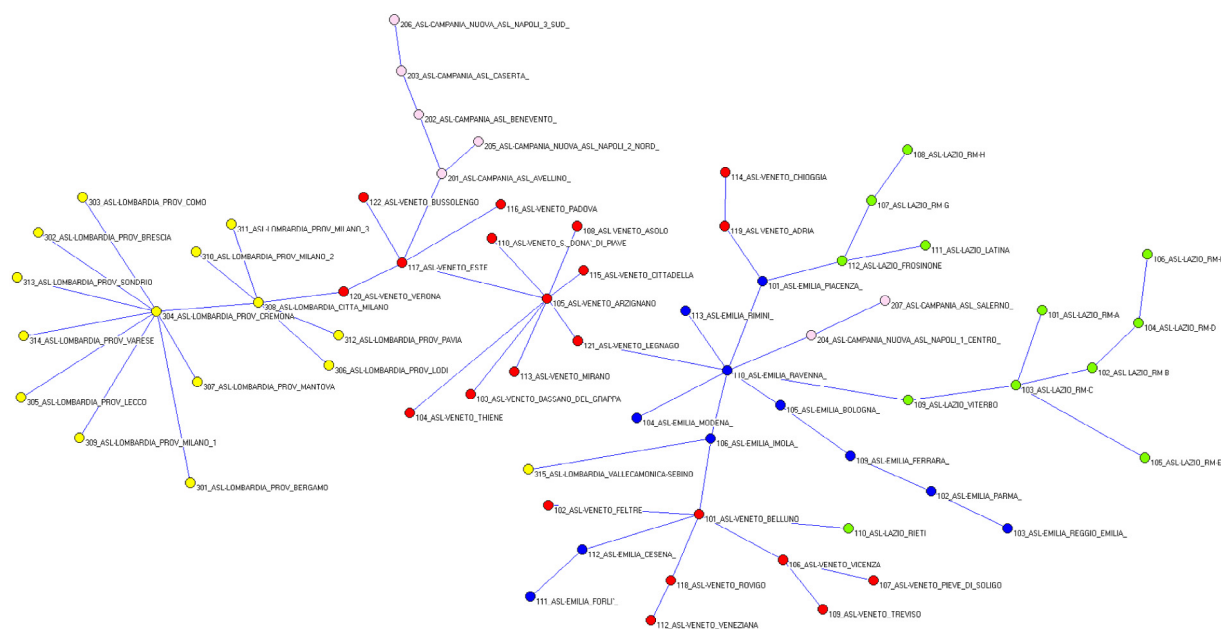


Fig. 2. MST for all the ASLs.

providers is among the most common feature of quasi markets (Longo, 2006), as is the presence of a third party payer, namely the purchaser. Purchasers have strong incentives to limit provisions by providers, who, on their part, aim to increase the production of health services to attract patients. With this model, the possible distortions arising within publicly-run systems should be avoided, or, at least, reduced. The presence of both third party payers and a larger number of providers ensures transparency in the financing criteria and introduces planning as a tool for controlling health care expenditure (Le Grand, 1999).

The mechanism works in the presence of strong budget constraints, enforced by tariff caps in cases where services and/or accesses override the planned budget; from the supply side, patient's free choice is granted by different providers.

Within this theoretical framework, at the end of '90s Lombardy was the only Italian Region to choose a separation between purchasers and providers, and to support patients' free choice, according to the principle that "money follows the patient" (Brenna, 2011). The uniqueness of the Lombardy model, which makes it the reference region for the present analysis, is often mentioned in national and international literature (Mapelli, 2000).

The MRG reproduces a great number of within-region connections, suggesting a compliance with a region-specific model.

The MRG in [Fig. 3](#) shows a comparison between the ASLs located to Lombardy and the ASLs located in another region (in this case, Veneto, another region located in Northern Italy) and highlights the existing similarities.

