Liuc Papers

Pubblicazione periodica dell'Università Carlo Cattaneo - LIUC

Numero 307, aprile 2017

Serie

Economia e Impresa 85

Massimiliano Serati, Fausto Pacicco

A proposal for a micro-territorial well-being index: the WIT

Serie: Economia e Impresa

Liuc Papers

ISSN:1722-4667

Direttore Responsabile: Piero Cavaleri
Direzione, redazione, amministrazione: Università Carlo Cattaneo - LIUC
C.so Matteotti, 22 - 21053 Castellanza (Va) - Italia
tel. 0331-5721 - fax. 0331-572320

Registro stampa Tribunale di Busto Arsizio n. 11/93 del 11.06.93

Comunicazioni di carattere organizzativo vanno indirizzate a:
Piero Cavaleri, *LIUC Papers*, Università Carlo Cattaneo, Biblioteca «Mario Rostoni»
Corso Matteotti 22, 21053 Castellanza (VA), Tel. 0331-572.267 # E-mail pcavaler@liuc.it

A PROPOSAL FOR A MICRO-TERRITORIAL WELL-BEING INDEX: THE WIT

Massimiliano Serati, Fausto Pacicco*[*]

1. Introduction

Policies have usually linked the sheer growth of economic indicators like the GDP to an increase in the people's well-being; while such indicators are undoubtedly linked to economic growth, this does not automatically cause an increase in the overall well-being.

Indeed, such issue has been known from economists from the very inception of National Account systems (Kuznets, 1937).

However, economic literature strains began to study the well-being phenomena starting from the 70s': while one strain focused on the subjective well-being, drawing from psychological surveys (Diener et al., 1999), another strain focused on objective data.

Drawing the information content from the social indicator field (Cambell et al., 1976), the first attempts of measuring well-being were slight modification of the GDP (or similar indicators), as the Nordhaus and Tobin attempt (1972) but soon this strain started to approach the issue with providing comprehensive set of indicators (batches of indicators approach) and/or providing synthetic indexes (usually linked to such batches).

The academic and public debate only recently regained the attention of policymakers (see for example Stiglitz et. al., 2009); it has also been pointed out that policies on local levels still lacks of clear assessments of well-being based on micro-territorial level (Breuer and Brueser, 2013).

In this paper, thanks to the use of the micro-territorial statistic platform *100% Lombardia*, an objective well-being index called Well-being Index for Towns (WIT) has been estimated from 2001 to 2015 for all the cities in Lombardia, an Italian region.

The proposed model is built on a cluster analysis, followed by a Bayesian dynamic factor and by a panel Vector Autoregression model with an exogenous variable (P-FAVARX).

The results show that clusters of cities do follow different well-being evolutions over time, due to policies initiatives, and that also a higher well-being increases the overall attractiveness of places.

[*] LIUC - Università Carlo Cattaneo, School of Economics and Management

2. Literature review

The debate about of which elements constitutes the well-being for populations recently gained new momentum, as established by the "*The Commission on the Measurement of Economic Performance and Social Progress*": this commission has been founded in February 2008 by the then France's president Nicholas Sarkozy, which was unsatisfied by the overall lack of knowledge about the impact of economical matters in the societal well-being.

Therefore, it asked to the economists Joseph Stiglitz, Amartya Sen and Jean Paul Fitoussi to create a commission able to identify current limitations to the actual economic measures.

The commission wrote a comprehensive document named "*Report by the Commission on the Measurement of Economic Performance and Social Progress*" (Stiglitz et al., 2009), which pointed out the main limitations of the most (mis-)used economic indicators by policy makers.

Such debate started earlier, as soon as the basis of the modern national statistics frameworks were developed: Kuznets itself, when was developing the basis of modern national accounting systems, warned about the possible misuse of sheer economic figures (such as GDP, GNP, etc.) and their inadequateness to depict complex phenomena, such as the level of well-being of populations (Kuznets, 1937)

Notwithstanding these early warnings, the policy makers focused their development efforts on maximising the growth of such indicators, wrongly linking the overall economic growth to a well-being growth.

Indeed, such measures does not take into account a wide range of different phenomena (see for example Afsa et al., 2008, for a complete discussion); non-market activities and services (i.e. household work, public services) can be erroneously priced, due to the absence of marketed counterparts but those can affect the overall well-being, either negatively or positively.

Thus, starting from the 70s', a branch of the economic research started to explore the viability of alternative ways for measuring and analysing the well-being; Nordhaus and Tobin (1972) developed two indexes the Measure of Economic Welfare (MEW) and the Sustainable MEW (SMEW), based on some adjustments made to the Net National Product (NNP) computations: their conclusion was that such indexes were not sensibly different from the NNP, but they suggested the need of further researches.

Indeed, these first attempts, along with the Japanese estimates of the SMEW as well as the Zolotas' Economic Aspect of Welfare Index, were modification of figures from measures present in the National Accounts (Redclift, 2006).

During the 80's, the academic debate seemed to neglect such themes, but it subsequently regained the policy makers' attention during the 90's, thanks to the Human Development Index

from the United Nation Development Program (Ul Haq, 1995), which is one of the most known index of well-being.

The HDI underlined the importance of including non-monetary measures in the well-being estimations, while other indexes such as the Index of Sustainable Welfare (ISEW, Daly et al., 1994) and the Genuine Progress Indicator (GPI, Talberth, 2007), introduced the importance of sustainability in such efforts.

From this moment on, many different indexes were developed (see for example Giannetti et al, 2015), usually summarising whole sets of indicators.

Indeed, such indexes, known as Objective Well-Being (OWB) are easily communicable, and are used as summaries of a more comprehensive approach known as Batches of Indicators approach; such works, which are also derived from the National Account framework in conjunction with social indicators (Campbell et al., 1976), consist of whole sets of indicators, with each one suited to explore one specific theme related the well-being.

Such approach is undoubtedly more comprehensive, as it specifically addresses each aspects of multi-faceted phenomena with dedicated indicators; it can also be "tailored" to specific themes, in order to foster political debates.

However, the provision of large sets of indicators is not a parsimonious choice: in order to fully understand the contribution of each indicator to the overall well-being requires extensive statistic competencies; thus, headlines OWB ease the burden of communicating the content of such works (Afsa et al. 2008).

