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SDG COMPOSITE INDICATORS FOR MEDITERRANEAN COUNTRIES: A NEW THEORETICAL APPROACH

Francesca Mariani, Mariateresa Ciommi, Maria Cristina Recchioni, Giuseppe Ricciardo Lamonica, Francesco M. Chelli

1. Introduction

The definition and construction of composite indicators is an appealing research strand. The increasing interest is also proved by the increasing number of papers devoted to this topic according to "Google Scholar" since 2020 there are about 8,000 items (papers, articles, reports and so on) that contain the expression "composite indicators" that is about the same number of works published between 2001 and 2012 (8440).

One of the reasons for this rise lies in its ability of producing rankings used to compare countries' performances and monitoring progress.

In a very general way, composite indicators are defined as a function of indicators and weights, where weights usually reflect a sort of relative importance, in the simplest case, they are constructed by averaging normalized country values (Saisana, 2014).

Since September 2015, the "2030 Agenda for Sustainable Development" has become a referent point for scholars interesting in analysing and monitoring progress toward sustainable development. The Agenda includes 17 Sustainable Development Goals (SDGs) which must be reached before the end of 2030. Goals include poverty/well-being in a broad sense (Goal 1, Goal 2, Goal 3, Goal 6, Goal 8, Goal 10 and Goal 16), education (Goal 4), gender disparities (Goal 5), energy, climate change and innovation (Goal 7, Goal 9 and Goal 13), sustainability in city and consumption (Goal 11 and Goal 12), life below water and on land (Goal 14 and Goal 15) and partnerships (Goal 17).

Each Goals typically is defined by means of 8-12 targets, which, in tourn has between 1 and 4 indicators.

Annually, all countries' performances are tracked and reported by Sachs et al. (2016) on behalf of Bertelsmann Stiftung and the Sustainable Development Solutions Network (SDSN) (2021). The report analyses 193-member states of the United Nations. Beside the dashboard values, authors also derive a composite indicator by Goals as well as an overall indicator. More in detail, the arithmetic mean is used to aggregate indicators relating to each Goal in turn, before 'averaging' the results into a single metric.

After this first attempt of aggregation, literature account for additional tries. For instance, Lafortune et al. (2018) use the arithmetic mean (CES function), the minimum (Leontief production function) and the geometric mean (Cobb-Douglas production function) for aggregating SDGs. Guijarro (2018) proposes a parametric weighting scheme for the calculation of the SDG Index based on the multicriteria Goal Programming (GP) approach. Finally, Biggeri et al. (2019) introduce an adjusted SDG Index based on the Multidimensional Synthesis of Indicators (MSI) method with the twofold objective of overcoming the perfect substitutability problem of the arithmetic mean and of avoiding the tendency of geometric mean approach to collapse to zero.

Recently, there is an increasing interest in monitoring SDG for some World sub-area. For instance, Otekunrin et al. (2019) compute a composite index to describe the status of African countries on the attainment of Sustainable Development Goals (SDGs). Lynch and Sachs (2021) provide an up-to-date benchmarking of the progress of the United States and the 50 states towards the Sustainable Development Goals. Similarly, the Sustainable Development Solutions Network (SDSN, 2021) publish a report on the progress of the European Union (EU), its member states, and other European countries.

Thus, this paper aims at merging these new strands of the literature: in one hand the use of new aggregation techniques and, on the other hand, the increasing interest in monitoring SDG progress for a specific geographical area. We apply the new aggregation method proposed by Marini and Ciommi (2022) for constructing composite indicators. The method allows to penalize countries that display a larger variability by introducing a penalty factor that considers the horizontal heterogeneity among indicators. More recently, the method has been extended by Mariani et al. (2022) from the Arithmetic and Geometric mean to all possible members of the power mean. Accordingly, we focus on the so-called Penalized Geometric Mean (hereafter pGM) and we compare results with the classical geometric mean (hereafter GM) and also with the Arithmetic Mean (hereafter AM). Hence, these composite indicators are used to compare the performance of 17 Mediterranean countries, partitioned into 9 European Mediterranean countries (MCs), namely Croatia, Cyprus, France, Greece, Italy, Malta, Portugal, Slovenia and Spain and 8 non-European Mediterranean countries (nMCs), namely Algeria, Egypt, Israel, Jordan, Lebanon, Morocco, Tunisia, and Turkey.

The rest of the paper is organized as follow. Section 2 briefly reviews the notation introduced in Mariani and Ciommi (2022) and describes the data used in the proposed application. Section 3 illustrates the results and Section 4 concludes.

2. Methods and data

Let n be the number of units (countries, in our case) and k be the number of indicators. Thus, data can be represented by a rectangular matrix, X whose entries x_{ij}, $i=1,\ldots,n$ and $j=1,\ldots,k$ denote the value of indicator j for country i. Let I denotes the normalized matrix, that is the matrix of normalized values obtained according a given method that ensure data to be in a fixed interval.[1] Thus $\underline{I_i}$ is a generic row of matrix I representing the normalized profile of country i. Then, according to Mariani et al. (2022), the p-order generalized mean is:

$$M_p(\underline{I_i}) = \left(\frac{1}{k}\sum_{j=1}^{k} I_{ij}^{p}\right)^{1/p} \qquad p \in \mathbb{R} \text{ and } p \neq 0 \tag{1}$$

where the geometric mean is a special case of the power mean for $p \to 0$.

As stressed in Mariani and Ciommi (2022), the so-called penalized Geometric Mean (pGM), is the solution of an optimization problem:

$$\min_{a\in\mathbb{R}} F(a) \quad where\, F(a) = \frac{1}{k}\sum_{j=1}^{k}\left(h_0(I_{ij}) - h_0(a)\right)^2 \tag{2}$$

The function $h_0(\cdot)$ is the Box–Cox function of order zero (Box and Cox, 1964)[2] defined as:

$$h_0(x) = \ln(x) \qquad x \in \mathbb{R}_+ \tag{3}$$

Mariani and Ciommi (2022) demonstrate that, for each unit i, the solution of problem (2) is the classical geometric mean $\mu_{0,i} = (\prod_{j=1}^{k} I_{ij})^{1/k}$. This quantity can be written in terms of the Box-Cox function as follow:

$$\mu_{0,i} = h_0^{-1}\left(\frac{1}{k}\sum_{j=1}^{k} h_0(I_{ij})\right) \tag{4}$$

Moreover, the error made by approximating the normalized indicators I_{ij} with $\mu_{0,i}$ coincides with the (biased) sample variance of I_{ij}. We denote this quantity as S_i^2. Since the magnitude of those variances depend on the size of the mean, we divide

[1] Here, we are not interested in the kind of normalization procedure.

[2] The Box-Cox transformations is a parametric family of transformations, from x to $x^{(\lambda)}$ that can be used with non-negative responses.

the normalized indicators by the corresponding geometric mean: $\tilde{I}_{ij} = {I_{ij}}/{\mu_{0,i}}$ and consequently, S_i^2 can be re-written as:

$$\tilde{S}_{0,i}^2 = \frac{1}{k}\sum_{j=1}^{k}(\ln(\tilde{I}_{ij}))^2 \tag{5}$$

Thus, keeping this in mind, the penalized geometric mean for unit i (pGM) is defined as follow (Mariani and Ciommi, 2022):

$$pGM^{\pm} = \mu_{0,i}h_0^{-1}(\pm\tilde{S}_{0,i}^2) = \mu_{0,i}e^{\pm\tilde{S}_{0,i}^2} \tag{6}$$

where the sign $\pm$ represents the well-known polarity. As shown in equation (6), pGM is just the product between the geometric mean $\mu_{0,i}$ and a penalty factor $h_0^{-1}(\pm\tilde{S}_{0,i}^2)$ that allows us to discriminate between unit with the same geometric mean but different geometric mean reliability. That is, in the case of positive (negative) polarity, the penalty factor gives smaller (larger) value to the units for which the geometric mean is less reliable.

To illustrate the appealing of this penalized geometric mean, we focus on Sustainable Development Goals and, in particular, we use data from Sachs et al. (2021). Data refers to 2021. The report includes 91 global indicators as well as 30 additional indicators for OECD countries. It provides both original values and normalized data. Here, we use the second one in order to keep the five-step decision tree discussed in Sachs et al. (2021). Moreover, using already normalized data allows us to compare the results of our penalyzed geometric mean with the so-called SDG index, that is an index computed by aggregating indicators within and across SDGs. Both the SDG for each Goal and the overall SDG are computed by means of the arithmetic mean, giving equal weights to each indicator and Goal, respectively.

As stressed by Sachs et al. (2021), to obtain normalized, the original data are scaled though a sort of min-max method, where the minimum and the maximum for each indicator are fixed as specific targets. Thus, using our notation, I_{ij} represents the normalized data. We compute a further step consisting in rescaling the normalized data form range [0,100] to [0,1] where 0 denotes worst possible performance and 1 is the optimum. This re-scale procedure allows us to limit the range the composite indicator in the interval [0,1].

As reported by Sachs et al. (2021), the Report includes countries having data for at least 80 percent of the variables included. Since dataset still presents several missing values, we add two additional and more restrictive criterions, that are, for each Goal, 1) we remove variable with more than 50% of missing value, 2) then, we remove country with more than 50% of missing value. In this way, from the original

193 countries, we range between 125 (for Goal 14) to 165 (Goal 2, 3, 5-9, 12 and 13). Nevertheless, even if a two-stage procedure to trait missing data has been adopted, for some indicators and some Goals there still remain unobserved data. For this reason, following Lafortune et al. 2018, for each Goal[3] l, $l=1,\dots,17$, and for each country i, the aggregation takes into account the effective number of indicators j for which that country has data.

3. Results and Discussions: the case of Goal 2

Among the 17 SDG, we focus on Goal 2: "End hunger, achieve food security and improved nutrition and promote sustainable agriculture", in-brief called "zero-hunger" Goal. Aim of Goal 2 is to ensure that everyone everywhere has enough good-quality food to lead a healthy life. UN has defined 8 Targets and 14 Indicators for SDG 2.[4]

We focus on Goal 2 since it is one of the Goal most effected by the global pandemic. For instance, moving from 2014 to 2019, the number of undernourished people has increased passing from 507 million to 650 million, and, in 2020, an additional 70-161 million people are likely to have experienced hunger as result of the pandemic.[5] Moreover, two billion people in the world do not have regular access to safe, nutritious and sufficient food. In 2019, 144 million children under the age of 5 were stunted, and 47 million were affected by wasting.[6]

Table 1 reports a description of the variables for Goal 2 as well as the lower bound and the upper bound used in the normalization step as collected by Sachs et al. (2021). Moreover, after applying the above-mentioned procedure to remove missing data, the Goal 2 collects data for 165 countries and the aggregation step is made by mean of 8 variables. In fact, among the 9 variables listed in Table 1, *yieldgap* has been removed from the analysis since it has only 27 observations and 28 countries have been dropped due to missing data. Moreover Table 1 reports both the number of the original missing values and the number of missing values after the selection procedure (in brackets).

