A STUDY ON THE ATTRACTIVENESS OF ITALIAN MUNICIPALITIES WITH THE RESULTS OF THE FIRST THREE EDITIONS OF THE PERMANENT POPULATION CENSUS[1]

Valeria Quondamstefano, Mariangela Verrascina

1. Introduction

In recent years, the debate on the measurement of multidimensional phenomena has caused, within the worldwide scientific Community of developed countries, a renewed interest. It is common awareness that several socio-economic phenomena cannot be measured by a single descriptive indicator and that, instead, they should be represented with multiple dimensions. Phenomena such as, for example, progress, poverty, and social inequality, require, to be measured, the "combination" of different dimensions, to be considered together as components of the phenomenon (Mazziotta and Pareto, 2013). This combination can be achieved by applying methodologies known as composite indicators (Salzman, 2003; Mazziotta and Pareto, 2011; Diamantopoulos and Riefler, 2008). The choice of a composite index is fundamental for the treatment of data. "A composite index is a mathematical combination (or aggregation as it is termed) of a set of individual indicators (or variables) that represent the different components of a multidimensional phenomenon to be measured (e.g., development, well-being or quality of life). Therefore, the composite indices are used for measuring concepts that cannot be captured by a single indicator" (Mazziotta and Pareto, 2018).

This paper aims to study a measure for quantifying and monitoring the attractiveness (or self-containment) of Italian municipalities. The term attractiveness (or self-containment) is used in the sense of a municipality's ability not to lose population or at least to maintain its population size and is interpreted according to the synthesis of the values obtained in the indicators considered by each municipality. As known, this phenomenon can't be represented exclusively by economic components but also by dimensions that represent domains having demographic and social nature. This work considers attractiveness (or self-containment) from a multidimensional point of view and wants to measure it for

[1] The article is exclusively expressing the authors' opinions. Although the paper is the result of joint work, sections are attributed as follows: paragraphs 1, 4, 5, 5.1, 5.2 and 6.1 to Valeria Quondamstefano and paragraphs 2, 3, 6.2 and 7 to Mariangela Verrascina.

Italian municipalities to highlight differences and similarities, also in time series, by using some elementary indicators calculated from the 2018, 2019 and 2020 editions of the Permanent Census of Population and Housing. The methodology is based on composite indicators to make the complex phenomenon more readable. In particular, the Adjusted Mazziotta-Pareto Index (AMPI) method was used. In addition, the CHAID (Chisquared Automatic Interaction Detector) 'regression tree' classification method is applied. The dependent variable is the AMPI, while the independent variables are the administrative subdivisions, some geographic characteristics and the demographic size of the municipality. The choice to use these indicators arises from the hypothesis that the geographical-territorial component can also represent a natural attraction (or self-containment) element.

The paper is structured as follows. Section 2 describes the Permanent Population and Housing Census, which is the reference for the construction of simple indicators; Section 3 presents the data used and the indicators calculated; Section 4 introduces and outlines the methodology employed in the analysis; Section 5 illustrates the exploratory analysis; Section 6 discusses the main results obtained using the synthetic indicator chosen (AMPI) and the classification method (CHAID). Section 7 contains the conclusions.

2. Permanent Census of Population and Housing

Starting in 2018, the Census of Population and Housing is Permanent[2]: no longer decennial and exhaustive, but annual on a representative sample of municipalities and private households, different from year to year. The Census moves from traditional to combined since it integrates data from administrative sources and data from sample surveys.

In the Permanent Population Census, the core of census data production is the *Registro Base degli Individui* (RBI), which, together with thematic registers (such as those on employment and education), is subjected to the annual sample surveys to correct and supplement the information contained therein. This step is made possible by the regular acquisition of administrative sources and their processing and use for statistical purposes[3]. The RBI is an Istat informative environment to support statistical production processes; in particular, it is the basic infrastructure for the production of official statistics referring to the population. It contains anonymous 'statistical' data, i.e., resulting from a method of statistical processing and validation from administrative and survey sources, and referring to a limited number of

[2] Istat.it - Censimento permanente popolazione e abitazioni.
[3] https://www.istat.it/it/files/2020/12/REPORT_CENSIPOP_2020.pdf

variables functional to the representation of the main structural characteristics of the population and households. The integration of the census with the Register System is aimed, on the one hand, at correcting over- and under-coverage errors[4] in the RBI and, on the other hand, at collecting information that is currently not available in the administrative data source.