All over the world both Batches of Indicators and OWB works flourish, developed by national statistic offices, research groups and individuals and supra-governmental agencies (Noll, 2002).

While some of these works have a regular frequency of releases (such as the HDI), other are mere "one-shot" attempt, referred to specific places and years; furthermore, while some of these works are presented for different geographical levels, like the GPI which has been estimated for countries, regions, provinces and cities (Posner and Costanza, 2011), it has not been attempted to develop a complete coverage of territories, both in terms of space and time.

Indeed, the analysis of well-being and conditions of micro-territorial entities, such as the cities, has been acknowledged as very important for strategies of development (Breuer and Brueser, 2013): it is inherently wrong to allocate urban development funds based on the information inferred from "higher" geographical levels.

Thus, starting from a newly developed comprehensive micro-territorial statistic platform, this paper aims to provide an OWB developed for all the cities in the Italian region of Lombardia, from the 2001 to 2015.

There is also another branch of economic literature that measures the well-being from a subjective point of view: it draws from the psychological surveys that "ask" directly to the subjects the life satisfaction. Thus, it is known as Subjective Well-Being (SWB).

While this field is undoubtedly a valuable contribution to the academic debate on the well-being, it has not been taken into account in this paper; for a detailed review of the SWB contributions, see Diener et al. (1999).

3. Data source and indicators selection

The dataset used in this paper is *100% Lombardia*, a comprehensive statistic platform developed by LIUC Università Carlo Cattaneo, Èupolis and Regione Lombardia.

100% Lombardia has a tree-structure, as it encompasses 4 macro thematic areas: Economic and business conditions, Socio-demographic aspects, Infrastructures, Territories and attractiveness.

These macro areas encompass many thematic sections, which are: Economic wealth, Demography, Business and job markets, Accessibility, mobility and commuting, Health, family, solidarity and social involvement, ICT and digital infrastructure, Tourism and culture, Education, creativity and talents, Territories and environment, Index of council virtuosity.

Thus, the platform has 161 indicators, of which 129 are 1st level indicators, i.e. built from the aggregation of raw data, and the rest are 2nd level indicators, i.e. built from aggregation of the previous ones.

Data is available for 1531 cities in Lombardia (the number of cities in 2014), a northern region of Italy, for the 2001-2015 timespan.

The platform is freely available on the Regione Lombardia's website (www.sisel.regione.lombardia.it), and it has been recognized as a valuable tool for local policy making from ISTAT (Istituto Nazionale di Statistica) the official statistical office in Italy, in the book "La nuova geografia dei Sistemi Locali" (ISTAT, 2015, in Italian).

Furthermore, its quality and methodology has been certified from the European Commission, as it has been used to identify 3 Lombardia's areas as admissible in the list of areas worthy of development funds from the Italian Ministry of Economy and Finance.

For further detail of how the platform has been developed, the idea behind it and how it has been validated see Serati and Pacicco (forthcoming).

With the aim of exploring micro-level similarities between different towns, 52 indicators were chosen from the *100% Lombardia* platform, following the main literature findings. A complete list of those indicators is in the appendix A.

Such indicators have been chosen to "map" similar projects, such as the Italian BES project (Benessere Equo e Sostenibile, from the ISTAT), which developed a batch of indicator approach with 12 domains; they have also been chosen to effectively evaluate the impact at micro-level of development agendas such as the UN's 2030 Agenda for Sustainable development (UN, 2015).

4. Methodology

The methodology applied here can be divided into 3 subsequent steps: a cluster analysis (CLA), followed by a Bayesian dynamic factor model (B-DFM), and then a panel factor augmented vector autoregressive model with an exogenous variable (P-FAVARX). Each of these step is reviewed in the following paragraphs.

4.1 Cluster Analysis

In order to find similarities between the cities of Lombardia, a CLA has been applied on the 52 indicators, with the addition of longitude and latitude to consider geographical proximities.

The term CLA encompasses a wide range of procedures that aim to retrieve data patterns, and to define stable and objective classifications between different subjects (Everitt et al., 2011).

Among the different techniques available (see for example Spath, 1980), a hierarchical clustering method has been chosen, to allow for a data-driven configuration of each clusters.

Indeed, such approach starts setting each observation as a cluster: then, it iteratively computes a proximity matrix and merges the closest two elements, until it reaches one single cluster or a stopped by a function set by the user (Tan et al., 2013). The chosen criterion for this analysis has been the Ward's method on Euclidean squared distance.

Ward's method (1963) merges clusters upon the size of the error sum of squares, thereby minimizing the within-cluster error sum of squares, given by

$$T_{Ess} = \sum_{c=1}^{C} T_c$$

With

$$T_c = \sum_{o=1}^{O} \sum_{v=1}^{V} (x_{co,v} - \bar{x}_{c,v})$$

Where c=1...C is the number of clusters, o=1...O is the number of objects and v=1...V is the number of variables. T_m is the error sum of squares, given by sum for each element of the squared Euclidean distance computed between the score of the *v*-th variable for each cluster and the average score for each cluster. All the indicators were standardized to avoid issues related to the use of different scales (Nardo et al., 2005).

Such method has been iteratively implemented with the Lance and Williams recurrence formula, which computes the distance as:

$$d_{(ab)c} = \alpha_a d_{ca} + \alpha_b d_{cb} + \beta d_{ab} + \gamma |d_{ca} - d_{cb}|$$

Where ab represents a group formed by their fusion and c the cluster which is evaluated for the next fusion; the parameters α, β and γ are set equals to:

$$\alpha = (n_c + n_a)/(n_c + n_a + n_b),$$

$$\beta = -n_c/(n_c + n_a + n_b),$$

$$\gamma = 0$$

as indicated by Everitt et al. (2011), with n indicating each clusters size before the fusion of cluster c with the cluster ab.

4.2 Bayesian dynamic factor model

The second step in the analysis has been the B-DFM application on the 52 indicators.

While the CLA has been useful in reducing the geographical component, outlining local patterns of co-movements in the indicators, the B-DFM has been used to summarize the information content, i.e. obtaining a single factor, able to describe the local well-being.

Starting from the CLA's results (see Results section), time series have been extended forward and/or backward, to provide a unique time range for the B-DFM[1]

However, when there was the availability of only 1 year, data has been simply repeated for whole timespan, to consider (at least) the cross-sectional differences and similarities.