Even if we are interested in Mediterranean countries, we compute the composite indicators for all countries, and we select the Mediterranean ones. For 17 Mediterranean countries we distinguish between European Mediterranean countries

[3] The procedure is general. Here Goals play the role of domains, according to the OECD (2008) notation.
[4] See https://sdg-tracker.org/zero-hunger for the complete list of Targets and Indicators for this Goal
[5] See https://sdgs.un.org/goals/goal2
[6] https://www.un.org/sustainabledevelopment/wp-content/uploads/2016/08/2_Why-It-Matters-2020.pdf

(MCs) and non-European Mediterranean countries (nMCs). Croatia, Cyprus, France, Greece, Italy, Malta, Portugal, Slovenia, and Spain belong to the first group, whereas for the second group we consider Algeria, Egypt, Israel, Jordan, Lebanon, Morocco, Tunisia, and Turkey.

Table 1 – *Analysed SDG Targets for Goal 2*

Code	SDG sub-indicator	Missing (After sel.)	Lower Bound (=0)	Upper Bound (Optimum, =100)	Justification for Optimum
undernsh	Prevalence of undernourishment (%)	47 (19)	42.3	0	SDG Target
stunting	Prevalence of stunting in children under 5 years of age (%)	30 (2)	50.2	0	SDG Target
wasting	Prevalence of wasting in children under 5 years of age (%)	30 (2)	16.3	0	SDG Target
obesity	Prevalence of obesity, BMI ≥ 30 (% of adult population)	30 (2)	35.1	2.8	Average of best performers
trophic	Human Trophic Level (best 2-3 worst)	34 (6)	2.47	2.04	Average of best performers
crlyld	Cereal yield (tonnes per hectare of harvested land)	30 (2)	0.2	7	Average of best performers
snmi	Sustainable Nitrogen Management Index (best 0-1.41 worst)	30 (2)	1.2	0	Technical Optimum
yieldgap	Yield gap closure (% of potential yield)	166 (Drop)	28	77	Average of best performers
Pestexp	Exports of hazardous pesticides (tonnes per million population	80 (52)	250	0	Technical Optimum

Our elaboration on Sachs et al. (2021).

For each country, we compute the Arithmetic Mean, the Geometric Mean and the Penalized Geometric Mean. Table 2 reports some basic statistics for the three methods for all countries (All) and for the selected Mediterranean ones (Medit).

Table 2 – *Basic statistics.*

	Arithmetic Mean		Geometric Mean		Penalized Geometric Mean	
	All	Medit	All	Medit	All	Medit
Min	0.2332	0.5510	0.2172	0.5178	0.1840	0.4523
Max	0.8246	0.7499	0.8106	0.7220	0.7830	0.6644
Range	0.5914	0.1989	0.5935	0.2042	0.5990	0.2121
Sd. dev	0.1069	0.0577	0.1077	0.0585	0.1112	0.0617
Coeff.var	0.1817	0.0907	0.1918	0.0969	0.2197	0.1150

Our elaboration.

Table 3 reports the comparisons between the standard SDG index computed according to Sachs et al. (2021) methodology, that is, by using the Arithmetic mean (AM), the classical Geometric mean (GM) and our methodology (pGM), both in terms of values and rank. Then, for GM and pGM, the magnitude of the decrease (or increase) with respect to the standard SDG Index (AM) is reported in percentage terms. Finally, the rank difference between pGM and AM is provided.

Table 3 – *Comparisons.*

	Values			Reduction		Rank			Rank diff
	AM	GM	pGM	GM on AM	pGM on AM	AM	GM	pGM	pGM vs AM
CYP	0.59	0.55	0.47	-6.93	-20,53	94	102	110	16
DZA	0.57	0.54	0.50	-3.78	-11,32	114	109	99	-15
EGY	0.64	0.61	0.56	-4.51	-13,69	49	56	60	11
ESP	0.64	0.61	0.54	-5.20	-15,64	56	61	74	18
FRA	0.74	0.70	0.61	-5.42	-17,10	10	11	23	13
GRC	0.66	0.63	0.58	-4.19	-12,57	39	38	45	6
HRV	0.75	0.72	0.66	-3.73	-11,41	6	7	6	0
ISR	0.62	0.58	0.51	-6.17	-18,31	69	81	96	27
ITA	0.71	0.68	0.62	-3.97	-12,24	19	19	18	-1
JOR	0.60	0.56	0.48	-6.42	-19,63	90	98	105	15
LBN	0.57	0.54	0.49	-4.76	-14,34	111	108	103	-8
MAR	0.62	0.60	0.56	-3.61	-10,79	65	62	58	-7
MLT	0.67	0.64	0.57	-4.89	-14,75	34	35	48	14
PRT	0.64	0.60	0.50	-7.13	-21,68	53	71	98	45
SVN	0.59	0.55	0.45	-7.61	-22,93	97	107	120	23
TUN	0.55	0.52	0.45	-6.04	-17,93	118	121	122	4
TUR	0.65	0.62	0.56	-4.47	-13,63	42	50	55	13

Our elaboration.

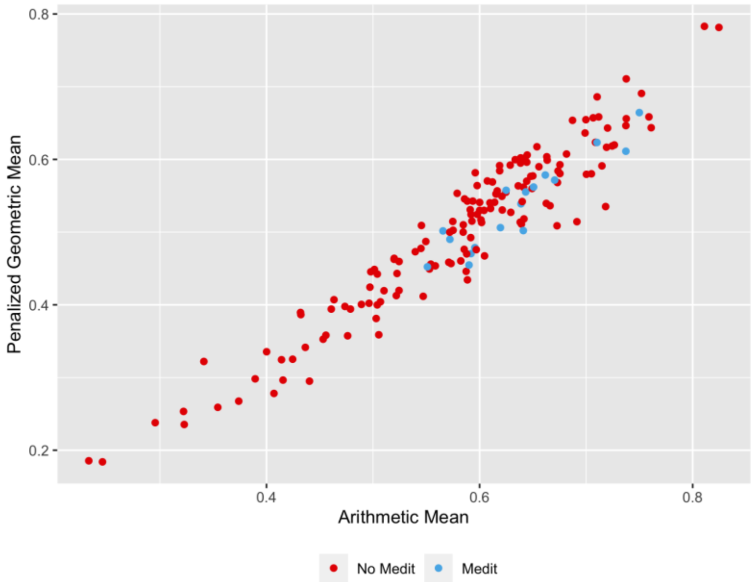
By analyzing the results for all Countries, the comparisons between Penalized Geometric Mean and Geometric Mean shows an absolute average ranking difference of 8.582 (position). The 95% of countries change their ranking position and the 82% of countries change at least 2 positions. Looking at Mediterranean Countries, Algeria (DZA) exhibits the largest improvement (from position 109 according to GM to position 99 with pGM), whereas Portugal (PRT) and Israel (ISR) register the largest worsening: Portugal moves from position 71 to position 98 and Israel loses 15 positions (from 81 to 96).

The comparisons between Penalized Geometric Mean and Arithmetic Mean reveals a higher absolute average ranking difference (about 12.90). The 98% of countries change their ranking position and the 88% of countries change at least 2 positions. Among Mediterranean Countries, Algeria improves of 15 positions (from 114 of the AM to 99 according the pGM) whereas Portugal and Israel are the most penalized in the position: 45 (from 53 according to the AM to 98 using pGM) and 27 (from 69 to 96), respectively.

What it is interesting is that countries with the largest improvement and worsening are the same.

Figure 1 reports the values of the penalized Geometric Mean (pGM) (vertical axis) versus the Arithmetic Mean (horizontal axis). Mediterranean countries are in blue, whereas the rest of the World is in red. The distribution of data exhibits a convexity meaning that the penalized Geometric Mean penalizes more countries with lower values.

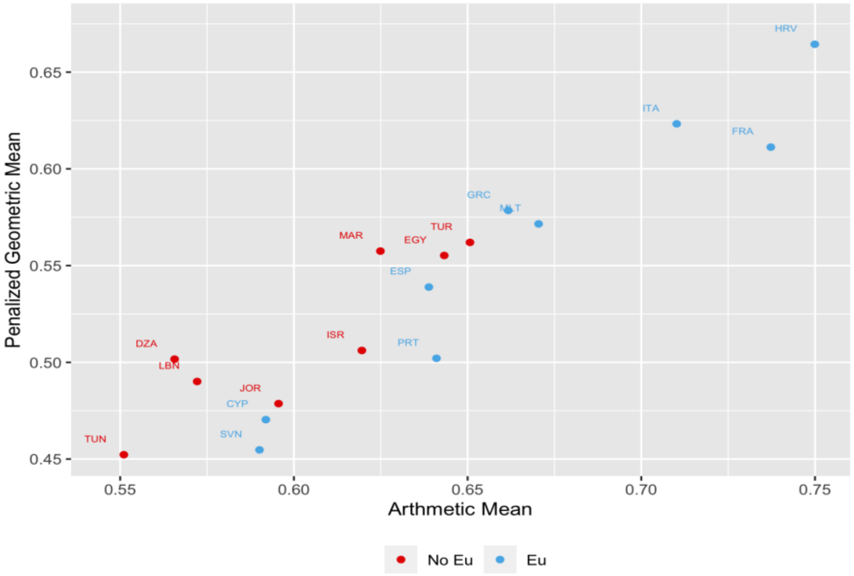
Figure 1 – *Penalized Geometric Mean vs Arithmetic Mean.*



Our elaboration.

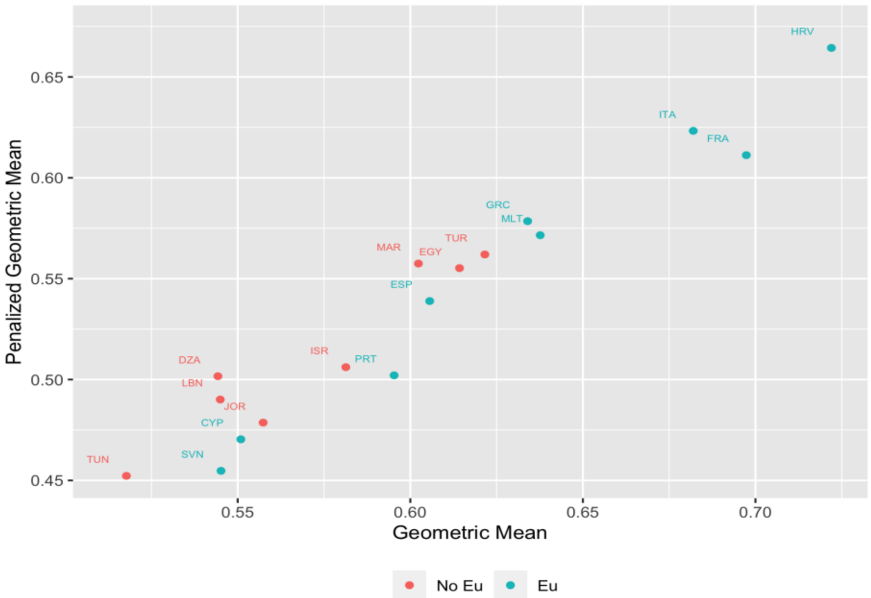
By combining results of Table 2 with Figure 1, what emerges is that the values of Mediterranean Countries are higher than the most of Worldwide countries. To better investigate those differences, we focus on Mediterranean Countries, and we compare the results of the penalized Geometric Mean (horizontal axes) with the Arithmetic mean (Figure 2) and the Geometric Mean (Figure 3).

Figure 2 – *Penalized Geometric Mean vs Arithmetic Mean for Mediterranean Countries.*



Our elaboration.

Figure 3 – *Penalized Geometric Mean for Mediterranean Countries vs Geometric Mean.*



Our elaboration.