The information on educational attainment is derived from the *Registro Tematico del Titolo di Studio*. This Register is the result of the integration of the *Base Informativa su Istruzione e Titoli di Studio* (in which data on educational qualifications obtained in Italy from 2011 onwards are recorded), the 15th General Population and Housing Census (2011) and the Permanent Census sample survey.

In 2020, due to Covid-19, it was not possible to carry out field surveys; however, Istat set itself the goal of producing a count of the resident population by gender, age, citizenship and educational attainment. Through an appropriate methodology, all available administrative information is integrated; some new sources have also been made available, i.e., sources that allow to pick up signs of life[5].

The combination of sample estimates and statistical registers produces a census-like output: the results are referable to the entire population. With the new census strategy, data are disseminated on an annual basis and at municipal territorial detail: currently, this is a reduced data set, which will be enriched over time as more information becomes available (and of good quality) in the archives. The new informative provision - annual municipal - allows to study phenomena in a timelier way and to carry out both temporal and spatial analyses.

3. Data

Results from the first three editions of the Permanent Census of Population and Housing, namely the 2018, 2019 and 2020 outputs, are considered the baseline data for the work[6]. Below are the 9 demo-social indicators[7] calculated are reported:

(A) *The average age of the population*. The ratio of the sum of the ages of all individuals to the total population.

(B) *The proportion of the population aged 0-17 years*. The ratio of the population aged 0-17 years to the total population (percentage).

[4] Identifying persons present in the Register as residents but not found in the territory and those found in the territory as usually residents but not present in the Register.

[5] https://www.istat.it/it/files/2021/12/CENSIMENTO-E-DINAMICA-DEMOGRAFICA-2020.pdf

[6] I.Stat: Statistiche Istat; Data Browser: Censimento permanente della popolazione e delle abitazioni (istat.it); Demo: Demo-Geodemo. - Mappe, Popolazione, Statistiche Demografiche dell'ISTAT.

[7] The territory included in the study consists of 7,895 Italian municipalities, which were as of Dec. 31, 2020. Eight municipalities were excluded from the analysis since they have indicators that cannot be calculated due to the absence of the population of some age groups needed to determine the indicators.

(C) Ageing index. The ratio of the population aged 65 years and over to the population aged 0-14 years (percentage).

(D) Young age dependency ratio. The ratio of the population aged 0-14 to the population aged 15-64 years (percentage). The denominator represents the population that is expected to support the one in the numerator. So, the index specifies how many young people (0-14 years old) there are per 100 individuals of working age and indirectly provides a measure of the sustainability of a population structure.

(E) Old age dependency ratio. The ratio of the population aged 65 years and over to the population aged 15-64 years (percentage). This ratio denotes how many people aged 65 and over there are for every 100 individuals of working age.

(F) Labour force turnover ratio (revised). The ratio of the population aged 65-69 years to the population aged 20-24 years (percentage). It is the percentage ratio of the population potentially leaving the labour force (65-69 years old) to the population potentially entering (20-24 years old). Higher values indicate that there are many more individuals exiting the labour force than potentially entering it. It, therefore, indicates a population close to retirement that far outnumbers those aged 20-24.

(G) Percentage of the population with a diploma of upper secondary education. The ratio of the population with a diploma of upper secondary education to the population aged 9 years and over (percentage).

(H) Percentage of the population with a master's degree or second-level academic diploma and Research Doctorate (PhD). The ratio of the population with a master's degree or second-level academic diploma and Research Doctorate (PhD) to the population aged 9 years and over (percentage).

(I) Foreign Population (per thousand persons). The ratio of foreign population to the total population (per thousand persons).