Dynamic factor models (DFM) derive from the static factor models, where Y is a vector of Vx1 variables/ indicators (of economic, social, demographic, etc. themes); is it possible to define the sequent model (Lopes and West, 2004):

$$Y = \lambda f + \epsilon$$

where f is a Fx1 vector of unobserved latent factors, ϵ is an $i.i.d. \sim N(0, \Sigma)$, λ contain the coefficient that "links" the M variables with F factors and F << M, also known as factor loadings.

The standard factor model allows to parsimoniously extract and condense information in a number of factors lower than the starting number of variables, thus omitting only a "residual" portion of information. For example, a possible interpretation of such factors is that f represents the systematic risks of an asset, λ is the exposure to such factor risks, while ϵ represents the idiosyncratic components.

However, such models do not allow for the evaluation of how factors behave over time, thus dynamic versions of such models were developed originally by Geweke (1977).

DFMs also gained importance in the monetary economics fields, especially as time series analysis tools able to overcome the traditional limitations of VAR models (Bernanke et al., 2005), developing the so-called FAVAR models (factor augmented vector autoregressive).

Following the Del Negro and Schorfheide (2011) approach, a DFM have the following structure:

$$Y_{i,t} = \alpha_i + \lambda_i f_t + \xi_{i,t}, \quad t = 1...T$$

Where f_t is a $F \times 1$ vector of factors identifying the common information between all the observables variables, and $\xi_{i,t}$ is an idiosyncratic process specific to each subject; α_i is a constant and λ_i is a $1 \times F$ vector of loadings that relate each $Y_{i,t}$ to the factor, for the same t.

Each factor follows a vector autoregressive processes of order p:

$$f_t = \Phi_{0,1} f_{t-1} + ... + \Phi_{0,p} f_{t-p} + \epsilon_{0,t}, \quad \epsilon_{0,t} \sim iidN(0, \Sigma_0)$$

Where Σ_0 and $\Phi_{o...p}$ are matrices of dimension $F \times F$, while $\epsilon_{0,t}$ represents a vector of innovations.

On the other hand, the $\xi_{i,t}$ follows an autoregressive process, of order q:

$$\xi_{i,t} = \phi_{i,1} \xi_{i,t-1} + ... + \phi_{i,q_i} \xi_{i,t-q_i} + \epsilon_{i,t}, \quad \epsilon_{i,t} \sim iidN(0, \sigma_i^2)$$

The $\epsilon_{i,t}$ terms are independent w.r.t the $\epsilon_{0,t}$, and such orthogonality assumptions are needed to identify the model.

However, without other assumptions, such factors are not identifiable; thus, a Bayesian approach to the estimation of the DFM has been chosen. For a complete discussion of how a such estimation can be carried out, see Koop and Korobilis (2009); it is important to point out that such factors require a Gibbs sampling procedure, and its results can be easily undermined

by high correlation between draws (Primiceri, 2005). Thus, 1000000 draws have been discarded, keeping 5000 draws, for each cluster.

4.3 Panel Vector AutoRegression

Due to the nature of data built through the two previous phases, a panel approach seemed to be mandatory, as it included both cross-section elements (the clusters from the CLA) as well as the time series extension (the B-DFM results).

However, to develop an econometric model able to tests how the OWB affects social economic and demographic variables, a Vector AutoRegression model seemed to be the obvious choice, "adjusting" it for panel data.

Panel VAR (P-VAR) models has been introduced in the seminal paper of Holtz-Eakin et al (1988), which developed a set of procedures in order to estimate vector autoregressions with panel data. It gained attention in the economic research, as a tool able to study and analyse intra-relationships between grouped units: such models avoid the burden of explicitly modelling the microstructure nested in DSGE models (Canova and Ciccarelli, 2013).

With n=1...N cross-sectional units and t=1...T periods, a P-VAR of order q has the following generic form:

$$Y_{n,t} = Y_{n,t-1}\Phi_1 + Y_{n,t-2}\Phi_2 + ... + Y_{n,t-q}\Phi_q + u_n + \epsilon_{n,t}$$

where $Y_{n,t}$ represents a $1 \times V$ vector of V dependent variables, and the error term $\epsilon_{n,t}$ is assumed to be an $i.i.d. \sim N(0, \Sigma)$; furthermore, in P-VAR models the term u_n is assumed to contain the specific panel fixed effects.

If in a such model is allowed the impact of exogenous variables, it is possible to extend it as in the following equation:

$$Y_{n,t} = Y_{n,t-1}\Phi_1 + Y_{n,t-2}\Phi_2 + ... + Y_{n,t-q}\Phi_q + X_{n,t}\Psi_{n,t} + u_n + \epsilon_{n,t}$$

where $X_{n,t}$ represents a $1 \times L$ vector of L exogenous variables.

The matrices $\Phi_1, \Phi_2, ..., \Phi_q$ and $\Psi_{n,t}$ contains the parameters of the model, which needed to be estimated.

However, such estimation it is not always an "easy" task: while it is possible to use a standard OLS method to obtain consistent estimates, the presence of lagged dependant variables in the right side of the equation produces inconsistent estimates, even with a large t (Judson and Owen, 1999).

Thus, as suggested by Love and Zicchino (2006) a Generalized Method of Moments has been preferred, in order to avoid such biases: such models benefit from the adoption of lagged

dependant variable as instruments, using observed realizations based on the assumption that the instrument list is uncorrelated with the errors (Holtz-Eakin et al., 1988). For further details, see the Abrigo and Love (2015) discussion for the estimation of P-VAR and P-VARX models in a GMM framework.

5. Results

A 20 clusters solution has been chosen among a range of different solutions, as it seemed an ideal trade-off between the identification of local peculiarities and territorial parcelization; after that, clusters were "re-adjusted" in order to compensate for minor imprecisions found in data, evaluating them on geographical basis.

The final solution includes 11 clusters, a number similar to the number of provinces in Lombardia: indeed, such choice allows us to have a number which can be easily compared to the traditional administrative classifications during policy making debates.

In order to have a unique index for well-being the model, thus becoming a comparable contribution in the field of OWB, only 1 factor for each cluster has been drawn from the above B-DFM. This OWB index has been named WIT, which is an acronym of Well-being Index for Towns.