Both figures show that non-European countries (red dots in Figure 2 and Figure 3) have, on average, worse performances respect to European Countries (blue dots), in fact they are distributed in the part of the graph on the left. Among European Countries, Cyprus (CYP) and Slovenia (SVN) display performance like the no-European ones whereas, among the no-European Countries, Turkey (TUR), Egypt (EGY) and Morocco (MAR) are ranked better than some European Countries such as Spain (ESP) or Portugal (PRT).

This can lead to some considerations concerning the Goal 2: in one hand, Cyprus and Slovenia are more similar to the no-European Countries than to European one, on the other hand, Turkey, Egypt and Morocco can be considered European Countries since their values are similar to those of Spain and Portugal. Moreover, unexpectedly, Croatia is the country with the highest performances, higher than France and Italy that are respectively ranked at the second and third position among Mediterranean Countries.

4. Conclusions and Further research

In this work we have analysed a particular member of the class of composite indicators obtained penalizing the p-order generalized mean with a factor that accounts for the (horizontal) variability of the sub- indicators introduced in Mariani et al. (2022), the so-called penalized Geometric Mean (pGM).

This index has several advantages: i) it allows for a discrimination among units with same generalized mean; ii) it accounts for the degree of (horizontal) variability experienced by each unit; iii) it is based on the minimum information loss principle, usually used for constructing composite indicators; iv) it manages way the interaction between sub-indicators in a more flexible.

This is a first attempt and further research will be conducted. For instance, we want to extend the analysis conducted for Goal 2 to all 17 Goals and, consequently, computing the analogous of the overall SDG Index aggregating the 17 SDG indices through the pGM methods (second stage aggregation).

Moreover, we believe that in some context could be of potential interest to add weighs reflecting a sort of relative importance of the sub-indicators. For this reason, it is necessary to develop a weighted version of the penalized Geometric Mean.

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SUMMARY

SDG composite indicators for Mediterranean countries: a new theoretical approach

Composite indicators provide summary picture of multidimensional phenomena, and the corresponding rankings facilitate evaluations and comparisons over time and space.

Standard composite indicators often assume compensability among indicators. We argue that the compensability hypothesis needs to be restricted especially when analyzing economic, social and environmental aspects.

Among all the member of the new family of composite indicators made by penalized versions of the generalized means introduced by Mariani et al (2022), we focus on the penalized Geometric Mean (pGM). This index is defined by means of a penalty factor that accounts for the (horizontal) variability of the normalized indicators opportunely scaled and transformed via the Box-Cox function.

To illustrate the appealing of our proposal, we compute penalized Geometric Mean and we compare it with the Arithmetic Mean and the Geometric Mean. We focus on data referring to the Sustainable Development Goals (SDGs) (Sachs et al., 2021). More in datail, among the 17 Goals, analyse Goal 2: “End hunger, achieve food security and improved nutrition and promote sustainable agriculture”, the so-called “Zero Hunger” and we compute the three indices for world-wide Countries with a focus on 17 Mediterranean Countries.

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WEIGHTING IN COMPOSITE INDICES CONSTRUCTION: THE CASE OF THE MAZZIOTTA-PARETO INDEX[1]

Matteo Mazziotta, Adriano Pareto

1. Introduction

Assigning weights to indicators is a very difficult operation and not without risks of a conceptual and methodological nature (Booysen, 2002; Salzman, 2003; OECD, 2008). Even no weighing still means assigning a weight, i.e., the same for all indicators (Greco et al., 2019).

The issue of choosing a weighting system for individual indicators that represents their different importance in expressing the phenomenon considered, necessarily involves the introduction of an arbitrary component. Subjective weighting can be adopted, implicitly, by assigning the same weight to all components (equal weights) or, explicitly, by means of a group of experts who establish the weight of each elementary indicator. Alternatively, an objective weighting can be adopted, implicitly, by choosing a normalization method that assigns a weight proportional to the variability of the elementary indicators or, explicitly, by calculating the weights using a multivariate analysis method, such as Principal Components Analysis (PCA).

The purpose of the explicit weighting is that each weight should represent the relative theoretical importance of the corresponding individual indicator. The explicit weights assigned to the individual indicators heavily influence the values of the composite index. Hence, the weights should be defined on the basis of a well-defined theoretical framework.

The techniques most used to explicitly weight the individual indicators are the following: a) no weighting or assignment of ‘equal’ weights, b) subjective or expert weighting, and c) weighting by PCA (Mazziotta and Pareto, 2017).

In the case a) if no explicit weight is defined, in addition to the implicit weighting induced by normalization, the individual indicators are weighted with equal weights. This implies that all the components of the composite index have the same importance, except for the implied weight, and this may not be correct.

[1] The paper is the result of the common work of the authors: in particular M. Mazziotta has written Sections 1, 4 and A. Pareto has written Sections 2, 3.

However, if there are no precise theoretical or empirical reasons for choosing different weights, this can be a valid solution in various contexts.

In the case b), subjective or expert weighting is an arbitrary weighting carried out by the researcher or by specialists in the phenomenon who define the weight of each individual indicator. The values obtained are then summarized using a specific function. Sometimes, the weights are defined by policy makers or through sample surveys in which the interviewed is asked to evaluate the importance of the various aspects that make up the phenomenon.

In the case c) PCA can be used to define the weights of the individual indicators by means of the coefficients obtained for the first main component. This empirical solution is relatively more objective than the others and has the advantage of considering the set of weights that 'explain' most of the variance of the indicators. However, the reliability of the weights obtained depends on the variance explained by the first component and on the structure of the correlations between the individual indicators which does not remain constant over time. And above all, it is absolutely not true that variability is a synonym of theoretical importance of the individual indicators.

In short, as mentioned, the issue of weighting is very complex, and each solution has advantages and disadvantages. Moreover, if it is true (and it is true) that the perfect composite index does not exist then it is equally true that it is not possible to have a system of weights without arbitrariness.

In this paper, the methodological problem of the assignment of weights is faced with respect to the two versions of the Mazziotta-Pareto Index (Mazziotta and Pareto, 2016).

2. Weighting the Mazziotta-Pareto Index

The Mazziotta-Pareto Index (MPI) - and its variant Adjusted MPI (AMPI) - is a composite index for summarizing a set of indicators that are assumed to be not fully substitutable. It is based on a non-linear function which, starting from the simple arithmetic mean of the normalized indicators, introduces a penalty for the units with unbalanced values of the indicators (Mazziotta and Pareto, 2016). This methodology is often applied to the calculation of both non-compensatory[2] composite indices of 'positive' phenomena, such as well-being and sustainable development, and 'negative' phenomena, such as poverty.

[2] In a non-compensatory approach, all the dimensions of the phenomenon must be balanced and an aggregation function that takes unbalance into account, in terms of penalization, is used (Casadio Tarabusi and Guarini, 2013).

In the MPI and AMPI, all components are assumed to have equal importance, which may not be the case (Boysen, 2002; Mazziotta and Pareto, 2020). In this Section a weighted version of the two indices (WMPI and WAMPI, where W stands for “Weighted”) is proposed, when a set of weights is available.

2.1. The WMPI

Given the matrix $\mathbf{X}=\{x_{ij}\}$ with n rows (statistical units) and m columns (individual indicators), we calculate the standardized matrix $\mathbf{Z}=\{z_{ij}\}$ as follows:

$$z_{ij}=100\pm\frac{(x_{ij}-\mathrm{M}_{x_j})}{\mathrm{S}_{x_j}}10 \tag{1}$$

where M_{x_j} and S_{x_j} are, respectively, the mean and standard deviation of the indicator j and the sign ± is the polarity[3] of the indicator j.

If a set of weights w_j (j=1, ..., m) is available; where w_j is the weight of individual indicator j ($0 < w_j < 1$) and $\sum_{j=1}^{m} w_j = 1$, we can calculate the weighted mean and weighted standard deviation of the standardized values of unit i (i=1, ..., n) as follows:

$$\overline{\mathrm{M}}_{z_i}=\sum_{j=1}^{m} z_{ij}w_j \;;$$

$$\overline{\mathrm{S}}_{z_i}=\sqrt{\sum_{j=1}^{m}(z_{ij}-\mathrm{M}_{z_i})^2 w_j}$$

Denoting with $\overline{\mathrm{cv}}_i=\overline{\mathrm{S}}_{z_i}\big/\overline{\mathrm{M}}_{z_i}$ the weighted coefficient of variation (Sheret, 1984) for unit i, the generalized form of the WMPI is given by:

$$\mathrm{WMPI}_i^{+/-}=\overline{\mathrm{M}}_{z_i}\pm\overline{\mathrm{S}}_{z_i}\,\overline{\mathrm{cv}}_i \tag{2}$$

[3] The polarity of an individual indicator is the sign of the relation between the indicator and the phenomenon to be measured (+ if the individual indicator represents a dimension considered positive and - if it represents a dimension considered negative).

where $\overline{\mathrm{M}}_{z_i}$ is the 'mean level', $\bar{\mathrm{S}}_{z_i}\overline{\mathrm{cv}}_i$ is the 'penalty' (i.e., the 'horizontal variability')[4] and the sign ± depends on the kind of phenomenon to be measured. If it is 'positive', then the WMPI$^-$ is used; else the WMPI$^+$ is used.

If $w_j = \frac{1}{m}$ (j=1, ..., m), we have: $\mathrm{WMPI}_i^{+/-} = \mathrm{MPI}_i^{+/-}$ (i.e., the classical MPI).

2.2. *The WAMPI*

Given the matrix **X**={x_{ij}}, we calculate the normalized matrix **R**={r_{ij}} as follow:

$$r_{ij} = 100 \pm \frac{x_{ij} - \mathrm{Ref}_{x_j}}{\mathrm{Max}_{x_j} - \mathrm{Min}_{x_j}} 60 \tag{3}$$

where Min_{x_j} and Max_{x_j} are the 'goalposts' for indicator j. (e.g., the minimum and maximum of indicator j), Ref_{x_j} is a reference value[5] for indicator j (e.g., the mean of indicator j) and the sign ± depends on the polarity of indicator j.

Denoting with $\overline{\mathrm{M}}_{r_i}$ and $\bar{\mathrm{S}}_{r_i}$, respectively, the weighted mean and weighted standard deviation of the normalized values of unit i, the generalized form of WAMPI is given by:

$$\mathrm{WAMPI}_i^{+/-} = \overline{\mathrm{M}}_{r_i} \pm \bar{\mathrm{S}}_{r_i}\overline{\mathrm{cv}}_i \tag{4}$$

where $\overline{\mathrm{cv}}_i = \bar{\mathrm{S}}_{r_i} \big/ \overline{\mathrm{M}}_{r_i}$ is the weighted coefficient of variation for unit i.

If $w_j = \frac{1}{m}$ (j=1, ..., m), we have: $\mathrm{WAMPI}_i^{+/-} = \mathrm{AMPI}_i^{+/-}$ (i.e., the classical AMPI).

[4] The penalty is a function of the indicators' variability in relation to the mean value and is used to penalize the units. The aim is to reward the units that, mean being equal, have a greater balance among the individual indicators.

[5] Note that the reference value is very important, since the set of reference values of all the indicators defines the 'balancing model' (Mazziotta and Pareto, 2021).

3. Some numerical examples

In this section, we present, through some numerical examples, the calculation of WMPI and WAMPI with negative penalty. Similar results are obtained for the two versions with positive penalty.