4. Composite indicator

Reducing dimensionality is a purely mathematical operation that consists in summarizing a set of individual indicators so that most of the information in the data is preserved. Many techniques have been developed for this purpose: Principal components analysis (PCA) is one of the oldest and most widely used (Hotelling, 1933), Partial Order Set Theory (Poset) is one of the most recent (Neggers and Kim, 1998; Davey and Priestley, 2002; Schröder, 2002). Constructing a composite indicator is a complex task. It is formed when individual indicators are compiled into a single index, based on an underlying model of the multi-dimensional concept that is being measured (OECD 2004). The main problems, in this approach, concern the

choice of theoretical framework, the selection of the more representative indicators and their treatment to compare and aggregate them. In this case, to synthesize the basic indicators into a single measure, the 'Adjusted Mazziotta-Pareto Index' (AMPI) is used, because the influence analysis demonstrates the validity compared to other methods in terms of robustness. It is a partially non-compensatory composite indicator based on a standardization of the individual indicators, at the reference time, which makes the indicators independent of the unit of measurement (De Muro and Mazziotta, 2011). It is based on a non-linear function which, starting from the arithmetic mean, introduces a penalty for the units with unbalanced values of the indicators. It is a formative composite indicator for summarizing a set of indicators that are assumed to be non-substitutable. The latent factor - in this case, the attractiveness of municipalities - depends on the basic indicators that 'explain' it and not vice versa. Basic indicators are converted into a common scale with a mean of 100 and a standard deviation of 10. Therefore, the transformed values will fall approximately in the open range (70; 130). Multidimensionality is synthesized in a single value: the composite indicator allows, in the case of the AMPI, a comparison in both space and time[8].

5. Descriptive data analysis

This chapter describes the exploratory analyses carried out on the matrix composed of 7,895 municipalities for the 9 elementary indicators for the first three editions of the Permanent Population and Housing Census.

5.1. Correlation analysis

The analysis carried out shows that the strongest correlations of the AMPI for the three years are with the basic indicators: 'Percentage of population with a diploma of upper secondary education (0.68; 0.68; 0.67) and 'Percentage of population with master's degree or second level academic diploma and Research Doctorate (PhD)' (0.67; 0.67; 0.65). Low correlation between AMPI and basic indicators occurs for 'Young-age dependency ratio' (0.32; 0.34; 0.33) and 'Proportion of population aged 0-17 years' (0.37; 0.40; 0.39).

Having chosen a formative measurement model for the analysis, the level of correlation between basic indicators is not relevant. In fact, in this approach,

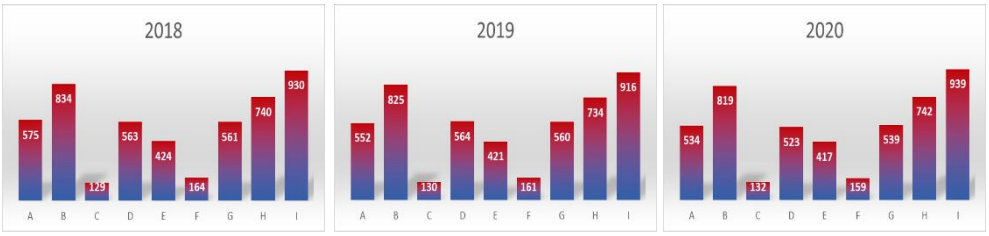
[8] For the methodology and mathematical properties of AMPI see Mazziotta and Pareto, 2016; Mazziotta and Pareto, 2020.

polarities and correlations are independent and basic indicators can have positive, negative or no correlations (Maggino, 2009). The latent variable is estimated by taking a weighted average (or other function) of the indicators that make up the concept (Shwartz and Restuccia, 2015).

5.2. Influence Analysis of Basic Indicators for AMPI Ranking Construction

The influence analysis (Figure 1) of the elementary indicators is carried out, i.e. it is identified by how many positions on average the ranking of each territorial unit moves if one indicator is eliminated at a time. Over the years, the most influential indicator is the 'Foreign Population (per thousand persons)' (I), and the least influential is the 'Aging index' (C).

Figure 1 – *Influence Analysis of Basic Indicators for AMPI Ranking Construction*.