At this point, to have a more extended time-span, data has been interpolated, so the dataset has 11 clusters for 57 quarters (from 2001 to 2015).

After that, a panel factor augmented vector autoregressive model with an exogenous variable (P-FAVARX) model has been estimated with 6 variables: WIT, Income per taxpayer, Average quotation of residential buildings, 3-year migration rate, Tourism index (a 1st level indicator built in the 100% Lombardia platform) and Birth rate

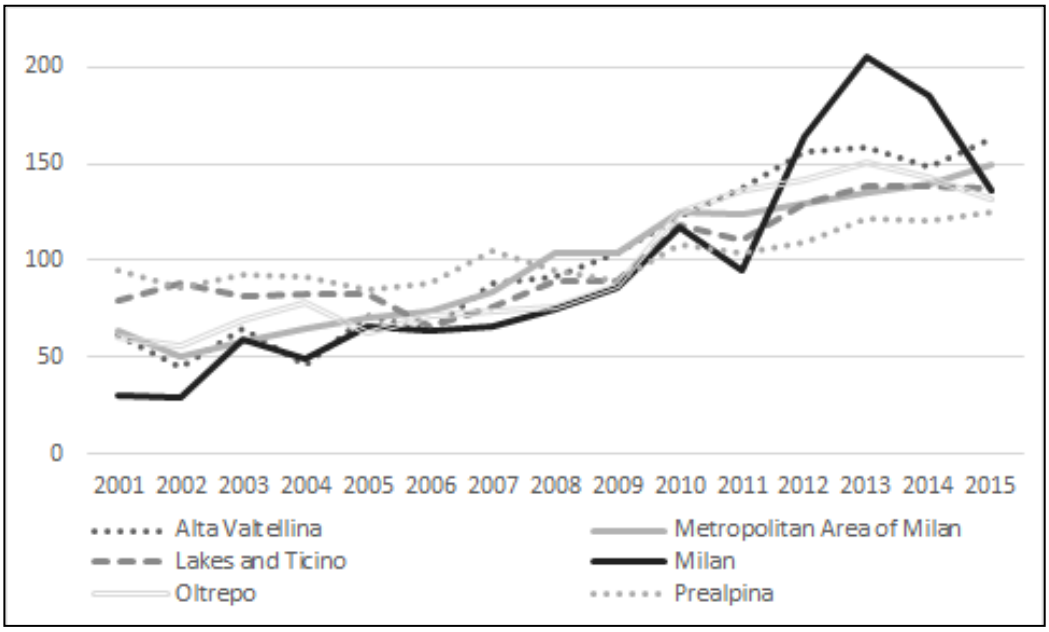
The other 5 indicators have been chosen in order to depict a truthful "paint" of how the well-being affects the attractiveness of territories: such phenomenon encompasses different human initiatives, such as sheer economic wealth (Income per taxpayer and Average quotation of residential buildings) but also business initiatives (represented by the inclusion of Tourism index), which in turn bestow influence on the human capital attracted (3-year migration rate) or generated (Birth rate) with regard to specific territories

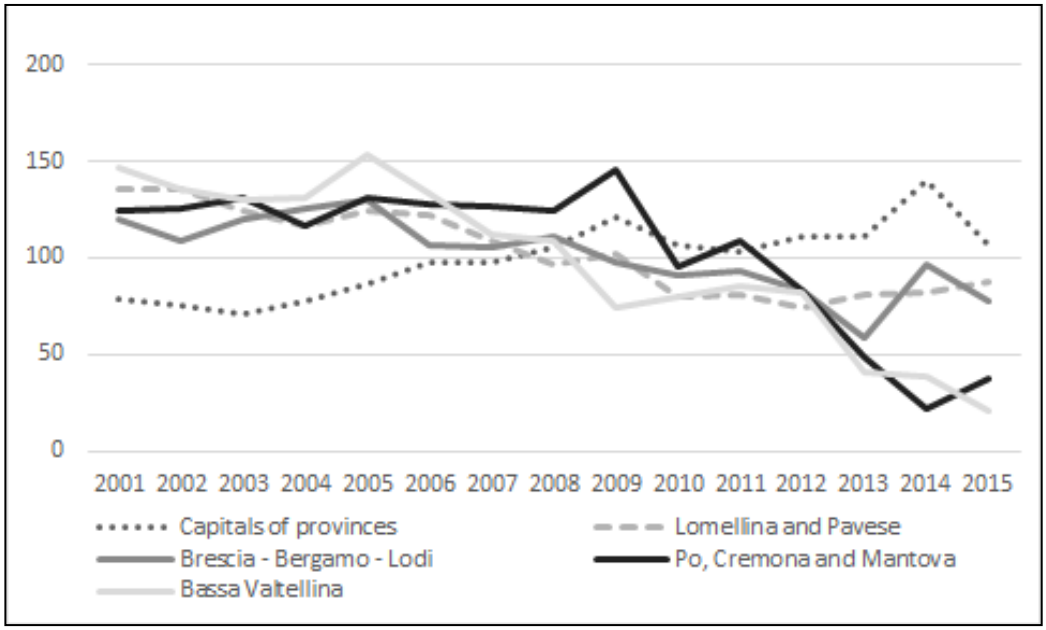
The inclusion of the exogenous variable is a necessity caused by the ISTAT 2011 census, as it produced data that was not totally consistent with previous and following data: due to the absence of other data sources, it was not possible to triangulate such data; therefore, it has been chosen to use an exogenous dummy variable, set to 1 only in the 4 years of 2011, in order to "absorb" such numerical inconsistencies.

The "final" dataset is made of 6 endogenous and 1 exogenous variables, for the 11 clusters and a time extension of 57 quarters.