Table 1 – *Computing the WMPI$^-$ con different weights.*

Unit	Original indicators			Normalized indicators			Mean	Std	CV	Penalty	WMPI$^-$	
	X_1	X_2	X_3	Z_1	Z_2	Z_3					Value	Rank
			Weights	**0.33**	**0.33**	**0.33**						
1	110	1	0.4	114.1	87.8	100.0	100.6	10.8	0.107	1.16	99.5	3
2	90	3	0.2	107.1	108.2	90.9	102.0	7.9	0.077	0.61	101.4	2
3	70	3	0.8	100.0	108.2	118.3	108.8	7.5	0.069	0.51	108.3	1
4	50	3	0.2	92.9	108.2	90.9	97.3	7.7	0.079	0.61	96.7	4
5	30	1	0.4	85.9	87.8	100.0	91.2	6.3	0.069	0.43	90.8	5
r	0.545	0.599	0.587									
			Weights	**0.60**	**0.20**	**0.20**						
1	110	1	0.4	114.1	87.8	100.0	106.0	10.7	0.101	1.07	105.0	1
2	90	3	0.2	107.1	108.2	90.9	104.0	6.6	0.063	0.42	103.6	3
3	70	3	0.8	100.0	108.2	118.3	105.3	7.2	0.069	0.49	104.8	2
4	50	3	0.2	92.9	108.2	90.9	95.6	6.4	0.066	0.42	95.1	4
5	30	1	0.4	85.9	87.8	100.0	89.1	5.5	0.062	0.34	88.7	5
r	0.894	0.328	0.304									
			Weights	**0.20**	**0.60**	**0.20**						
1	110	1	0.4	114.1	87.8	100.0	95.5	10.5	0.110	1.15	94.3	4
2	90	3	0.2	107.1	108.2	90.9	104.5	6.8	0.065	0.45	104.0	2
3	70	3	0.8	100.0	108.2	118.3	108.6	5.8	0.053	0.31	108.2	1
4	50	3	0.2	92.9	108.2	90.9	101.7	8.0	0.079	0.63	101.0	3
5	30	1	0.4	85.9	87.8	100.0	89.8	5.1	0.057	0.29	89.5	5
r	0.266	0.912	0.310									
			Weights	**0.20**	**0.20**	**0.60**						
1	110	1	0.4	114.1	87.8	100.0	100.4	8.4	0.083	0.70	99.7	2
2	90	3	0.2	107.1	108.2	90.9	97.6	8.2	0.084	0.69	96.9	3
3	70	3	0.8	100.0	108.2	118.3	112.6	7.4	0.066	0.49	112.1	1
4	50	3	0.2	92.9	108.2	90.9	94.7	6.8	0.071	0.48	94.3	5
5	30	1	0.4	85.9	87.8	100.0	94.7	6.5	0.069	0.44	94.3	4
r	0.286	0.302	0.909									

In Table 1, the WMPI$^-$ is calculated for a matrix **X** of 5 statistical units and 3 incorrelated individual indicators, with four different sets of weights. In the first case, an equal weighting approach is followed (0.33 for each individual indicator), and we have WMPI$^-$=MPI$^-$. In the other three cases, we give the greatest weight (0.60), each time, to a different individual indicator and equal weights (0.20) to the other two. For each case, the table reports the individual indicators (X_1-X_3), the normalized indicators (Z_1-Z_3), the weighted mean, standard deviation and coefficient of variation and the WMPI$^-$ (value and rank). In the last row is also shown the correlation (*r*) between the WMPI$^-$ and the original indicators.

Table 2 – *Computing the WAMPI$^-$ con different weights.*

Unit	Original indicators			Normalized indicators			Mean	Std	CV	Penalty	WAMPI$^-$	
	X_1	X_2	X_3	Z_1	Z_2	Z_3					Value	Rank
			Weights	**0.33**	**0.33**	**0.33**						
1	110	1	0.4	130.0	64.0	100.0	98.0	27.0	0.275	7.43	90.6	4
2	90	3	0.2	115.0	124.0	80.0	106.3	19.0	0.178	3.39	102.9	2
3	70	3	0.8	100.0	124.0	140.0	121.3	16.4	0.135	2.23	119.1	1
4	50	3	0.2	85.0	124.0	80.0	96.3	19.7	0.204	4.02	92.3	3
5	30	1	0.4	70.0	64.0	100.0	78.0	15.7	0.202	3.18	74.8	5
r	0.407	0.739	0.535									
			Weights	**0.60**	**0.20**	**0.20**						
1	110	1	0.4	130.0	64.0	100.0	110.8	26.1	0.236	6.16	104.6	3
2	90	3	0.2	115.0	124.0	80.0	109.8	15.3	0.139	2.13	107.7	2
3	70	3	0.8	100.0	124.0	140.0	112.8	16.5	0.146	2.41	110.4	1
4	50	3	0.2	85.0	124.0	80.0	91.8	16.2	0.177	2.86	88.9	4
5	30	1	0.4	70.0	64.0	100.0	74.8	12.8	0.171	2.19	72.6	5
r	0.823	0.472	0.310									
			Weights	**0.20**	**0.60**	**0.20**						
1	110	1	0.4	130.0	64.0	100.0	84.4	26.7	0.317	8.46	75.9	4
2	90	3	0.2	115.0	124.0	80.0	113.4	17.1	0.150	2.57	110.8	2
3	70	3	0.8	100.0	124.0	140.0	122.4	12.8	0.105	1.34	121.1	1
4	50	3	0.2	85.0	124.0	80.0	107.4	20.4	0.190	3.87	103.5	3
5	30	1	0.4	70.0	64.0	100.0	72.4	14.0	0.193	2.70	69.7	5
r	0.140	0.955	0.253									
			Weights	**0.20**	**0.20**	**0.60**						
1	110	1	0.4	130.0	64.0	100.0	98.8	20.9	0.212	4.43	94.4	2
2	90	3	0.2	115.0	124.0	80.0	95.8	19.6	0.204	3.99	91.8	3
3	70	3	0.8	100.0	124.0	140.0	128.8	15.7	0.122	1.91	126.9	1
4	50	3	0.2	85.0	124.0	80.0	89.8	17.2	0.192	3.30	86.5	4
5	30	1	0.4	70.0	64.0	100.0	86.8	16.3	0.188	3.05	83.7	5
r	0.241	0.399	0.885									

As we can see, when the individual indicators have the same weight (0.33), the correlations with the WMPI$^-$ (that is the MPI$^-$) are very similar. In particular, we have $r(\text{WMPI}^-, X_1)=0.545$; $r(\text{WMPI}^-, X_2)=0.599$ and $r(\text{WMPI}^-, X_3)=0.587$.

On the contrary, when one individual indicator has a weight greater (i.e., is more important) than the others (0.66), the WMPI$^-$ is biased towards it. For instance, when w_1=0.60, w_2=0.20 w_3=0.20, we have $r(\text{WMPI}^-, X_1)=0.894$;

r(WMPI$^-$, X_2)=0.328 and r(WMPI$^-$, X_3)=0.304. Therefore, the ranking according to the WMPI$^-$ is much the same as that based on the most important individual indicator.

However, it is interesting to note that when individual indicators have different weights, the penalty changes. Thus, one unit that is more balanced with a certain set of weights (and then less penalized) may be more unbalanced with another set of weights (and then more penalized). It is the case of unit 1 that, with equal weighting, has a penalty of 10.8·0.107=1.16; whereas with weight w_3=0.60 has a penalty of 8.4·0.083=0.70[6].

Table 2 shows the calculation of the WAMPI$^-$, where a different normalization method is used (see formula 3). In this case, the 'goalposts' for each indicator are the minimum and maximum, and the reference value is the mean. Moreover, normalized indicators have the same range (and not the same variance as in the WMPI$^-$) and then the penalties are larger overall. Nevertheless, the result does not change and also the WAMPI$^-$ is most correlated with the individual indicators with the greatest weight. Indeed, if w_1=0.60 then r(WAMPI$^-$, X_1)=0.823, if w_2=0.60 then r(WAMPI$^-$, X_2)=0.955, and if w_3=0.60 then r(WAMPI$^-$, X_3)=0.885.

4. Concluding remarks

A composite index is a mathematical combination (or aggregation as it is defined) of a set of elementary indicators (or variables) that represent the different components of a multidimensional phenomenon to be measured (e.g., development, well-being, quality of life, corruption, etc.). Therefore, composite indices are used to measure concepts that cannot be captured by a single indicator.

Ideally, a composite index should be based on a theoretical framework that allows individual indicators to be selected, combined and weighted to reflect the size or structure of the phenomenon being measured. However, its construction is not simple and often requires a series of decisions / choices (methodological or not) to be made.

The decision to weigh in the same way both the individual indicators within any domains and the composite domain indices that will subsequently calculate the composite of the composites is justified by the arbitrariness that would be introduced if an objective approach were used (statistical techniques) or subjective (panel of experts) of weight assignment. However, weighing in the same way is a

[6] Note that with w_2=0.6 the penalty of unit 1 is similar to the penalty with equal weighting (1.15 vs 1.16), since the weighted standard deviation is less, but the weighted coefficient of variation is greater, and therefore the product does not change.

“non-neutral” choice, since it is decided to place both individual indicators and composite domain indices on the same level of importance.

The need to adapt these two composite indices with a system of weights arose during the pandemic when numerous international institutions had the need to measure the performance of the health system during the Covid emergency. In this context, the delicacy of the topic dealt with and the different nature of the individual indicators have focused attention on the different theoretical importance of the indicators themselves.

Introducing a weighting system in the MPI and AMPI allows to summarize a set of partially substitutable indicators that are assumed to have different importance. The experimentation of assigning weights to the MPI and the AMPI has brought comforting results, since the final composite indices actually undergo changes as a function of the intensity of the weight.

Certainly, the paper does not solve the problem of which system of weights is more appropriate, but it demonstrates how these two methodologies can be adaptable to a set of weights coming from objective and subjective approaches.

However, some aspects need to be further investigated. In particular:

- how the properties of the indices change with the introduction of weights;
- how outliers in indicators with high weights affect the values of the indices;
- how much the values of the indices differ from the values of other aggregation functions, such as the weighted geometric mean.

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SUMMARY

This paper presents a weighted version of the Mazziotta-Pareto Index (MPI) and Adjusted MPI (AMPI). Since the MPI and AMPI are based on the calculation of the mean and standard deviation of normalized values, for each unit, we calculate the weighted mean and weighted standard deviation of normalized values. The weighted coefficient of variation is then obtained by simply dividing the weighted standard deviation by the weighted mean. Finally, the two standard formulas can be applied. Some numerical examples are also shown, in order to assess the effect of different weighting schemes on the results.

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JUSTICE AS A PILLAR OF QUALITY OF LIFE: DISTRIBUTION OF TRUST IN JUSTICE ACROSS EUROPEAN COUNTRIES

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You shall not distort justice;
you shall not be partial, and you shall not take a bribe,
for a bribe blinds the eyes of the wise and perverts
the words of the righteous (*Deuteronomy*, 16:19 NASB95)

1. Introduction

The term *justice* has often been emerging in public debate and government policies. *Justice*, however, contains a twofold meaning. This point was emphasized by Aristotle (2020 [335-322 BC]: Book V), who distinguished between *distributive* justice, which involves equal shares for equals, unequal for unequals and different in different regimes, and *corrective* justice, which is meant to restore a fair balance in interpersonal relations when that balance has been violated. This second meaning is at the core of Hobbes' *Leviathan* (1985 [1651]), the work that laid the foundations of modern political science. According to Hobbes, in order to move from the state of nature to that of civil society, people must create rules of justice by means of agreements. These rules must then be enforced by a higher authority in charge of deterring people from violating them, protecting the law-abiding citizens, and making them obtain recovery for the injuries they have suffered.

