

The well-being in the Italian urban areas: a local geographic variation analysis

Il benessere nelle aree urbane italiane: un'analisi della variabilità locale

Eugenia Nissi and Annalina Sarra

Abstract Following the place-based well-being literature, this paper is aimed at assessing inequality between Italian province capital cities in terms of their performance in promoting human and ecosystem well-being. The case study rely on the theoretical framework adopted by ISTAT within the Ur-Bes project. The available indicators are used to derive a multidimensional urban well-being index. To this end we adopt a two-steps procedure. Firstly, by using the geographically weighted PCA we assess the spatial variability for each Ur-Bes pillar data and obtain for each dimension a composite index. In the second stage, the ranking of the Italian province capital cities according to their efficiency in promoting equitable and sustainable well-being is facilitated by DEA.

Abstract *In questo lavoro ci si propone di valutare il benessere equo-sostenibile delle province italiane. Il caso studio fa riferimento al modello concettuale di benessere adottato dall'ISTAT nell'ambito del progetto Ur-Bes. Gli indicatori disponibili sono utilizzati per ricavare un indice multidimensionale del benessere urbano. A tal fine, viene impiegata una procedura a due fasi. Inizialmente, attraverso la ACP ponderata geograficamente, si valuta la variabilità spaziale per ciascun dominio dell' Ur-Bes e si ottiene per ogni dimensione un indice composito. Nella seconda fase, l'impiego della tecnica DEA consente di ottenere un indice globale di misura del benessere equo-sostenibile e di confrontare l'efficienza delle province italiane nel promuoverlo.*

Key words: well-being, unitary input DEA, GW PCA, efficiency ranking

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1 Introduction

The last two decades have witnessed a growing interest on the measurement of well-being and quality of life, as documented in many theoretical and empirical studies. Some of these researches focus on the well-being assessment at local level (see, among others, Bai et al., 2012). Basically, the root of understanding local well-being (in regions and cities) lies in the intersection of well-being and public policy. In this respect, more fine-grained measures of well-being will help policy-makers to enhance the design and targeting of policies and improve their capacity to respond to the paramount and varied needs of residents. Well-being is a multidimensional phenomenon, whose definition and theorization requires the specification of a conceptual framework for its assessment at national as well as at local level. The conceptual framework providing grounds for the discussion in this paper has been that adopted by ISTAT within the "Equitable and Sustainable Well-Being" project, whose Italian acronym, used hereafter, is BES (see ISTAT- Cnel, 2012), which, in turn, is based on the conceptual model published by OECD (Hall et al. 2010). This theoretical framework reflects the conceptual complexity of well-being and highlights its dependency upon attributes specific to each person and on attributes shared with other people or revealing the relations between them or how a society is peaceful, resilient, cohesive.

Our case study considers the Italian Province capital cities as units of analysis and employs the urban Bes (Ur-BES) report data, which refers to 64 particular indicators, belonging to 11 dimensions, identified within the equitable and sustainable well-being initiative (BES). The paper sheds light on the construction of a multidimensional urban well-being index for the Italian Province capital cities and, following the place-based well-being literature, on assessing inequality between Italian province capital cities in terms of their performance in promoting human and ecosystem well-being. In our analysis, a special focus is placed on the importance of surveying the spatial dimension of the local well-being indicators and their related variables. Most of the existing literature on the construction of composite indicators neglects to consider the spatial heterogeneity of the units in the computation of their relative composite indicators scores. As matter of fact, it may happen that the value of a composite indicator may be more dependent on a certain sub-indicator in a given location, and another sub-indicator in different location. To ascertain this kind of spatial dependence can reveal useful for policy decision makers in tackling problems in an efficient way, and distinguishing their causes at local level. With regards to this research issue, we propose a two-step approach. Firstly, for each of the well-being dimensions we employ the Geographically Weighted (GW) Principal Component Analysis (PCA). The GW PCA, introduced by Harris et al. 2011, can be deemed a local version of the traditional PCA in that it takes spatial variations across a study region into account and produce maps of spatial variations of each local principal component and local variance at each place. This variant of global PCA is