5.1 The WIT from 2001 to 2015

For the sake of exposition, the 11 clusters have been separated into 2 different graphs, represented in graphs 5.1 and 5.2[2]





Graphs 5.1 (above) and 5.2 (below) – The graphs respresents the WIT evolution over time for the 11 clusters

The upper graph depicts the 6 clusters that "performed" well over time with regard to the well-being measured by the WIT, showing positive trends; whereas, the other graph depict the remaining 5 clusters which have a negative trend over time. The name of each cluster has been chosen with regard to how the cities are placed on the geographical map, as represented in figure 5.1

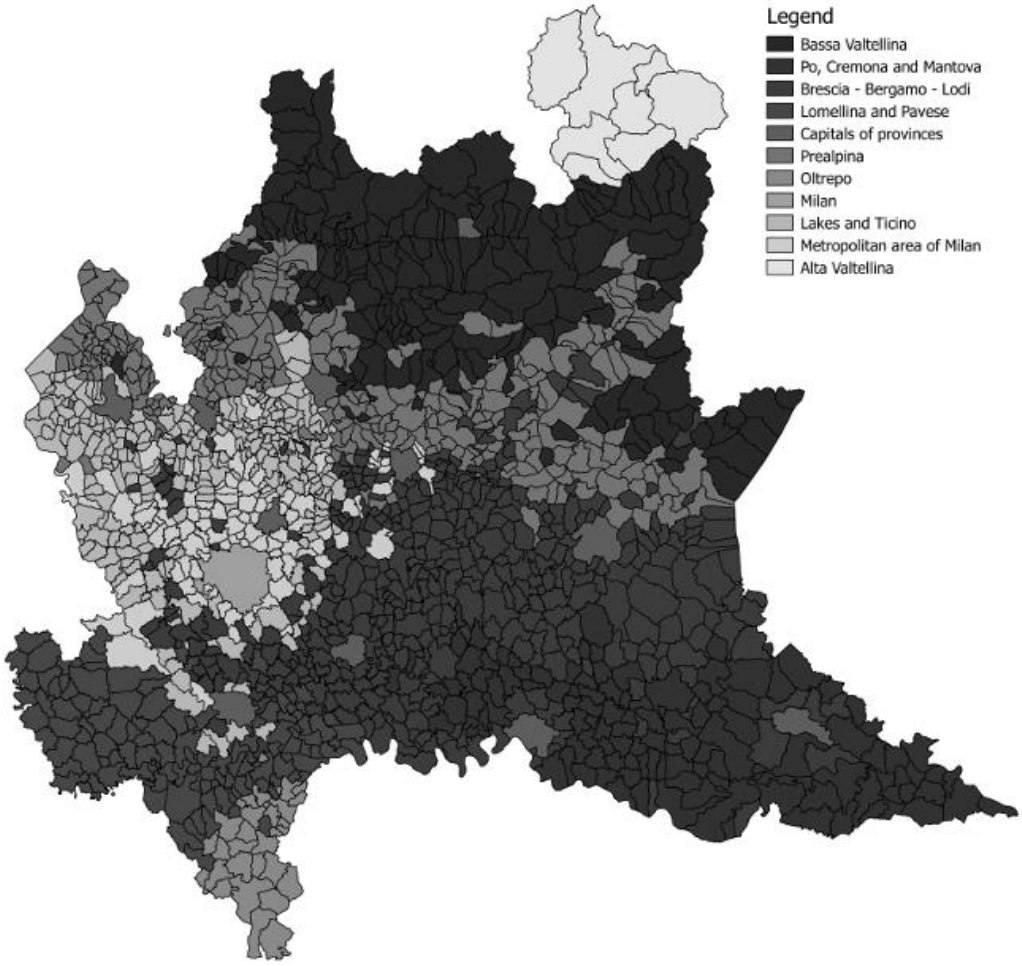


Figure 5.1 – This figure represents the 11 clusters

The cluster of "Alta Valtellina" showed a steadily increase in the WIT, starting from the 9th position in the 2001 and ending 1st in the 2015; this territory is bestowed with a renowned mountainous territory, an important attraction for tourists and skiers: thus, it seems plausible that compared to other territories this area benefited of better economic conditions and better economic endowment. Indeed, if we compare it to the cluster of "Bassa Valtellina" (in graph 5.2) it is possible to see that it ranked last: between these 2 clusters the main differences are the heights and the infrastructure for winter tourists, it seems plausible to link such differences to these aspects

Milan and its metropolitan area showed also a sharp increase in their well-being value, also due to the businesses investments in these areas, culminated with the universal exposition EXPO 2015 in Milan: indeed, the investments heighten the WIT of both areas, but the city of Milan showed a quite fast decrease in the last 2 years, probably due to overcrowding phenomena, which was not mirrored in the nearby metropolitan area.

The rest of the clusters in the graph 5.1 show similar upward trends: it is possible to notice how the cluster "Lakes and Ticino" performed better than "Oltrepo" and "Prealpina" clusters, probably due a highest concentration of firms, that seems to be not affected by overcrowding phenomena.

Furthermore, the cluster of "Oltrepo" increased the overall well-being thanks to the many initiatives of wine and food tourism, thus being able to follow a path of overall growth, reflected in the WIT.

In graph 5.2., the cluster of Capitals of provinces seems to have followed an upward trend until around the 2008, but then "stopped" to gain in terms of well-being: the social, demographic and economic endowment of such cities seems to have not been able to counter the great global crisis, thus stopping the previous growth path.

The rest of the clusters showed in the graph 5.2. were not able to counter the decreasing trend of overall well-being: a weaker infrastructure, less economic initiatives and less social initiatives undermined such places.

5.2 P-FAVARX's results

The P-FAVARX introduced above has been estimated on 1st difference data to have a stable model. As reported in the table 5.1, the MAIC information criteria suggests the selection of a model with 4 lags: while the other criteria suggest a higher number of lags, it seemed more appropriate to set it equal to 4, due to the modest extension of the time sample.

Table 5.1 reports also all the eigenvalues of the P-FAVARX(4): the model respect the stability condition, without any modulus outside the unit circle, so it is stable. Also, the 18th lag of variables has been instrumented, as required in the GMM estimation procedure: the Sargan-Hansen test of overidentifying restriction (reported in the same table) do not reject the null hypothesis, thus such specification is valid.