In the last decades, the first meaning of justice seems to have attracted more interest than the second one. The term *justice* has been widely used as a synonym for social justice. This, in its contemporary sense, implies a fair income distribution among the community members and a better distribution of opportunities at the hands of the State. However, while social justice represents a complementary attribute of civil society, justice in itself – in its corrective form – is a necessary condition for the existence of civil society. Without corrective justice, rules would be breached with impunity, and the covenant between people and political authority, which is the source of civil society, would be structurally violated. Indeed, the individual would give up the freedom that he/she had in the state of nature, without receiving the expected return of the protection of the law. Therefore, a trustworthy justice system is the fundamental prerequisite of civil society. Yet, in many countries, the justice system suffers from corruption and ineffectiveness, and citizens might perceive judges and prosecutors as dishonest and/or incompetent.

On the other hand, social justice is not in opposition to corrective justice. A civil society with an efficient and fair justice system may also provide a substantial level of social justice. In contrast, extended social justice policies can be accompanied by an inefficient and/or unfair justice system. In fact, in both past and present, totalitarian regimes, in which political power dominates over the justice system, have often adopted extensive redistribution and social assistance policies. Several countries with fairly level income distributions (World Bank, 2022a) and broad social assistance policies have a relatively poor justice system, as rated by international agencies (World Justice Project, 2022).

Despite the attraction exerted by the social justice issue, there has been over the past years an increasing interest in measuring the citizens' trust in justice, the effectiveness and timeliness of the justice systems, the judges' independence, fairness and competence (European Union, 2020; European Union, 2021; World Bank, 2022b; World Justice Project, 2022). Over the last decades, *trust* has been regarded as a primary determinant of both the quality of life and development, via the creation of social capital (Putnam, 1993; Fukuyama, 1995). Still, trust concerns not only confidence in other people but also confidence in institutions. In the last case, trust can be defined as the probability – as perceived by citizens – that an institution delivers on its commitments, conditional on its past behaviour (World Bank, 2017). Ultimately, citizens' trust in their country's justice system is an irreplaceable opportunity for gauging the correctness and efficiency of that system, the quality of society, and, in general, the quality of life. Still, surveys meant to assess life satisfaction and quality of life (e.g. Eurofound, 2018) – while measuring also features relatively more individual, such as health and social relations – do pay special attention to the functioning of the welfare state by focusing on income distribution, social benefits, and public services. But, more often than not, they ignore citizens' satisfaction with an institution such as the justice system.

In the present paper, we will focus on the reliability of justice systems across European countries, as perceived by their citizens. We hypothesize that:

- H1. The perceived quality of the justice system varies across countries, but citizens' opinions are consistent over time, and find external confirmations.
- H2. The perceived quality of the justice system significantly impacts the quality of life, as shown by one's life satisfaction.

2. Data and methods

Micro data on trust in justice are the primary measure in this paper. They come from Standard EuroBarometer Surveys (European Union, 2021), which ask citizens from 40 European countries whether they "tend to trust" or "tend not to trust" justice and their country's legal system. EuroBarometer gathers citizens' opinions about the justice system as well as other opinions and attitudes regarding a variety of issues.

Thus, EuroBarometer allows micro-level analyses of the impact of trust in justice on other aspects of the interviewee's life. Of particular interest are the interviewees' opinions about their life satisfaction ("On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead?").

World Bank Governance Indicators (hereafter WGI), in turn, provide further measures related to justice and the legal system (World Bank, 2022b). The indicators consist of macro data covering 214 world countries and are based on information provided by various sources. Among them are surveys of individuals or domestic firms with first-hand knowledge of the governance situation in the country (e.g., World Economic Forum's Global Competitiveness Report, Gallup World Poll). A second source are analysts at major development agencies (e.g., European Bank for Reconstruction and Development and World Bank) and other public sector providers (e.g., the United States Department of State). A third source are nongovernmental organizations (e.g., Freedom House and Bertelsmann Foundation). And a fourth source are business information providers (e.g., Economist Intelligence Unit).

WGIs comprise six measures: voice and accountability, political stability and absence of violence/terrorism, government effectiveness, regulatory quality, rule of law, and control of corruption. The last two measures are particularly relevant to the functioning of the justice/legal system. Rule of law captures "the extent to which agents have confidence in and abide by the rules of society, and in particular, the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence" (Kaufmann *et al.*, 2011). Control of corruption, in turn, captures "perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the State by elites and private interests" (Kaufmann *et al.*, 2011).

World Justice Project (hereafter WJP) (2022) provides additional data on the functioning of the justice system. WJP publishes macro data covering 139 world countries (2021). Its source is twofold: a qualified respondents' questionnaire completed by in-country legal practitioners, experts, and academics, and a population survey conducted by local polling companies, using a representative sample of 1,000 respondents in each country. WJP produces a rule of law index summarizing eight factors: constraints on government powers, absence of corruption, open government, fundamental rights, order and security, regulatory enforcement, civil justice, and criminal justice. Apart from the absence of corruption, which largely corresponds to control of corruption by WGI, the factors civil justice and criminal justice are potentially more suitable to measure the quality of justice systems. Civil justice measures whether civil justice is affordable, free of discrimination, corruption and improper government influence, not subject to unreasonable delay and effectively enforced. Criminal justice measures whether criminal justice is impartial, free of corruption and improper government influence, timely and effective, the rights of the accused guaranteed, criminal investigation effective and the correctional system effective in reducing crime.

3. Results

Figure 1 shows the distribution of trust in justice across European countries. One can immediately perceive the wide deviation from the mean shown by the values of certain countries. Because trust in justice values consist in percentages, ordinary measures of the amount of variation or dispersion of a set of values – such as the standard deviation – are not appropriate to the task. We recurred, therefore, to the median absolute deviation (MAD) from the average value.[1] In as many as eight countries, trust in justice values exhibit a positive/negative deviation of more than 1.5 MAD, confirming the dispersion of the trust in justice values, of which at H1. We notice also a polarization of the geo-political areas, with “Balkans and Southeastern Europe” and “Western and Nordic Europe” at the two ends of the scale.

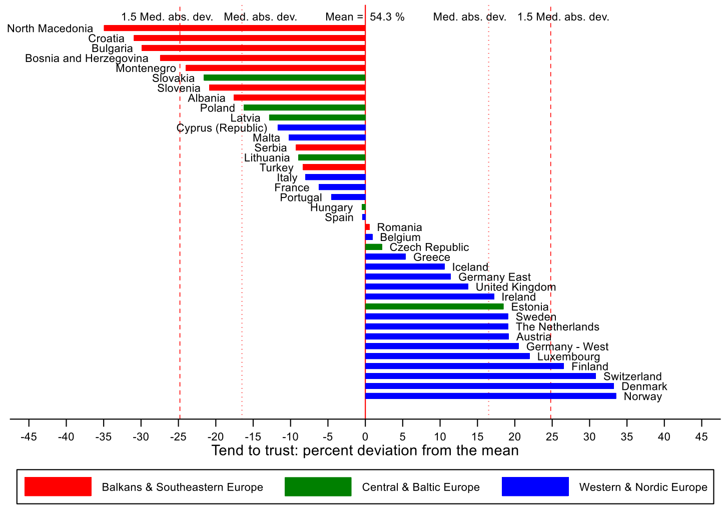
Next, we assessed whether trust in justice values of the 2021 survey are consistent with values recorded in previous surveys. Table 1 shows the correlations between the values from the EuroBarometers of 2015, 2017, 2019 and 2021. The minimum correlation value is 0.865 and the maximum 0.955, with an average of 0.901. The consistency over time of trust in justice data is evidence of their reliability. Yet, this consistency is not absolute and slightly declines as the time gap increases. Figure 2 shows the distribution of trust in justice values recorded in 2021 against the values recorded in 2015. We can notice some values relatively distant from the predicted ones. Most of them are produced by values for the year 2021 significantly lower than those recorded in 2015. In particular, the broadest decrease in value regarded Montenegro, followed by Turkey, Croatia, North Macedonia, and Poland. These countries have registered, since 2015, political changes that – according to the evaluations made by international agencies – have affected the independence and impartiality of their justice systems (Amnesty International 2022). Ultimately, the analysis of the evolution of trust in justice values suggests that the citizens’ perception of their justice system – while being consistent over time – is reactive to major political and social changes.

Nevertheless, these qualities of trust in justice values do not make them impervious to subjectivity. Trust in justice is based on the citizens’ perception, which

[1] We wanted to obtain 1.5 MAD intervals relatively wider to identify only outermost outliers. Therefore, we chose the deviations from the mean, which are larger than those from the median. Then, we chose the median of the deviations because our distributions were left-skewed and the medians greater than the means.

personal values and attitudes can heavily influence. Moreover, poor knowledge of the situation in other countries could distort this perception. It is therefore essential to check whether citizens' trust in justice is in tune with indicators of legality, justice system efficiency and enforcement actions based on the opinion of experts working for international evaluation agencies. Table 2 reveals that trust in justice values strongly correlate with expert evaluations on the rule of law, control of corruption, civil justice, and criminal justice.

Figure 1 – *Trust in justice across European countries. Bars with 1 and 1.5 MAD intervals.*



Source: Standard Eurobarometer 2021.

Table 1 – *Trust in justice over time. European countries. Pearson correlations and (p-value).*

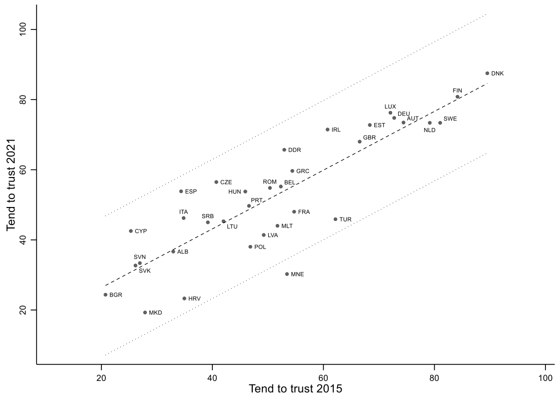
Variables	(1)	(2)	(3)
(1) Tend to trust 2021	1		
(2) Tend to trust 2019	0.935 (0.000)	1	
(3) Tend to trust 2017	0.904 (0.000)	0.953 (0.000)	1
(4) Tend to trust 2015	0.865 (0.000)	0.920 (0.000)	0.955 (0.000)
N = 34-38			

Source: Standard Eurobarometer 2015, 2017, 2019, 2021.

The biplot in Figure 3 allows a graphical display of both the five interrelated indicators and the observations (countries). The biplot shows the relatively narrow cosines between the indicators and the close-by placement of the countries with the highest trust in justice values, from Denmark and Norway to the United Kingdom (Iceland and East Germany – see Figure 1 – are not taken into account in WJP).

Further scatter plots help to better understand the association between trust in justice and indicators of legality, justice system efficiency and enforcement actions.

Figure 2 – *Evolution over time (2015-2021) of trust in justice data. European Countries. Scatter with fit line and 1.5 MAD intervals.*[2]



Source: Standard Eurobarometer 2015 and 2021.