Overall, Lombardy is characterized by strong connections related to expenditure patterns between the observed units. An exception is represented by the ASL Valle Camonica, which is recognized by the ANN as being part of the Veneto region rather than Lombardy (Fig. 3). This evidence could be explained considering that this ASL serves a mountain area which is poorly connected with the others geographically: thus, the ASLs Valle Camonica shows no fuzzy dependency with the other ASLs located in Lombardy, as it is not affected by the quasi-market structure and the high level of autonomy enjoyed by the ASLs located in the same Region.

Fig. 4 shows a comparison between Lombardy and Emilia–Romagna. Here, the only fuzzy dependency between ASLs belonging to the two regions is the one between the ASLs of Mantova and Parma, the former located in Lombardy and the latter in Emilia–Romagna. Although located in different regions, these ASLs are geographically very close (<100 km), and this may explain similarities in the expenditure pattern and even in the governance model.

The MRG in Fig. 5 considers the comparison between the health expenditure determinants of the ASLs located in Lombardy and Lazio.

The ASLs belonging to Lazio region exhibit a poor number of fuzzy dependencies, thus reproducing a high heterogeneity in the health expenditure determinants. Most of them have only one within-region connection, often attributable to geographic reasons (see for example the correlation between Latina and Frosinone, Viterbo and Rieti, Roma C and both Roma A and Roma E).

It is worth pointing out that the ASL Valle Camonica, located in Lombardy, shows the only fuzzy dependency with ASL Rieti, which is located in Lazio and serves a mountain area as well.

The same holds for the ASLs located in the Campania region, which can be observed in Fig. 6. In this case, the ASL of Caserta appears as the only unit located in Campania whose health expenditure determinants show fuzzy dependencies