Lag order selection criteria						
Lag	**CD**	**J**	**J-pvalue**	**MBIC**	**MAIC**	**MQIC**
1	0.9964856	362.9464	0.2924776	1734.129	335.0536	888.7262
2	0.9927514	348.8278	0.1641603	1598.028	299.1722	813.1835
3	0.992616	340.5272	0.0492336	1456.108	257.4728	731.8227
4	0.9950158	288.8125	0.1314691	1291.505	237.1875	654.4251
5	0.9996109	162.7668	0.9995588	1201.234	291.2332	651.3583

Panel VAR-Granger causality Wald test			
Ho: Excluded variable does not Granger-cause Equation variable			
Ha: Excluded variable Granger-causes Equation variable			
Equation \ Excluded	chi2	df	Prob > chi2
f1D			
reddD	916.345	4	0.000
quotD	298.722	4	0.000
tmigD	544.398	4	0.000
turistD	1467.537	4	0.000
natalD	37.431	4	0.000
ALL	3123.256	20	0.000
reddD			
f1D	1234.618	4	0.000
quotD	1138.941	4	0.000
tmigD	1036.762	4	0.000
turistD	4076.070	4	0.000
natalD	283.041	4	0.000
ALL	7795.938	20	0.000
quotD			
f1D	1290.120	4	0.000
reddD	530.496	4	0.000
tmigD	2070.173	4	0.000
turistD	828.238	4	0.000
natalD	142.657	4	0.000
ALL	6514.852	20	0.000
tmigD			
f1D	1427.822	4	0.000
reddD	1530.046	4	0.000
quotD	474.891	4	0.000
turistD	6265.429	4	0.000
natalD	493.958	4	0.000
ALL	12955.205	20	0.000
turistD			
f1D	927.054	4	0.000
reddD	2056.978	4	0.000
quotD	547.259	4	0.000
tmigD	1937.659	4	0.000
natalD	63.280	4	0.000
ALL	8581.051	20	0.000
natalD			
f1D	1139.459	4	0.000
reddD	1053.621	4	0.000
quotD	1282.037	4	0.000
tmigD	80.406	4	0.000
turistD	2114.281	4	0.000
ALL	7330.272	20	0.000

Eigenvalue stability condition		
Eigenvalue		
Real	Imaginary	Modulus
0.912037	0.275827	0.9528336
0.912037	-0.275827	0.9528336
0.6788573	0.6346793	0.9293359
0.6788573	-0.6346793	0.9293359
0.5123169	-0.7383245	0.898661
0.5123169	0.7383245	0.898661
0.8427715	-0.0682211	0.8455282
0.8427715	0.0682211	0.8455282
0.6413717	-0.468068	0.7940058
0.6413717	0.468068	0.7940058
0.6646882	0.2537444	0.711475
0.6646882	-0.2537444	0.711475
-0.517532	-0.4822734	0.7074087
-0.517532	0.4822734	0.7074087
-0.0685257	0.6406107	0.6442653
-0.0685257	-0.6406107	0.6442653
0.3728669	0.5193108	0.639307
0.3728669	-0.5193108	0.639307
-0.3815942	-0.4083308	0.5588812
-0.3815942	0.4083308	0.5588812
-0.5209453	0.0369901	0.5222569
-0.5209453	-0.0369901	0.5222569
-0.2619711	0.3868609	0.4672154
-0.2619711	-0.3868609	0.4672154

Test of overidentifying restriction	
Hansen's J chi2(411)	P-value
466.87683	0.029

Table 5.1 – This table shows some of the P-FAVARX specifications

In order to study how such index behaves in the endogenous model, is it possible to interpret the impulse response functions (IRFs), which are the reactions over time of the endogenous variables to a positive shock to those variables (Hamilton, 1994).

Thus, the cumulated IRFs of the 6 variables to a 1 S.D. shock to the WIT were analysed for a 24 quarters time-horizon; IRFs are reported in the figure 5.2, represented in the same order as the causality order of the P-FAVARX(4), which is: WIT, Income per taxpayer, Average quotation of residential buildings, 3-year migration rate, Tourism Index and Birth rate. Such order relies on the relative "speed" of how one indicator varies if compared to the rest: indeed, such specification is robust to pairwise permutation in the chain. The confidence intervals have been estimated through 2500 Monte Carlo simulations using 95% CIs.

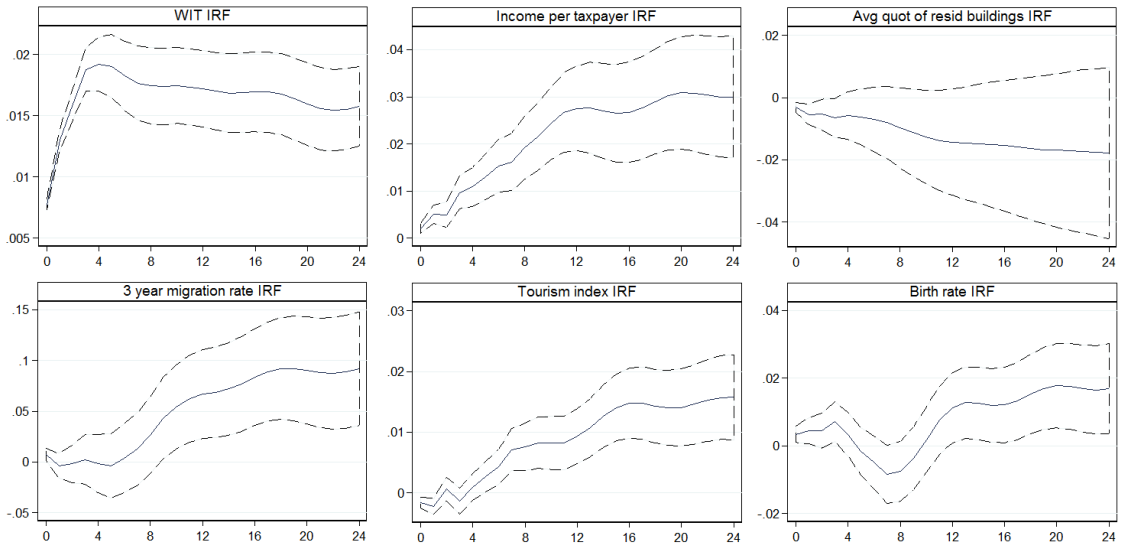


Figure 5.2 – This figure shows the P-FAVARX variable IRFs

The first graph in the upper row shows how the WIT behaves on a shock on itself: indeed, the index underlines the resilience of the well-being, as its cumulated IRF is strictly positive and different from zero for all the 24 quarters. Thus, an "investment" on the WIT increase is a sustained one, leading to an enduring well-being increase.