Table 2 – *Trust in justice and indicators of justice system efficiency and enforcement actions. European countries. Pearson correlation coefficients and (p-values).*

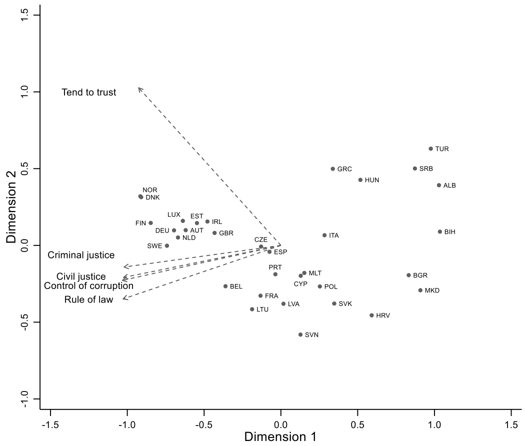
Variables	(1)	(2)	(3)	(4)
(1) EU Barometer: Trust in justice	1			
(2) World Bank: Rule of law	0.782 (0.000)	1		
(3) World Bank: Control of corruption	0.800 (0.000)	0.967 (0.000)	1	
(4) World Justice Project: Civil justice	0.790 (0.000)	0.924 (0.000)	0.926 (0.000)	1
(5) World Justice Project: Criminal justice	0.799 (0.000)	0.917 (0.000)	0.910 (0.000)	0.926 (0.000)
N = 33-37				

Source: Standard Eurobarometer 2021, World Bank Governance Indicators 2020, World Justice Project 2021.

Figure 4 plots trust in justice against rule of law (WGI). Rule of law scores for Turkey, Albania and Serbia are much lower than those expected from their trust in justice. We notice that Turkey, Albania and Serbia are also countries with very low scores of rule of law: it is not unreasonable to imagine that – when a country is particularly lacking in rule of law – confidence in justice may be a self-heartening answer to the perception that rules are too often broken.

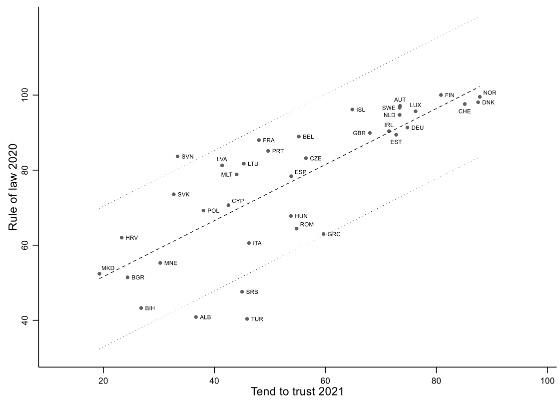
[2] In this Figure and in the following ones, countries' acronyms are those from ISO 3166-1 alpha-3.

Figure 3 – *Trust in justice and other indicators of justice system efficiency and enforcement actions. European countries. Biplot, with std variables, symmetrically scaled (alpha=0.5).*



Source: Standard Eurobarometer 2021, World Bank Governance Indicators 2020, World Justice Project 2021.

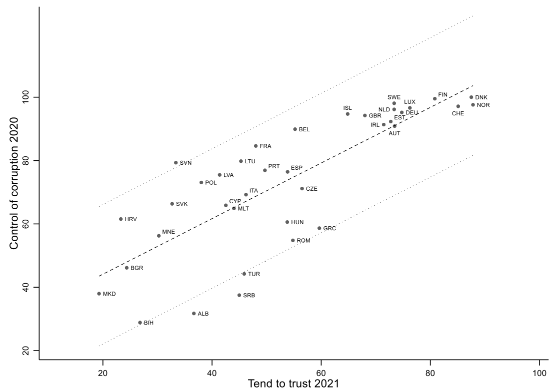
Figure 4 – *Trust in justice and rule of law. European countries. Scatter with fit line and 1.5 MAD intervals.*



Source: Standard Eurobarometer 2021, World Bank Governance Indicators 2020.

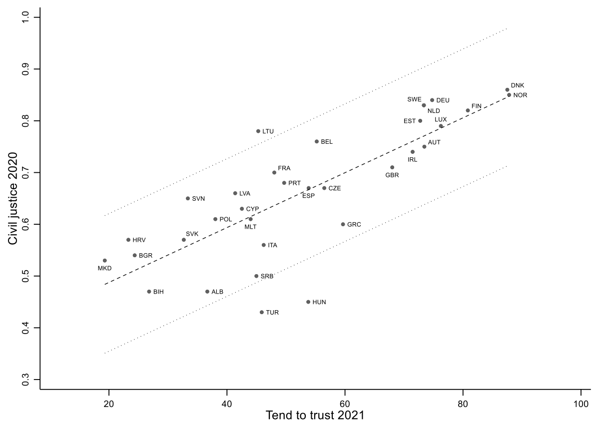
The distribution of trust in justice against that of control of corruption (WGI) shows somewhat similar findings (Figure 5). Serbia, Albania and Turkey are again the major outliers. The two scatters showing the distribution of trust in justice against WJP's civil justice (Figure 6) and criminal justice (Figure 7) also display some outliers. As for civil justice, Hungary and Turkey are countries with much lower expert evaluations than we would expect from their citizens' trust in justice. The opposite occurs with Lithuania. As for criminal justice, Turkey, Hungary, Serbia and Greece are the major outliers.

Figure 5 – *Trust in justice and control of corruption. European countries. Scatter with fit line and 1.5 MAD intervals.*



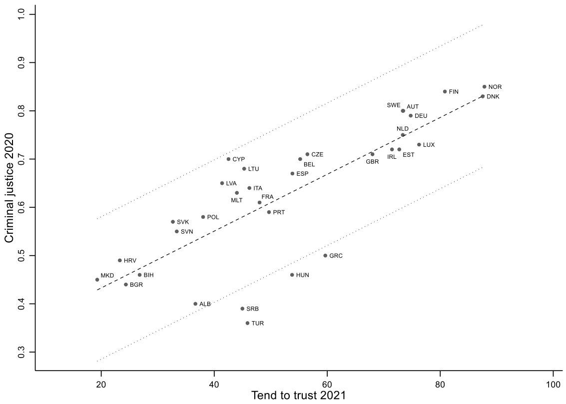
Source: Standard Eurobarometer 2021, World Bank Governance Indicators 2020.

Figure 6 – *Trust in justice and civil justice. European countries. Scatter with fit line and 1.5 MAD intervals.*



Source: Standard Eurobarometer 2021, World Justice Project 2021.

Figure 7 – *Trust in justice and criminal justice. European countries. Scatter with fit line and 1.5 MAD intervals.*



Source: Standard Eurobarometer 2021, World Justice Project 2021.

Overall, the substantial concordance between trust in justice and indicators of justice system efficiency and enforcement shows that citizens' perceptions of their justice system are reliable and supported by external sources. Partial discordances between trust in justice and the aforementioned indicators seem to stem from some heterogeneity in content, despite their belonging to the same broader domain.

The reliability of the European citizens' trust in justice indirectly espouses the hypothesis that their perception of such an essential matter as justice impacts their quality of life and affects their life satisfaction. Yet, we need some direct empirical evidence to prove this hypothesis. Table 3 is a first attempt in this direction.

Table 3 – *Tabulation of trust in justice and life satisfaction. European countries.*

TRUST IN INSTITUTIONS: JUSTICE / LEGAL SYSTEM	LIFE SATISFACTION				
	Very satisfied	Fairly satisfied	Not very satisfied	Not at all satisfied	Total
Tend to trust	5573	11398	1681	210	18862
Tend not to trust	2404	8945	3468	872	15689
Total	7977	20343	5149	1082	34551

Pearson design based F (2.95, 1.0 e05) = 192.94 P = 0.0000. Source: Standard Eurobarometer 2021.

The tabulation of trust in justice and life satisfaction shows that trust in justice is significantly associated with higher life satisfaction and vice versa. However, life satisfaction is affected by several socio-economic and individual factors and, therefore, the statistical association in Table 3 could be a spurious one. Thus, in Table

4, we recurred to a generalized structural equation model (GSEM) to measure the said association in depth.

Table 4 – *The effect of trust in justice, national government and parliament on life satisfaction, controlling for gender, age, education, left/right political placement, Gini, and country-specific effects. European countries. GSEM using ordered logistic regressions.*

DEPENDENT, Independent Variables and *Effects*	Exp(b)	Robust Std. Err.	Z	P>Z
Direct Effects				
LIFE SATISFACTION				
-Trust in Justice (base: Tend to trust)				
Tend not to trust	0.609	0.019	–16.21	0.000
-Trust in National Government (base: Tend to trust)				
Tend not to trust	0.629	0.022	–13.03	0.000
-Trust in National Parliament (base: Tend to trust)				
Tend not to trust	0.745	0.027	–8.03	0.000
- Gender (base: Man)				
Woman	1.071	0.027	2.70	0.007
- Age (base: 15-24)				
25-39	0.978	0.078	–0.27	0.785
40-54	0.800	0.063	–2.82	0.005
55-98	0.828	0.065	–2.41	0.016
- Education years (base: Up to 15)				
16-19	1.293	0.062	5.32	0.000
20+	1.771	0.090	11.29	0.000
- Left/Right Placement (1 to 10)	1.044	0.007	6.69	0.000
- Gini index (by country)	0.958	0.013	–3.10	0.002
TRUST IN NATIONAL GOVERNMENT				
-Trust in Justice (base: Tend to trust)				
Tend not to trust	6.450	0.185	65.11	0.000
TRUST IN NATIONAL PARLIAMENT				
-Trust in Justice (base: Tend to trust)				
Tend not to trust	7.185	0.212	66.92	0.000
Indirect Effects				
LIFE SATISFACTION				
-Trust in Justice (base: Tend to trust)				
Tend not to trust	28.157	1.697	–16.59	0.000
- Country-specific effects (base: Spain)				
Joint test: chi2(102) = 5190; Prob. > chi2 = 0.000				
Obs = 25,961 to 34,084 (Countries = 38)				
Log likelihood = –60288				

Source: Standard Eurobarometer 2021.

Firstly, we compared the impact on life satisfaction of trust in justice with the impact of trust in national government and trust in parliament. Secondly, we added a few standard controls (gender, age, education), the interviewee's left/right political placement, and income inequality (by country). Thirdly, we measured the effects of trust in justice on life satisfaction as they are mediated by the association between trust in justice and both trust in government and trust in parliament. Fourthly, we measured the country-specific effects to control for differences across European countries. Table 4 shows that the statistical impact of trust in justice on life satisfaction is greater than that of trust in national government and parliament; that the Gini index impacts – as expected – life satisfaction, but much less than trust in justice; and that trust in justice has a large impact on both trusts in national government and parliament, with also indirect effects on life satisfaction.

4. Conclusions

Our findings show that citizens' trust in justice presents vast differences across European countries. However, citizens' perception of their country's justice system is consistent over time, and variations in the said perception can be easily ascribed to real changes in the political and social domain. Moreover, citizens' perception of their country's justice system shows a substantial concordance with indicators based on international agencies' evaluation of justice system efficiency and enforcement actions. These results suggest that citizens' perception of their country's justice system is – on the whole – more reliable and less subjective than expected. Moreover, the perception of the justice system's quality impacts life satisfaction more than the perceptions of the dependability of the other two branches of the tripartite organization of civil society, namely government and parliament. Lastly, the impact of trust in justice on life satisfaction is much larger than that of income equality, suggesting that the perception of living in a country characterized by a fair and efficient justice system is more momentous than an evener income distribution: in other words, suggesting that justice is prior to social justice.