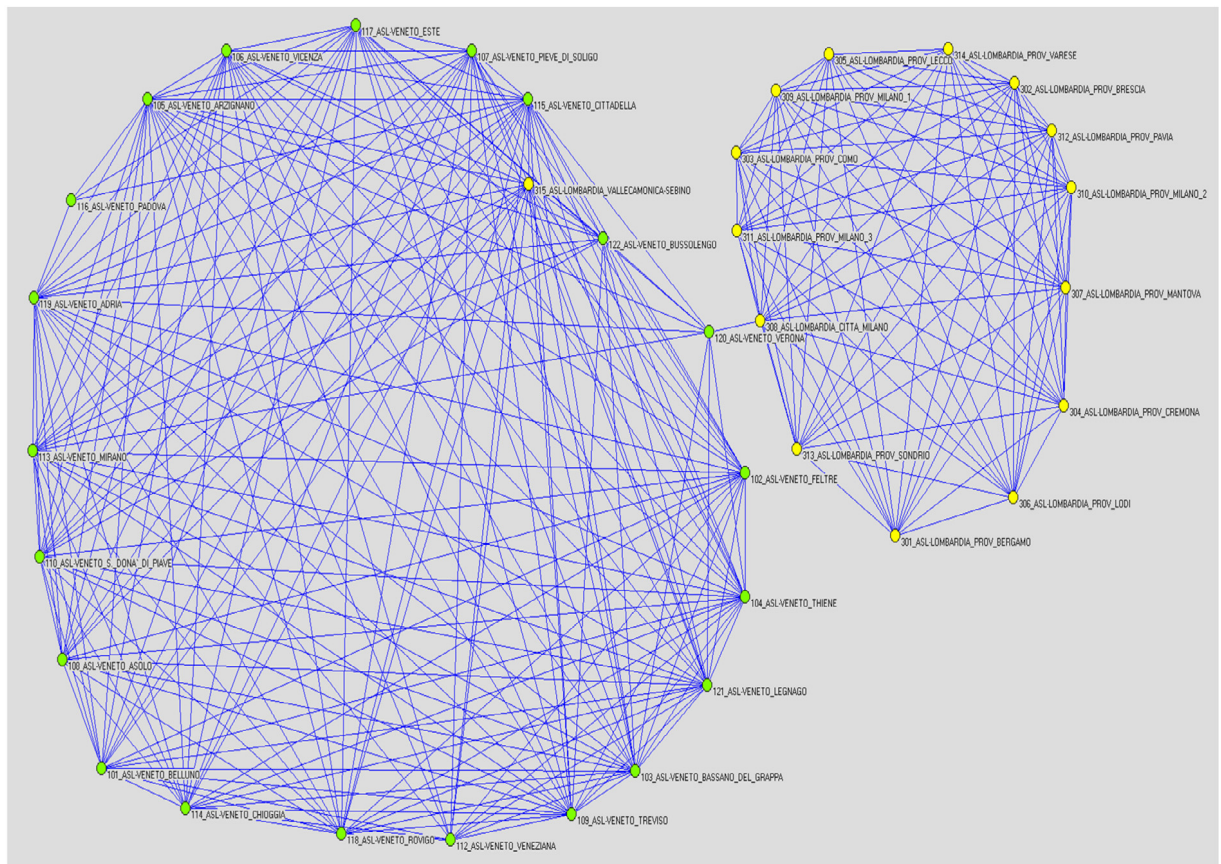


Fig. 3. MRG Lombardy (yellow nodes)—Veneto (green nodes). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

with ASL Lecco (belonging to Lombardy). This time, ASL Valle Camonica shows just one fuzzy dependency with the ASLs belonging to Lombardy.

5. Conclusions

This contribution reported an application of the ANN approach to the investigation of the determinants of healthcare expenditure within Italian local health units.

The ANN trained with budgetary data, related to 66 Italian ASLs in the year 2010, proved to be able to detect fuzzy dependencies consistently with regional belonging.

Through this kind of analysis, it is possible to identify the existence of regional models that justify the healthcare spending behaviors.

Such conclusions show their relevance from a health policy perspective. Once similarities across observed units are identified, this could pave the way for further investigations aimed at predicting the impact of health policies for resource allocation, based on reproducing the health expenditure dynamics of a reference region.

The added value of using ANN approach lies in its capacity to take into account variables that cannot be fully captured by functional dependencies through the detection of “fuzzy” dependencies. Each single datum often interacts in parallel with all the others, and its meaning relates to such a “many-to-many” interaction.

In the present analysis, the healthcare expenditure determinants within each ASL may be strongly affected by demographic, epidemiological, as well as institutional and regulatory constraints.

In the application carried out, we deliberately kept the information on regional belonging hidden, since we needed a sufficiently reliable criterion to test the efficacy of ANN approach in analyzing healthcare expenditure data.

However, it is worth clarifying that, while the ANN *per se* does not reveal the existing information hidden in a dataset, by detecting and highlighting fuzzy dependencies, the model provides the analyst with objective hints on where to look for this information. It also constitutes the basis for a detailed analysis of the characteristics of each observed unit.