Similarly, the income per taxpayer IRF is positive, reinforcing the idea that an increase in well-being bestows its positive effects also on monetary means.

While the average quotation of residential buildings is negative for the first 3 quarters, it then becomes not significantly different from zero: indeed, such effect can be positive for the attractiveness of locations, because an increased WIT does not heighten the residential buildings quotation

The first graph of the lower row represents the IRF of the 3-year migration rate: it becomes significantly different from zero and positive after 9 quarters, indicating that the WIT attractiveness is somewhat "slow", probably due to an "assessment of well-being": if individuals notice an increase in the overall well-being, they start to assess it, through temporary

visits. Indeed, the Tourism Index becomes positive after 5 quarters, a sign of the increased attractiveness.

Thus, after an "evaluation" of the increased WIT and its resilience, proved by the WIT's IRF, people start to relocate permanently themselves in such places, causing an increase in the 3-year migration rate.

Finally, the birth rate IRF (the 3rd graph of the lower row) also confirms the phenomenon observed in the previous IRFs: after an initial period of non-significant response, the birth rate becomes positive after 12 quarters, indicating that people slowly assess the well-being increase in an initial period, and then decide to being "stable" in a determinate location and starting to have children.

6. Conclusion

In this paper, an objective well-being index has been built, with regard to a micro-territorial level.

While the literature has numerous contribution on both the objective and subjective indexes, there is not a comprehensive and multifaceted index on a micro-territorial level: indeed, the choice of the city as a level of analysis allows the researcher to consider phenomena that will be "evened out" or simply ignored due to the lack of data.

Thus, starting from the 100% Lombardia platform, 52 indicators have been chosen, and a cluster analysis underlined the presence of common trends between groups of cities. Then, with the implementation of a Bayesian Dynamic Factor Model (B-DFM), the 52 indicators have been condensed into a single synthetic index, named WIT (acronym of Well-being Index for Towns), pointing out how the well-being evolved through time in each cluster, from 2001 to 2015.

Finally, a Panel Factor Augmented Vector AutoRegression with an exogenous variable (P-FAVARX) showed how the WIT interacts with other variables (how influences and it is influenced) thanks to the study of the impulse response functions.

The WIT proved to be a somewhat "resilient" indicator, i.e. showing a sustained higher level after a positive shock, as well as how it positively influences the income per taxpayer, the 3-year migration rate, and the tourism index. In a short amount of time, even the birth rate becomes positive and significant, while the average quotation of residential buildings is largely non-significant.

References

Abrigo M. R., Love I. (2015), *Estimation of panel vector autoregression in Stata: A package of programs*, «University of Hawaii at Manoa - Department of Economics Working Paper Series».

Afsa C. et al. (2008), *Survey of existing approaches to measuring socioeconomic progress*, in *Background paper for the first meeting of the CMEPSP*.

Bernanke B. S., Boivin J., Eliasz P. (2005), *Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach*, «The Quarterly Journal of Economics», 120(1), 387--422.

Breuer W., Brueser D. (2012), *Determining indicators of quality of life differences in European cities*, «SSRN Working Paper».

Campbell A., Converse P. E., Rodgers W. L. (1976), *The quality of American life: Perceptions, evaluations, and satisfactions*, Russell Sage Foundation.

Canova F., Ciccarelli M. (2013), *Panel Vector Autoregressive Models: A Survey*, in *VAR Models in Macroeconomics–New Developments and Applications: Essays in Honor of Christopher A. Sims*, «Advances in Econometrics», 32, 205-246, Emerald Group Publishing Limited.

Daly H. E., Cobb J. B., Cobb C. W. (1994), *For the common good: Redirecting the economy toward community, the environment, and a sustainable future*, Beacon Press.

Del Negro M., Schorfheide F. (2011), *Bayesian macroeconometrics*, in *The Oxford handbook of Bayesian econometrics* 293, 389.

Diener E. et al. (1999), *SWB: Three decades of progress*, «Psychological Bulletin», 125(2), 276-302.

Everitt B. S. et al. (2011), *Hierarchical clustering*, in *Cluster Analysis, 5th Edition*, 71-110.

Geweke J. (1977), *Wage and price dynamics in US manufacturing*, in *New Methods in Business Cycle Research: Proceedings From a Conference*, 111-56.

Giannetti B. et al. (2015), *A review of limitations of GDP and alternative indices to monitor human wellbeing and to manage eco-system functionality*, «Journal of Cleaner Production», 87, 11-25.

Hamilton J. D. (1994), *Time series analysis*, Vol. 2, Princeton university press Princeton.

Holtz-Eakin D., Newey W., Rosen H. S. (1988), *Estimating vector autoregressions with panel data*, «Econometrica: Journal of the Econometric Society», 1371-1395.

ISTAT (2015), *La nuova geografia dei sistemi locali*, 79-81.

Judson R. A., Owen A. L. (1999), *Estimating dynamic panel data models: a guide for macroeconomists*, «Economics letters», 65(1), 9-15.

Koop G., Korobilis D. (2010), *Bayesian multivariate time series methods for empirical macroeconomics*, Now Publishers Inc.

Kuznets S. (1937), *National Income, 1919-1935*, NBER.

Lopes H. F., West M. (2004), *Bayesian model assessment in factor analysis*, «Statistica Sinica», 41-67.

Love I., Zicchino, L. (2006), *Financial development and dynamic investment behavior: Evidence from panel VAR*, «The Quarterly Review of Economics and Finance», 46(2), 190-210.

Nardo M. et al. (2005), *Handbook on constructing composite indicators*, «OECD iLibrary».

Noll H.-H. (2002), *Social indicators and Quality of Life research: Background, achievements and current trends*, «Advances in Sociological Knowledge», 151-181.

Nordhaus W. D., Tobin, J. (1972), *Is growth obsolete?*, in *Economic Research: Retrospect and Prospect*, Volume 5, Economic Growth, Nber, , 1-80.

Posner S. M., Costanza R. (2011), *A summary of ISEW and GPI studies at multiple scales and new estimates for Baltimore City, Baltimore County, and the State of Maryland*, «Ecological Economics», 70(11), 1972-1980.

Primiceri G. E. (2005), *Time varying structural vector autoregressions and monetary policy*, «The Review of Economic Studies», 72(3), 821-852.