chosen due its merits in assessing the spatial variability of each Ur-BES pillar data dimensionality and checking how the elementary indicators influence the corresponding spatially-varying component. In the second stage of our empirical procedure, the synthesis of Ur-Bes elementary indicators obtained through the GW PCA, is included in a unitary Data Envelopment Analysis (DEA) model to derive a spatial composite index. The employment of DEA facilitates the ranking of the Italian province capital cities according to their efficiency in promoting equitable and sustainable well-being. The rest of paper proceeds as follows. In Section 2 we give some details of the theoretical background of the GW PCA technique, then we present the basic of DEA model, as well as the specific model selected for our case study. The results are discussed in Section 3.

2 Methodological approach

In our two step-procedure we start by reducing the dimensionality of Ur-Bes elementary indicators by using GW PCA. Next, the reduced set of variables is employed in a unitary input DEA model to assess the relative efficiency of the Italian Province capital cities in producing equitable and sustainable wellbeing. The following sub-sections describe both GW PCA and DEA techniques.

2.1 Geographically Weighted PCA

GW PCA is a local spatial form of the PCA able to provide locally derived sets of principal components for each location (Harris et al. 2011). GW PCA adapt PCA for spatial effects with respect to spatial heterogeneity. We assume that the vector of observed well-being variables at location i have a multivariate normal distribution, with mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$ ($x_i \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$). The mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$ are now function of location i , with coordinates (u, v) . This implies that each element of the mean vector and the variance matrix is, in turn, function of position and are expressed as $\boldsymbol{\mu}(u, v)$ and $\boldsymbol{\Sigma}(u, v)$, respectively. The geographically weighted principal components are obtained through the decomposition of the geographically weighted variance-covariance matrix:

$$\boldsymbol{\Sigma}(u, v) = \mathbf{X}^T \mathbf{W}(u, v) \quad (1)$$

where $\mathbf{W}(u, v)$ is a diagonal matrix of weights. As for any geographically weighted methods, diverse kernel functions (gaussian, exponential, bi-square) can be employed to generate the diagonal matrix of weights, under the con-

control of a parameter known as bandwidth. Geographically weighted principal components are obtained using the decomposition of the variance-covariance matrix. More specifically, the local principal component at location (u_i, v_i) can be written as:

$$\mathbf{L}(u_i, v_i)\mathbf{V}(u_i, v_i)\mathbf{L}(u_i, v_i)^T = \mathbf{\Sigma}(u_i, v_i) \quad (2)$$

where $\mathbf{L}(u_i, v_i)$ is the matrix of the geographically weighted eigenvectors and $\mathbf{V}(u_i, v_i)$ is the diagonal matrix of the geographically weighted eigenvalues. For p variables, the GW PCA provides p components, p eigenvalues, p set of component loadings and p set of component scores for each data location in the study area. Full technical details underlying GW PCA are described in Harris et al (2011).

2.2 Unitary input DEA model

Data Envelopment Analysis (DEA) is a widely used non-parametric method of measuring the efficiency of organisational units, termed Decision Making Units (DMUs), within production contexts, characterised by multiple outputs and inputs (Charnes et al., 1978). Over the past three decades, the scope of DEA has broadened considerably. In particular, DEA has been employed as a valid instrument to construct social and economic well-being indicators (see, among others, Despotis 2005). The adaption of DEA to the measuring of environmental and social aspects has required the changing of the objective function in the standard model in order to recognize the change in focus. To deal with the case of the production of human well-being and ecosystem, it is possible to conceptualise a production process where each city is a "firm" which uses government resources to produce well-being outputs, such as better education, improvement of health status, greater access to labour markets, reduction of environmental pollution and so on. Accordingly, each city is assumed to have one "government" and hence one unit of input, and it produces the aforementioned outputs. Because we do not have the classic production context, but we can only rely on secondary variables, obtained as rates or combinations of primary variables, a DEA model with a single constant input can be suitably adopted. For the purpose of our work, we make use of the approach proposed by Lovell and Pastor (1999), in which the CCR and BCC models are equivalent. By adopting the output orientation, the linearized unitary input DEA-model is expressed by the following linear programming:

$$\max \quad h_0 \quad (3)$$

$$s.t \quad \sum_{k=1}^n \lambda_k y_{jk} \geq h_0 y_{j0} \quad \forall j \quad (4)$$

$$\sum_{k=1}^n \lambda_k \leq 1 \quad (5)$$

$$\lambda_k \geq 0 \quad \forall k \quad (6)$$

In equations (3-6) h_0 denotes the inverse of efficiency of the DMU under analysis (DMU_0), y_{jk} is the j th output ($j = 1 \dots s$) of the DMU_k ($k = 1 \dots n$) and λ_k is the individual contribution of each DMU in the formation of DMU_0 's target. Nissi and Sarra (2018) propose an integrated DEA-entropy approach to strengthen the discrimination power of that model.

3 Results and Conclusions

Our analysis is restricted to 103 province capital cities and takes into account eight out of eleven domains of the original Ur-Bes dataset: “*Health*”, “*Education and Training*”, “*Work and Life Balance*”, “*Economic well-being*”, “*Social Relationships*”, “*Security*”, “*Landscape and Cultural Heritage*”, “*Environment*”. Following the methodology described in the previous section, we first compute a spatial composite index for each pillar of Ur-Bes through the GW PCA. The GW PCA analyses have been carried out in R using the GW-model package (Gollini et al.2013). We used a bi-square kernel function with adaptive bandwidths, whose sizes are selected automatically and objectively via cross-validation and not based on a priori decision. The output of the GW PCA allows to highlight the local change in the structure of multivariate data and how the original well-being indicators influence the local principal components retrieved for each of the Ur-Bes pillars. The GW PCA makes possible to display the localized proportions of the total variance (PTVs) and ascertain if the spatial patterns in the PTVs vary significantly across the study region. In general, for the majority of the urban well-being domains, the maps of PTVs, not displayed here, reveal that the highest PTVs are often located in the province capital cities of the South of Italy. Some exceptions are recorded for the “*Security*” pillar, for which the PTVs data are lower in the province capital cities of Central Italy. In the areas where highest PTVs are detected the local correlation (or local collinearity) among well-being data is assumed high, suggesting that not all Ur-Bes indicators need to be considered. By retaining only the first component, that accounts for a substantial proportion of the variability in the original data, it is possible, for a given local well-being domain, to extricate how each of the elementary indicators influences the selected pillar. For instance, in the domain “*Health*”, the local principal components reveal multifaceted geographical variations in the variables with the largest loadings. From GW PCA results, we see that first component is mainly represented, in the province capital cities of Piemonte and Trentino

Alto Adige, by the age-standardised cancer mortality rate (19-64 years old); by life expectancy at birth (male) in most cities of central Italian regions and in Sardinia, and by life expectancy at birth (female) and mortality rate for road accidents (15-34 years old) for the Southern province capital cities. The spatial variation of the first local component of the "Education and Training" domain, reveals that it mainly considers the participation to primary school and this elementary indicator dominates in the most urban areas, with some exceptions for a number of province capital cities of Calabria and Sicily, where the leading variable is represented by the early leavers from education and training. This analysis is replicated for each dimension of Ur-Bes. Once weights are obtained for each variable in each location, the spatial composite indicator for the urban well-being dimensions, has been computed as the weighted sum (linear combination) of the variables, location by location. For the arising composite indices a data transformation has been undertaken to respect their positive or negative linkages with equitable and sustainable well-being and assure strictly positive data. In the second stage of the analysis, the overall well-being index is obtained via a unitary input DEA model, with entities defined only by outputs. We found that efficiencies are between 78.8% and 100%, while the mean efficiency is 97.2%. A large number of efficient cities are located in the North and Central part of Italy. Thirty-four cities achieve a well-being efficiency score which is below the average. In the last positions of the ranking we find Napoli, Salerno, Foggia, Bari, Benevento, Isernia, Caserta, Ascoli Piceno, Chieti, Macerata and Agrigento.

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