6. Results

This part illustrates the outcomes emerging from the application of the AMPI method and the CHAID 'regression tree' classification method.

6.1. AMPI ranking of Italian municipalities

Figure 2 shows the mapping of Italy for the years 2018, 2019 and 2020 according to the level of attractiveness (or self-containment) of Italian municipalities.

Figure 2 *– AMPI ranking: Maps of Italian municipalities.*

The municipalities with the highest level of attractiveness are shown in dark green, while those with the lowest level are shown in light green. The proposed scale is given by the deciles measured in the three years. Comparing the situation over the three years, a fairly similar trend can be seen: municipalities with a high level of attractiveness are concentrated in the North of Italy, along the Via Emilia (from Piacenza to Rimini), and in the Centre of Italy (in particular in the Metropolitan City of Rome).

Figure 3 – *AMPI ranking: the 10 best and 10 worst Italian municipalities*.

2018 Edition

G. Area	Region	Province	Municipality	AMPI	Ranking
North-West	Lombardy	Milano	Basiglio	103.93	1
North-West	Lombardy	Milano	Milan	103.73	2
Centre	Lazio	Roma	Sacrofano	103.56	3
North-West	Lombardy	Pavia	Rocca de' Giorgi	103.32	4
North-West	Piedmont	Torino	Claviere	103.31	5
North-West	Lombardy	Varese	Ranco	103.16	6
North-West	Lombardy	Como	Camplone d'Italia	103.15	7
North-East	Emilia-Romagna	Bologna	Bologna	103.04	8
North-East	Veneto	Padova	Padua	102.96	9
Centre	Lazio	Roma	Rome	102.90	10

2019 Edition

G. Area	Region	Province	Municipality	AMPI	Ranking
North-West	Lombardy	Pavia	Rocca de'Giorgi	104.10	1
North-West	Lombardy	Milano	Milan	104.00	2
North-West	Lombardy	Milano	Basiglio	103.94	3
Centre	Lazio	Roma	Sacrofano	103.61	4
North-West	Lombardy	Como	Camplone d'Italia	103.57	5
North-West	Piedmont	Torino	Claviere	103.25	6
North-East	Emilia-Romagna	Bologna	Bologna	103.24	7
North-East	Veneto	Padova	Padua	103.11	8
North-West	Lombardy	Milano	San Donato Milanese	103.10	9
North-West	Lombardy	Bergamo	Bergamo	103.05	10

2020 Edition

G. Area	Region	Province	Municipality	AMPI	Ranking
North-West	Lombardy	Milano	Milan	104.41	1
North-West	Lombardy	Milano	Basiglio	104.16	2
North-East	Emilia-Romagna	Bologna	Bologna	103.58	3
North-East	Veneto	Padova	Padua	103.44	4
North-West	Lombardy	Como	Camplone d'Italia	103.41	5
North-East	Emilia-Romagna	Parma	Parma	103.39	6
North-West	Lombardy	Bergamo	Bergamo	103.34	7
North-West	Lombardy	Milano	San Donato Milanese	103.29	8
Centre	Lazio	Roma	Sacrofano	103.28	9
Centre	Lazio	Roma	Rome	103.23	10

2018 Edition

G. Area	Region	Province	Municipality	AMPI	Ranking
North-East	Emilia-Romagna	Piacenza	Zerba	78.36	7,895
North-West	Piedmont	Cuneo	Roaschia	82.97	7,894
South	Abruzzo	Chieti	Colledimacine	84.16	7,893
North-West	Piedmont	Alessandria	Monglardino Ligure	85.62	7,892
North-East	Emilia-Romagna	Piacenza	Cerignale	86.02	7,891
North-West	Liguria	Genova	Rondanina	87.97	7,890
South	Abruzzo	L'Aquila	Villa Santa Lucia degli Abruzzi	88.32	7,889
North-West	Liguria	Genova	Gorreto	88.62	7,888
North-West	Lombardy	Brescia	Magasa	89.55	7,887
South	Abruzzo	L'Aquila	San Benedetto in Perillis	89.90	7,886