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SUMMARY

A well-functioning and trustworthy justice system is the fundamental prerequisite of civil society. Yet, in many countries, the justice system suffers from corruption and ineffectiveness, and citizens might perceive judges and prosecutors as dishonest and/or incompetent. Our analysis tackles this problem and explores how citizens' trust in their own country's justice/legal system affects life satisfaction in 38 European countries. Data come primarily from the EuroBarometer, World Bank, and World Justice Project.

Our findings show that citizens' trust in justice is highly heterogeneous across European countries. However, cross-country trust in justice tends to be significantly consistent over time, and is substantially in tune with the indicators of quality of justice/legal systems provided by international agencies and based on experts' evaluations. Lastly, trust in justice impacts life satisfaction, and its impact is greater than that of trust in the other two branches of government organization, namely the executive and the legislative.

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CLUSTERING TIME SERIES: AN APPLICATION TO COVID-19 DATA

Margherita Gerolimetto, Stefano Magrini

Introduction

Clustering time series has recently received a lot of attention from the literature. Similarly to cross-sectional clustering, several algorithms have been developed to carry out time series clustering and the choice of which one is more adapt depends on both the aim of the analysis itself and the typology of data at hand (for good reviews see Liao, 2005; Fu, 2011). Among all clustering algorithms, those that have been mostly used in the time series literature are: hierarchical, partitioning and model-based. Given so, it is possible to broadly identity two approaches for time series clustering: i) one that modifies cross-sectional data algorithms so that they can be employed also for time series data; ii) another that converts time series data into a cross-sectional object treatable with traditional clustering methods.

Within the first approach, a crucial issue is represented by the capability of identifying dissimilarities between time series. The usual Euclidean distance is a rather improper measure since it does not consider the correlation structure of the time series itself. Consistently with this, several proposals have been presented in literature to measure dissimilarity between pairs of time series, some of which are described in the second section of this paper.

As for the second approach, the fundamental element is the choice of the features to extract. In this vein, Wang et al. (2006) present a method for clustering time series that concentrates on their structural characteristics, whose pattern similarities are identified using Self Organizing Maps (Kohonen, 2001), an unsupervised neural network algorithm. The structural features are obtained from the time series by applying operations that best capture the underlying characteristics, for example, trend, seasonality, kurtosis, etc. In this work, we resort to the spline literature (De Boor, 1978) and consider, as a particular feature to extract, the coefficients of the p basis functions into which a series is decomposed when it is smoothed via a spline.

We apply some clustering time series methods, selected from both approaches, to analyze the daily time series of Covid-19 deaths for Italian regions between February 2020 and February 2022. Results show that there are patterns of regions that tend to stick together across the various groupings obtained with the considered methods of clustering.

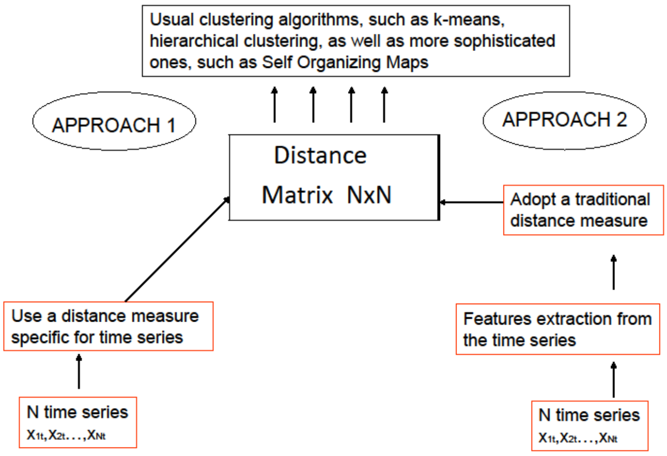
The structure of the paper is as follows. In the second section, we will present an overview on clustering time series. In the third section, we focus on clustering spline decomposition coefficients. In the fourth section, we will present our empirical analysis and some conclusions.

Time series clustering

The aim of clustering is to identify patterns by organizing data into homogenous groups where the within group object similarity is minimized and the between group objects dissimilarity is maximized. Clustering has been originally conceived for static data and, among the best-known algorithms, we mention k-means, where each cluster is represented by the mean value of the objects in the cluster, and hierarchical clustering, where data are grouped into a tree of clusters adopting agglomerative and divisive algorithms. Just like static data clustering, time series clustering requires the choice of the algorithm to form the clusters. In addition, time series data require a preliminary phase where the dynamic nature is accounted for. As anticipated in the Introduction, this can be done by choosing between two approaches.

Practically, the first approach, a.k.a *raw-data-based,* works with raw data and modifies the concept of distance measure so that it becomess compatible with the time series objects. The second approach, a.k.a *feature-based* or *model-based,* instead transforms the raw time series data into a features vector of lower dimension (or, alternatively, into a set of model parameters) and then carries out the grouping using conventional clustering methods. For a data set of *N* time series, the entire framework is displayed in Figure 1.

Figure 1 – *Conceptual map of time series clustering.*



Raw-data-based clustering

In the *raw-data-based* approach, the dynamic nature of the objects to cluster is handled by defining an appropriate measure of distance/similarity, bearing in mind that the Euclidean distance, typically adopted in static data clustering, is not adequate for time series data because it does not take into consideration the time dependence structure. Here, given two time series X_t and Y_t, where t =1,…,T, we will present an overview of some measures of distance proposed in the literature.

A very interesting measure of distance that overcomes the limits of the Euclidean distance is represented by the Dynamic Time Warping (DTW) distance (Keogh and Ratanamahatana, 2004). DTW algorithms come from the engineering literature and their aim is comparing discrete sequences with continuous sequences. In the present context, the logic of DTW is to firstly align the time series (intuitively, they must be stretched and compressed locally so they resemble each other as much as possible) and then some measure of distance is calculated between observations that match. The alignment of the time series is the core of the DTW and it is implemented through the so-called warping function, $\phi(k)$ that remaps the time index of X_t and Y_t

$$\phi(k) = \left(\phi_x(k), \phi_y(k)\right) \tag{1}$$

where $\phi_x(k) \in \{1, \dots, T\}$ and $\phi_y(k) \in \{1, \dots, T\}$. The average cumulated distortion between the warped time series is given by

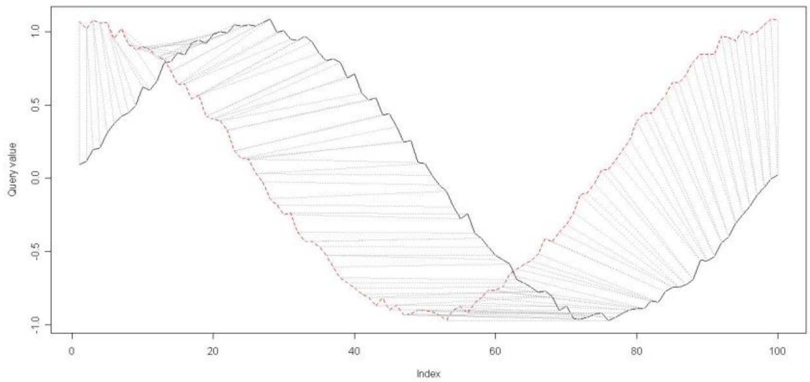
$$d_\phi(x, y) = \sum_{k=1}^{T} d\left(\phi_x(k), \phi_y(k)\right) \frac{m_\phi(k)}{M_\phi} \tag{2}$$

and the optimal alignment is the warping path $\phi(k)$ such that distortion is minimized. Moreover, on the warping function it is imposed monotonicity to ensure reasonable paths

$$\begin{aligned} \phi_x(k+1) &\geq \phi_x(k) \\ \phi_y(k+1) &\geq \phi_y(k) \end{aligned} \tag{3}$$

Eventually, the DTW distance between X_t and Y_t is the Euclidean distance between observations aligned via the warping function, as in the example in Figure 2.

Figure 2 – *Example of alignment of the time indexes of two time series (simulated data).*



Note: DTW time index matching of two time series (simulated from sinusoidal waves)

Another way of overcoming the limit of the Euclidean distance is the proposal by Galeano and Peña (2000) who present a method to assess similarity between time series focused on the comparison of their autocorrelation functions (ACF).[1] In particular, they define a metric based on the distance between the estimated

[1] Some developments of this method are in D'Urso and Maharaj (2009) and Alonso and Peña (2019).

autocorrelation coefficients of time series X_t and Y_t, denoted by, respectively $\hat{\rho}_x$ and $\hat{\rho}_y$

$$d_{ACF} = \sqrt{\left(\hat{\rho}_x - \hat{\rho}_y\right)' \Omega \left(\hat{\rho}_x - \hat{\rho}_y\right)} \tag{4}$$

where Ω is some matrix of weights. In the same vein, but on the frequency domain side, Caiado et al. (2006) propose a metric built on the logarithm of the normalized periodogram of series X_t and Y_t, at frequencies $w_j=2\pi j/T$, $j=1,\ldots,[T/2]$, denoted by, respectively, $\log NP_x(w_j)$ and $NP_y(w_j)$

$$d_{LNP} = \sqrt{\sum_{j=1}^{[T/2]} \left(\log NP_x(w_j) - \log NP_y(w_j)\right)^2} \tag{5}$$

that is in fact the Euclidean distance between $\log NP_x(w_j)$ and $NP_y(w_j)$. Moreover, the authors propose a measure of distance based on the Kullback-Leibler information metric, still calculated in the frequency domain

$$d_{KLFD} = \sum_{j=1}^{[T/2]} \left[\frac{NP_x(w_j)}{NP_y(w_j)} - \log \frac{NP_x(w_j)}{NP_y(w_j)} - 1 \right] \tag{6}$$

Those reported in this section are just some examples of measures of distance that we considered of interest and hence adopted in the following empirical analysis. By no means, this must be intended as an exhaustive presentation. For example, given their different logic, we did not discuss the proposal by Piccolo (1990), who developed a measure of distance between ARIMA models based on their AR(∞) parametrization, nor the time series clustering method based on forecast densities by Alonso et al. (2006).

Feature-based clustering

Raw-data-based clustering implies working with high dimensional spaces and this can sometimes be a serious issue also because of the amount of noise typical of data collected at fast sampling rates. In such cases, feature-based clustering can address this concern.

The idea behind the feature-based approach is dimension reduction. This implies that distance/similarity is evaluated among features extracted from each time series instead of the original time series themselves. This allows the use of simpler measures of distance, such as Euclidean, because the extracted features resemble a static object as in traditional clustering. Once the distance between the features is calculated, the usual clustering algorithm can be adopted. As we said before, these can be k-means or hierarchical clustering, but Wang et al. (2006) also proposed the use of more sophisticated methods, such as Kohonen Self Organizing Maps.

It is important to remark that while most feature extraction methods are generic in nature, the extracted features are instead application dependent. Put it differently, one set of features that work well in one application might be not relevant in another.

Wang et al. (2006) proposed to treat the time series data to obtain a set of global measures of, for example, trend, seasonality, serial correlation, non-linear autoregressive structure, skewness, kurtosis. These (and other more specialized time series features) concisely represent the relevant characteristics of each time series, thus providing a finite set of inputs to a clustering algorithm that can then assess similarity and differences between time series. In other words, every time series is seen as a single object and from the complexity of a matrix of N time series, each of extension T (the time series length) as in approach 1, here we have N objects whose extension is p, much smaller than T.