Redclift M. (2005), *Sustainability : critical concepts in the social sciences*, Routledge.

Serati M., Pacicco F. (forthcoming), *100% Lombardia: A micro-territorial statistic platform for policy making*.

Spath H. (1980), *Cluster analysis algorithms for data reduction and classification of objects*, Ellis Horwood Chichester.

Stiglitz J., Sen A. K., Fitoussi J.-P. (2009), *The measurement of economic performance and social progress revisited: reflections and overview*.

Talberth J., Cobb C., Slattery N. (2007), *The genuine progress indicator 2006*, «Redefining Progress», 26, Oakland, CA.

Tan P.-N., Steinbach M., Kumar, V. (2013), *Data mining cluster analysis: Basic concepts and algorithms*.

Ul Haq M. (1995), *Reflections on human development*, Oxford university Press.

United Nations (2015), *Transforming our world: the 2030 Agenda for Sustainable Development*, United Nations, New York.

Ward Jr J. H. (1963), *Hierarchical grouping to optimize an objective function*, «Journal of the American statistical association», 58(301), 236-244.

Notes

[1] Such operation has been made with an AR(1) model, on flipped-back series in the case of a backward extension

[2] The WIT value here represented has been scaled in order to have an average value of 100, always for the sake of exposition

Sommario

La letteratura sulla misurazione del well-being è composta da diversi contributi, che spaziano da misure soggettive, alle batterie di indicatori, alla creazione di indici oggettivi sintetici. Tuttavia, fino ad oggi, vi è una mancanza di tali misure a livello micro-territoriale, cioè misurata città per città. Questo paper, grazie alla piattaforma statistica 100% Lombardia, mira a sviluppare un possibile indice, chiamato WIT (acronimo di Well-being Index for Towns), utilizzando una cluster analysis, un modello a fattore dinamico bayesiano ed un panel-FAVARX.

Abstract

The literature on the evaluation of how the well-being is measured is full of different contributions, ranging from the subjective measure, to the batch of indicators approach, to the provision of synthetic objective indexes. However, up to date, there is still a lack of such measures on micro-territorial level, i.e. on town-by-town basis. This paper, thanks to the statistic platform 100% Lombardia, aims to develop such indexes, named WIT (Well-being Index for Towns), using a cluster analysis, a Bayesian dynamic factor model and a Panel-FAVARX.

Nota biografica sugli autori

Massimiliano Serati

Massimiliano Serati è Professore Associato di Politica Economica presso la Scuola di Management e Economia dell'Università Cattaneo – LIUC. Laureatosi nel 1993 in Discipline Economiche e Sociali presso l'Università Bocconi, nel 1999 ha conseguito il Dottorato di Ricerca in Economia Quantitativa presso l'Università di Pavia. Ha svolto attività di consulenza per Banca d'Italia, per i Ministeri dello Sviluppo Economico e della P.A, per Regione Lombardia, Unioncamere Lombardia, Confindustria e Confindustria Lombardia. Dal 2012 è Direttore del CeRST - Centro di Ricerca sullo Sviluppo dei Territori e dei Settori - della LIUC e Coordinatore di T.R.A.V.E.L., l'Osservatorio Turistico Lombardo attivato dal CeRST in collaborazione con Unioncamere Lombardia. Col 2017 è diventato direttore del nascente Osservatorio SEA – LIUC sullo sviluppo del turismo aereo intercontinentale in Lombardia.

In ambito macroeconomico, si occupa prevalentemente di temi connessi con la Politica Monetaria, il Ciclo Economico, il Mercato del lavoro, la produzione di previsioni macroeconomiche e la costruzione di scenari economici, combinando sempre l'approccio teorico con l'impiego di strumenti econometrici per l'analisi empirica. In ambito territoriale si occupa di Analisi, sviluppo e valorizzazione delle attrattività territoriali con particolare enfasi per le dimensioni culturali e turistiche, nonché di costruzione mediante metodologie econometriche di Indicatori socio-economici di monitoraggio per l'analisi del territorio

E' autore di numerosi lavori di ricerca pubblicati su riviste accademiche nazionali e internazionali e di alcune monografie.

Fausto Pacicco

Dottore di ricerca in Gestione Integrata d'Azienda, LIUC - Università Carlo Cattaneo. Ricercatore del CERST - Centro di ricerca per lo Sviluppo del territorio, LIUC - Università Carlo Cattaneo, la sua attività di ricerca riguarda principalmente tecniche econometriche di stima e costruzione di indicatori. È docente di Economia pubblica e Politica economica presso la LIUC - Università Carlo Cattaneo

Biographical sketches

Massimiliano Serati

Massimiliano Serati is Associate Professor of Economics at the School of Management and Economics, University Cattaneo - LIUC. He graduated in 1993 in Economics from Bocconi University, in 1999 he received his PhD in Quantitative Economics from the University of Pavia. He has worked as a consultant for the Bank of Italy, for the Ministries of Economic Development and P.A, Lombardy Region, Unioncamere Lombardia, Confindustria and Confindustria Lombardia. Since 2012 he is Director of CeRST - Research Center on Development of Territories and Sectors - LIUC and Coordinator of T.R.A.V.E.L., the Lombardy's Tourist Observatory activated by CeRST in collaboration with Unioncamere Lombardia. In 2017 he became director of the newly-born Observatory SEA - LIUC on the development of intercontinental air tourism in Lombardy.

In the macroeconomic area, it deals mainly with themes related to Monetary Policy, the Economic Cycle, the labour market, the production of macro-economic and construction forecasts of economic scenarios, always combining the theoretical approach with the use of econometric tools in the empirical analysis. At a local level deals with the analysis, development and enhancement of territorial attractiveness, with particular emphasis on the cultural and tourist dimensions. He also works to the construction, using econometric methods, of monitoring socio-economic indicators for the territorial analysis.

He is author of many research papers published in national and international academic journals and of some monographs.

Fausto Pacicco

PhD in Management, Finance, and Legal Disciplines for Integrated Company Management, LIUC – Università Carlo Cattaneo. Researcher for CERST - Centro di ricerca per lo Sviluppo del territorio, LIUC – Università Carlo Cattaneo, his research interests are econometrics and economic indicators. Teaches Public economics and Economic Policy at LIUC - Università Carlo Cattaneo