2019 Edition

G. Area	Region	Province	Municipality	AMPI	Ranking
North-East	Emilia-Romagna	Piacenza	Zerba	79.79	7,895
North-West	Piedmont	Cuneo	Roaschia	82.39	7,894
North-East	Emilia-Romagna	Piacenza	Cerignale	86.37	7,893
South	Abruzzo	L'Aquila	San Benedetto in Perillis	86.40	7,892
North-West	Lombardy	Brescia	Magasa	86.88	7,891
North-West	Liguria	Genova	Rondanina	87.32	7,890
North-West	Piedmont	Alessandria	Denice	87.97	7,889
North-West	Piedmont	Cuneo	Pamparato	88.48	7,888
South	Abruzzo	Chieti	Colledimacine	88.76	7,887
North-West	Lombardy	Pavia	Ceretto Lomellina	88.86	7,886

2020 Edition

G. Area	Region	Province	Municipality	AMPI	Ranking
North-East	Emilia-Romagna	Piacenza	Zerba	80.72	7,895
North-West	Piedmont	Cuneo	Roaschia	81.22	7,894
North-West	Lombardy	Brescia	Magasa	81.26	7,893
North-West	Piedmont	Acti	Tonengo	88.07	7,892
North-West	Piedmont	Cuneo	Pamparato	88.49	7,891
North-West	Liguria	Imperia	Olivetta San Michele	88.83	7,890
South	Abruzzo	L'Aquila	Villa Santa Lucia degli Abruzzi	89.46	7,889
North-West	Liguria	Genova	Gorreto	89.48	7,888
North-West	Piedmont	Alessandria	Monglardino Ligure	89.51	7,887
North-East	Emilia-Romagna	Piacenza	Cerignale	89.67	7,886

Figure 3 shows the 10 best and the 10 worst Italian municipalities by AMPI ranking. In the 3 years of analysis in the top positions are Metropolitan Cities (Rome,

Milan and Bologna), and provincial capitals (Padua and Bergamo). In the last positions, in addition to Southern municipalities, as expected, are northern municipalities belonging to border areas (border municipalities).

6.2. Classification method – Variables and results

The 'regression tree' classification method CHAID (Chisquared Automatic Interaction Detector) is a multiple tree statistics algorithm that allows visualising data quickly and efficiently, by creating segments and profiles according to the results.

The composite indicator AMPI is considered as the dependent variable, while some geographical-territorial information is considered as the independent variable; in particular: Geographical area, Region, Province, Altitude zone[9], Degree of urbanisation[10], Population density[11], Demographic size of municipalities class, Classification of municipalities in coastal, island and coastal zone[12] (Eurostat, 2019). The latter classification is specially created considering the information of proximity to the coast with the idea that being a coastal municipality can also be a geographical-territorial characteristic that can influence the attractiveness (or self-containment) of the municipality.

The results (Figure 4) show instead that this information is not discriminating, in fact, in the three years, the classification is not among the independent variables necessary to create the groups of similar municipalities (nodes). Thus, not all independent variables are found to be influential in the classification. In addition to the variable 'Classification of municipalities in coastal, island and coastal zone' that do not appear in any year of analysis, for the first year the variable 'Geographical area' is not among the independent variables that discriminate, while for the last two years the variable 'Degree of urbanisation' is not included.

[9] *Altitude zone* derives from the division of the national territory into homogeneous zones resulting from the aggregation of contiguous municipalities based on altimetric threshold values.

[10] *Degree of urbanisation (DEGURBA)* is a classification that indicates the character of an area. Based on the share of the local population living in urban clusters and urban centres, it classifies Local Administrative Units (LAU or municipalities) into three types of area: *Cities* (densely populated areas), *Towns and suburbs* (intermediate density areas), *Rural areas* (thinly populated areas). Statistics by degree of urbanisation provide an analytical and descriptive lens on urban and rural areas.

[11] Relation between the number of inhabitants and the surface of the territory (number of inhabitants per km^2).

[12] *Coastal municipality*: the character of a coastal municipality has been given to all municipalities whose territory touches the sea. *Island municipality*: Municipalities belonging to minor maritime and lake islands. *Coastal zones*: Classification of municipalities according to the degree of proximity from the coast. Municipalities located on the coast or having at least 50 per cent of the area at a distance from the sea of less than 10 km are considered to belong to Coastal zones.