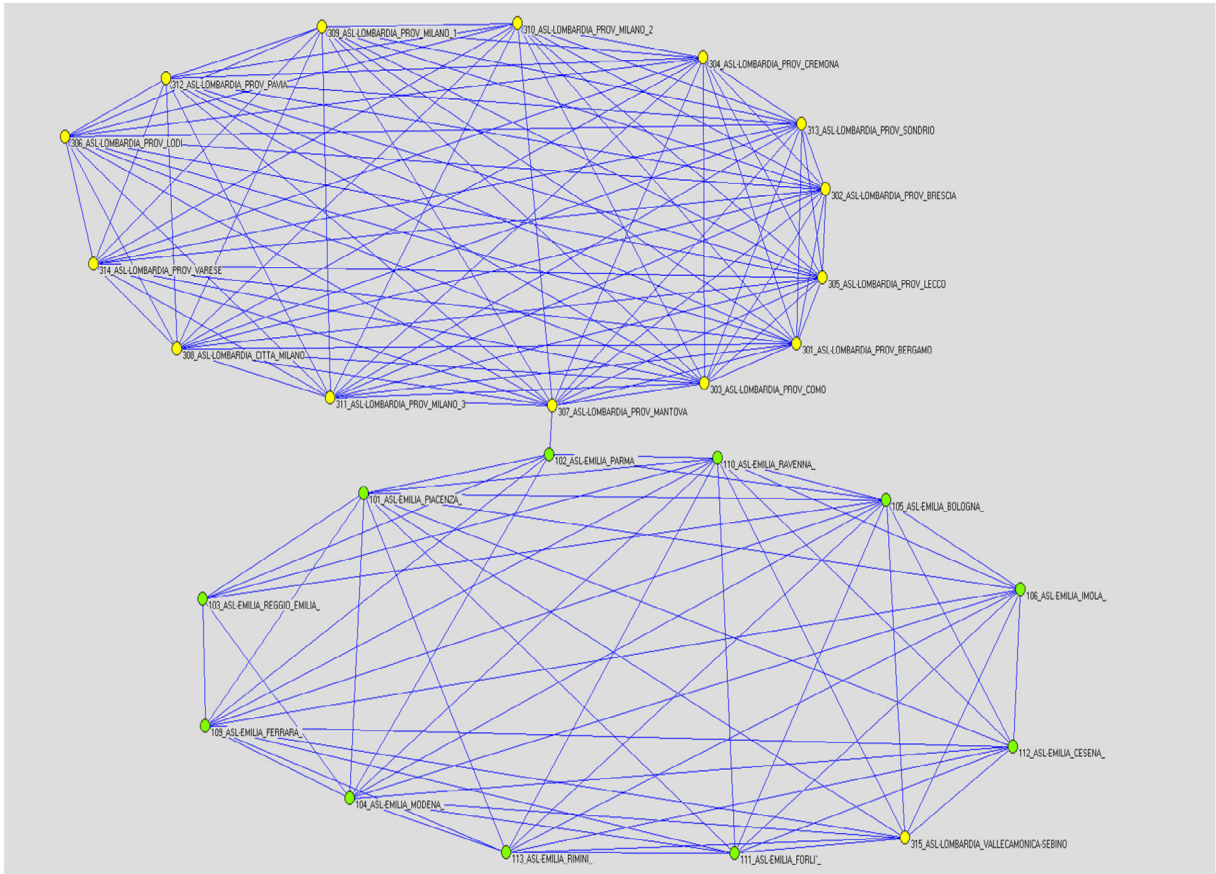


Fig. 4. MRG Lombardy (yellow nodes)—Emilia-Romagna (green nodes). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The use of ANN approach to analyze healthcare data might be considered as complementary to the traditional statistical approaches – for example in clustering observations – and can help to formulate hypotheses about the impact of policy measures within a regional system or to validate the results obtained using other statistical techniques.

Appendix A

A.1. The AutoCM mathematical specification

In this study, the application of AutoCM is aimed at capturing the hidden information not provided in the dataset (*i.e.*, the regional belonging of ASLs).

The construction of the ANN starts with a training process. Initially, variables are scaled between 0 and 1 and all weights begin with the same positive value close to zero.

All the input patterns that enter the network accumulate some corrections along different cycles, as shown in (A.1). In particular, a cycle has to be meant as the ANN processing of a pattern from the input layer up to the output layer.

$$h_i^{[p]}(n) = x_i^{[p]} \cdot \left(1 - \frac{v_i(n)}{C} \right) \quad (\text{A.1})$$

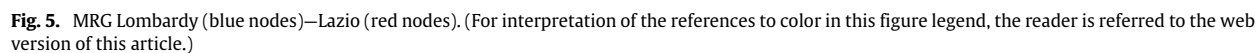
where:

$h_i^p(n)$ i th hidden node of the p th pattern during the n th epoch

x_i^p i th input node of the p th pattern

$v_i(n)$ weight of the connection between the i th input node and in the i th hidden node during the n th epoch, that is a number of cycles equal to the number of input patterns to be processed

C constant.



The algorithm then calculates the output layer. For each output node, an initial operation saves the net input calculation, that is, the reduction (contraction) of all the hidden nodes through the weights between the hidden layer and output layer, as shown in (A.2).

$$Net_i^{[p]}(n) = \sum_{j=1}^N h_j^{[p]}(n) \cdot \left(1 - \frac{w_{ij}(n)}{C}\right). \quad (A.2)$$

$Net_i^{[p]}(n)$ Contraction of all the hidden nodes through the weights between the hidden layer and output layer of the p th pattern during the n th epoch

$w_{ij}(n)$ weight of the connection between the j th hidden node and the i th output node during the n th epoch

N the number of nodes per layer.

A second operation calculates the output value by further contracting the corresponding value of the hidden node through the previously calculated net input for the output node (Eq. (A.3)).

$$y_i^{[p]}(n) = h_i^{[p]}(n) \cdot \left(1 - \frac{Net_i^{[p]}(n)}{C^2}\right). \quad (A.3)$$

$y_i^{[p]}(n)$ i th node in the output of the p th pattern during the n th epoch.

During the training in each epoch, in addition to the calculation of the output values (A.3), the algorithm calculates the correction quantity of the input weights. For the N -mono dedicated layers between the input and hidden layers, the algorithm considers the result of the difference between the values of the corresponding input and hidden nodes, further modulated for the input node itself (Eqs. (A.4) and (A.5)).

$$\Delta v_i(n) = \sum_{p=1}^M \left(x_i^{[p]} - h_i^{[p]}(n)\right) \cdot \left(1 - \frac{v_i(n)}{C}\right) \cdot x_i^{[p]} \quad (A.4)$$

$$v_i(n+1) = v_i(n) + \alpha \cdot \Delta v_i(n) \quad (A.5)$$

where

$\Delta v_i(n)$ correction quantity of the input weights i th node in the output during the n th epoch

M the number of patterns

α constant learning rate.

Similarly, for N^2 weights between the hidden and output layers, the algorithm calculates the contraction, based on the weight being considered, between the corresponding hidden and output nodes (Eqs. (A.6) and (A.7)).

$$\Delta w_{ij}(n) = \sum_{p=1}^m \left(h_i^{[p]}(n) - y_i^{[p]}(n)\right) \cdot \left(1 - \frac{w_{ij}(n)}{C}\right) \cdot h_j^{[p]}(n) \quad (A.6)$$

$$w_{ij}(n+1) = w_{ij}(n) + \alpha \cdot \Delta w_{ij}(n) \quad (A.7)$$

where

$\Delta w_{ij}(n)$ correction quantity of the weight of the connection between the j th hidden node and the i th during the n th epoch.

These equations are iterated until the AutoCM energy function is minimized (Eq. (A.8)):

$$\lim_{n \rightarrow \infty} \Delta w_{ij} = 0, \quad \forall v_i = C. \quad (A.8)$$

At the end of this process AutoCM generates a trained matrix of weights, w , where all the connection values identify fuzzy dependencies among the input variables.

The matrix w , including the AutoCM weights, as well as the S values can be requested to the authors.

Appendix B

B.1. Macro aggregates of income statement B—costs of production, employed in the analysis

- Purchase of goods (B1). This section includes items of expense for both health goods – such as pharmaceuticals, medical devices, haemocomponents and haemoderivatives – and non-health goods, such as meals, beddings, stationery.

- Purchase of services (B2). This macro aggregate includes healthcare services purchased from several kind of public and private providers. In particular, healthcare services consist of pharmaceutical care (services purchased under specific agreements with public and private pharmacies), in-hospital care, outpatient ambulatory care, ambulatory care in hospitals, integrated care, rehabilitative care, and other healthcare services. Remuneration of private practice within public facilities, training of health professionals, contribution to voluntary associations also fall into the aggregate of “purchases of services” as well as external expert advice. Finally, transport for emergency and non-health services, such as laundry, heating, cleaning, data processing, etc., belong to this aggregate.
- Routine maintenance of health and non-health equipment (B3).
- Costs for lease of third-party assets (B4).
- Wages and salaries (B5–B8) includes the salaries of healthcare staff, healthcare professionals, technical staff and administrative staff.
- Other management expenses (B9) is a residual aggregate that includes management costs such as subsidies, insurance premiums, legal expenses.
- Depreciation of material assets (B10–B12).
- Bad debt provision (B13).
- Changes in inventories of finished goods (B14).
- Funds (B15).

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