Figure 4 – *The best and worst nodes.*

	2018 Edition	2019 Edition	2020 Edition
Best node	**NODE 92**	**NODE 71**	**NODE 74**
	1-Demographic size of municipalities class: 20,001 persons and over	1-Geographical area: North-East, Centre	1-Geographical area: North-East, Centre
	2-Region: Liguria, Lombardy, Autonomous Province of Bolzano, Autonomous Province of Trento, Veneto, Friuli-Venezia Giulia, Emilia-Romagna, Marche, Umbria, Lazio, Abruzzo, Molise, Basilicata	2-Population density: over 730 persons per km2	2-Population density: over 730 persons per km2
	3-Population density: over 730 persons per km2	3-Demographic size of municipalities class: 20,001 persons and over	3-Demographic size of municipalities class: 20,001 persons and over
	Number of municipalities: **134**	Number of municipalities: **68**	Number of municipalities: **70**
Worst node	**NODE 17**	**NODE 91**	**NODE 94**
	1-Demographic size of municipalities class: between 501 and 1,000 persons	1-Geographical area: Islands	1-Geographical area: Islands
	2-Region - Sardinia	2-Province: Oristano, Sud Sardegna	2-Province: Oristano, Sud Sardegna
		3-Population density: up to 2,000 persons	3-Population density: up to 1,000 persons
	Number of municipalities: **72**	Number of municipalities: **114**	Number of municipalities: **75**

The regression model using the composite AMPI index as the dependent variable and the geographic-territorial indicators as the independent variables makes it possible to identify some groups of municipalities with similar AMPI index values. The analysis focuses only on the extreme nodes, the best and the worst nodes. In the worst node small, rural, sparsely populated municipalities fall, characterized by a strong weight of the elderly and low presence of young people, a strong unbalance toward the older age groups, predominantly located in southern and insular Italy. On the contrary, in the best node medium and large municipalities, densely populated fall, characterized by a lower average age, and a higher proportion of the population with medium-high educational level, predominantly located in northern and central Italy (Figure 5).

There is a clear opposition between the densely populated medium-large municipalities of central-northern Italy (the best nodes of the tree) and the very small rural municipalities of southern Italy, particularly Sardinia (the worst nodes).

Figure 5 – *Maps of municipalities in the best and worst nodes.*

As expected, the result shows small variations since the phenomena analysed undergo slight deviations from year to year. However, the analysis provides the opportunity to identify a stable trend that emerges over the entire period under

consideration. Although in the three years the regression model develops different paths and takes into account different independent variables, the extreme nodes contain approximately the same municipalities, i.e., those municipalities represent the two Italian extreme realities.

The characteristic feature that markedly distinguishes the municipalities in the worst node is the ageing of the population. Most of the indicators taken into account are derived from the age structure of the population: the values obtained show that these are municipalities with a low proportion of young people, with a conspicuous presence of an older population and consequently a higher average age than the national mean. There is also a low presence of foreigners in these municipalities, which does not ensure generational turnover. Low proportions of the population with medium-high educational attainment are a direct effect of the ageing population too.

These municipalities not only have no attractiveness, they also have low self-containment capacity (i.e. the population born in a municipality remains to live in the same municipality) and they are therefore the municipalities most vulnerable to depopulation.

7. Conclusion

The one presented is an exploratory analysis with available data from the three censuses. This work is born to show the potential of using annual data from the Permanent Census and how the annual municipal dissemination allows for temporal and spatial analyses, which can be even more detailed as more census outputs become available or by supplementing the currently released data with additional information.

The Permanent Census of Population and Housing allows longitudinal analyses and, integrated with other information, will allow analyses of the life histories of population groups and will aid the planning of specific local policies by facilitating the eventual identification of particularly vulnerable or distressed population groups (subpopulations) or territories.

References

DAVEY B. A., PRIESTLEY H. A. 2002. *Introduction to lattices and order.* Cambridge: Cambridge University Press.

DE MURO P., MAZZIOTTA M. 2011. Composite Indices of Development and Poverty: An Application to MDGs, *Social Indicators Research*, Vol. 104, pp. 1-18.

DIAMANTOPOULOS A., RIEFLER P. 2008. Advancing Formative Measurement Models, *Journal of Business Research*, Vol. 61, pp.1203-1218.

EUROSTAT. 2019. *Methodological manual on territorial typologies*. Luxembourg: Publications Office of the European Union.

MAGGINO F. 2009. La Misurazione dei Fenomeni Sociali Attraverso Indicatori Statistici. Aspetti Metodologici. *Working Papers*, Università degli Studi di Firenze.

MAZZIOTTA M., PARETO A. 2020. *Gli indici sintetici*. Torino: G. Giappichelli Editore.

MAZZIOTTA M., PARETO A. 2018. Measuring Well-Being Over Time: the Adjusted Mazziotta-Pareto Index Versus Other Non-Compensatory Indices, *Social Indicators Research*, Vol. 136, pp. 967-976.

MAZZIOTTA M., PARETO A. 2016. On a Generalized Non-compensatory Composite Index for Measuring Socio-economic Phenomena, *Social Indicators Research*, Vol. 127, No. 3, pp. 983-1003.

MAZZIOTTA M., PARETO A. 2013. Methods for Constructing Composite Indices: One for All or All for One, *Rivista Italiana di Economia Demografia e Statistica*, Vol. 67, No. 2, pp. 67-80.

MAZZIOTTA M., PARETO A. 2011. Un Indice Sintetico Non Compensativo per la Misura della Dotazione Infrastrutturale: Un'Applicazione in Ambito Sanitario, *Rivista di Statistica Ufficiale*, Vol. 1, pp.63-79.

NEGGERS J., KIM H. S. 1998. *Basic posets*. Singapore: World Scientific.

OECD. 2008. *Handbook on Constructing Composite Indicators*. Paris: OECD Publications.

SALZMAN J. 2003. Methodological Choices Encountered in the Construction of Composite Indices of Economic and Social Well-Being. *Technical Report*, Center for the Study of Living Standards, Ottawa.

SCHRÖDER B. 2002. *Ordered set: An introduction*. Boston: Birkäuser.

SHWARTZ M., RESTUCCIA J.D. 2015. Composite Measures of Health Care Provider Performance: A Description of Approaches, *The Milbank Quarterly*, Vol. 93, pp. 788-825.

SUMMARY

Starting in 2018, the Census of Population and Housing is Permanent: no longer decennial and exhaustive, but annual on a representative sample of municipalities and private households, different from year to year. The combination of sample estimates and statistical registers produces a census-like output: the results are referable to the entire population. The new informative provision - data disseminated at municipal level on annual basis - allows to study phenomena in a timelier way and to carry out both temporal and spatial analyses.
The work is a study on the attractiveness (or self-containment) of Italian municipalities using the results of the first three editions of the Permanent Census of Population and Housing, through dimensions representing domains of a socio-demographic nature, with the aim of highlighting differences and similarities between municipalities. Some elementary indicators have been produced for 7,895 Italian municipalities referring to the years considered.

The basic indicators are summarised by means of the *Adjusted Mazziotta Pareto Index* (AMPI), whereby multidimensionality is summarised in a single value. The composite AMPI calculated allows a comparison in space and time. In addition, the CHAID (*Chi-squared Automatic Interaction Detector*) 'regression tree' classification method is applied. The dependent variable is the AMPI, while the independent variables are the administrative subdivisions, some geographic characteristics and the municipality demographic size.

The application of the CHAID 'regression tree' classification method confirms that there is a clear opposition between the densely populated medium-large municipalities of central-northern Italy (the best nodes of the tree) and the very small rural municipalities of southern Italy, particularly Sardinia (the worst nodes). The municipalities belonging to the extreme nodes are represented on the maps to visualize the different realities that coexist on the Italian territory.

Valeria QUONDAMSTEFANO, Istat, quondamstefano@istat.it
Mariangela VERRASCINA, Istat, verrasci@istat.it