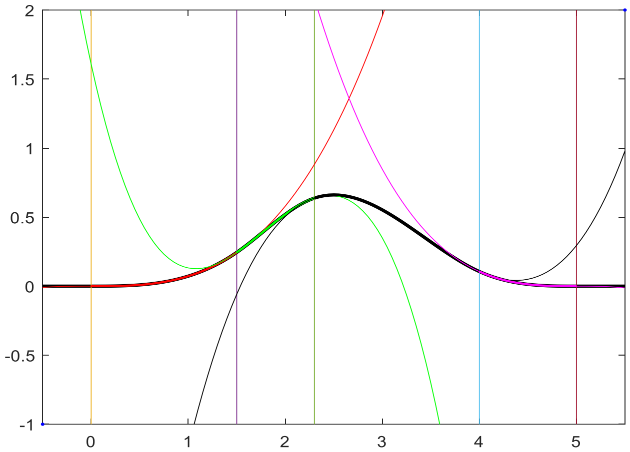
Feature-based **clustering with splines**

With the idea that the set of features to be extracted can always be updated and extended, here we resort to the spline literature and propose to extract the coefficients of the p basis functions into which a series is decomposed when it is smoothed via a spline. The objective is to concisely represent the time series, capturing not just the absolute value of the series but also its0 shape. This is done via B-Splines, which are a way to approximate non-linear functions by using a smooth piece-wise combination of polynomials (De Boor, 1978) and the positions where the pieces meet are known as knots. An example of B-spline with 4 knots and degree 3 is in Figure 3.

Specifically, B-Splines have two components, a basis function and the coefficients. The basis determines the hyperparameters, *i.e.* how many knots and what degree of polynomial to use in each model. The coefficients are then multiplied by this basis to approximate the original data. The idea is that by combining p polynomials using different weights, or coefficients, it is possible to obtain a non-linear estimate of the original time series. Least squares estimates can be used to get the best fitting coefficients.

Once the p coefficients of the basis functions are estimated for each time series of the data set, every time series is seen as a single object whose dimensionality is p. A Euclidean distance matrix can easily be calculated and any clustering algorithm can be adopted.

Figure 3 – *Example of cubic B-spline (simulated data).*



Note: Red, pink, black and green curves are the basis functions into which the simulated mexican hat-shaped function is decomposed via B-spline.

Empirical analysis

We now present our empirical analysis. We employ daily time series of Covid-19 deaths from 23/02/2020 to 29/03/2022 for the 19 Italian Regions and the 2 autonomous provinces of Trento and Bolzano. In particular, we consider two sets of data: i) deaths per 100,000 inhabitants and ii) deaths per 100,000 inhabitants normalized. The source of our data is “Istituto Superiore della Sanità” sticking on the official definition of Covid-19 deaths.

In our analysis with the R package Tsclust (Montero and Vilar, 2014), we adopt several clustering methods leading to as many outcomes. On the one hand, this is motivated as a form of robustness check, starting from what concerns the determination of the number of clusters. On the other hand, it is interesting to observe how results differ across clusterings. The methods we consider are selected from both the raw-data-based approach and the feature-based one. As for the first approach, we consider 4 distance matrices, calculated using the before presented distances (d_{ACF}, d_{LNP}, d_{KL}, d_{DTW}); for each of them, clustering is carried out using 5 algorithms: k-means and 4 hierarchical algorithms (Single linkage, Complete linkage, Average linkage, Ward). Eventually, the most interesting results are those based on d_{ACF} and d_{LNP}, using a k-means algorithm (only for deaths/hab) with 3 clusters.

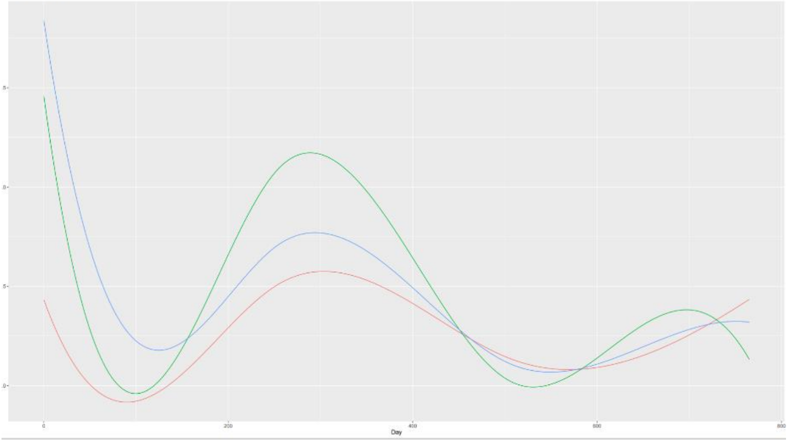
As for the second approach, the features we focus on are the coefficients of the basis functions in the spline decomposition of the time series. Specifically, we employ a cubic B-spline with 6 knots and the basis function coefficients are estimated via by least squares (for both deaths/hab and deaths/hab normalised). Given the results of the clustering analysis with the first approach, we consider here only the k-means algorithm for which the number of clusters provided as input is 3.

In the impossibility of showing the results of all clusterings (yet results for the other methods and the other data set are available upon request), we present only the outcome of the feature-based spline clustering applied to the data set on deaths per 100,000 inhabitants.

In particular, the following figures present the average spline of each of the three groups (Figure 4) in red, blue and green and the detailed composition of the groups (Figure 5). From Figure 4 it is possible to appreciate the different shape of the splines, and specifically the different slopes between peaks and troughs. From Figure 5 we observe that red group features Abruzzo, Basilicata, Calabria, Campania, Lazio, Molise, Puglia, Sardegna, Sicilia, Toscana, Umbria. The blue group contains Emilia Romagna, Liguria, Lombardia, Marche. Finally, the green group includes Bolzano, Friuli-Venezia-Giulia, Valle d'Aosta, Veneto.

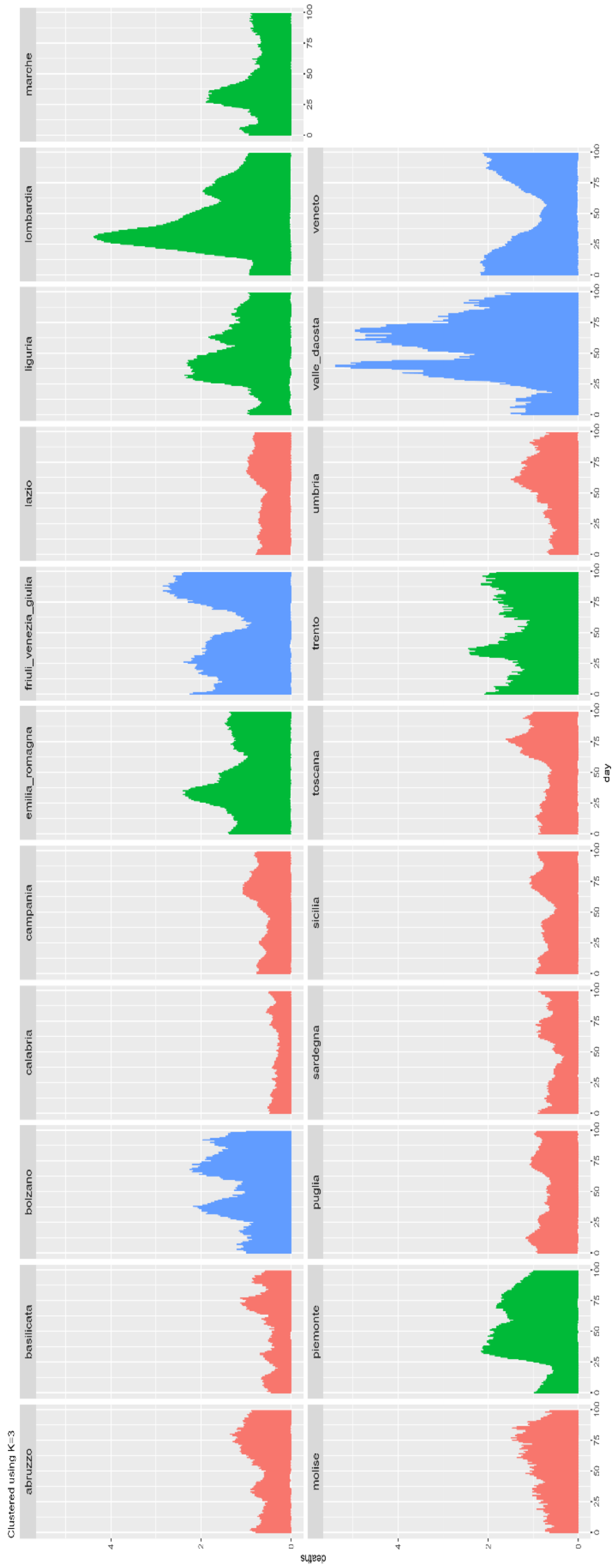
Putting together the analyses conducted with the two approaches, we focus on 4 sets of results: *i)* raw-data clustering with d_{ACF} and d_{LNP}, using a k-means algorithm (only for deaths/hab) *ii*) feature-based clustering with spline for both deaths/hab and deaths/hab normalized. This leads to 4 clusterings; in each of them, the 21 time series have been divided into 3 groups.

Figure 4 – *Splines for cluster centers (data set: daily deaths per 100,000 inhabitants).*



Note: Average B-splines for each group (red, blue and green). B-spline with 6 knots and the basis function coefficients are estimated via east squares.

Figure 5 – *Composition of the 3 clusters- red, blue and green group.*



Note: clustering method: feature-based clustering via spline with k-means algorithm for k=3; data set: daily deaths per 100,000 inhabitants).

Figure 6 represents with different colors the patterns of associations among regions that emerge systematically across the 4 clusterings. These have been detected by building a matrix (bottom panel of Figure 6) that reports 1 every time a pair of regions sticks together over all clusterings. These pairs are then reported in the map (top panel of Figure 6) to make the geographical pattern more evident.

Figure 6 – *Patterns common to all clusterings.*

	ITC1	ITC2	ITC3	ITC4	ITH1	ITH2	ITH3	ITH4	ITH5	ITI1	ITI2	ITI3	ITI4	ITF1	ITF2	ITF3	ITF4	ITF5	ITF6	ITG1	ITG2
ITC1				1																	
ITC2																					
ITC3																					
ITC4	1																				
ITH1																					
ITH2																					
ITH3																					
ITH4																					
ITH5																					
ITI1																					
ITI2														1	1						
ITI3																					
ITI4																					
ITF1											1				1						
ITF2											1			1							
ITF3																				1	
ITF4																					
ITF5																			1		
ITF6																		1			
ITG1																1					
ITG2																					

Piemonte and Lombardia (pale orange in the map) stick together over all groupings. The same holds for Sicilia and Campania (yellow), for Basilicata and Calabria (light blue), for Umbria, Molise and Abruzzo (green). This means that the time series of these regions tend to share some features and this emerges in a rather robust way, given the variety of methods with which these clustering are carried out.

These results are interesting not only from the methodological perspective of comparing different methods of time series clustering, but also because it represents a preliminary step of a wider project, whose aim is to investigate possible determinants of differential Covid-deaths/hab across regions.

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SUMMARY

In this paper we present an attempt of clustering time series focusing on Italian data about COVID-19. From the methodological point of view, we first present a review of the most important methods existing in literature for time series clustering. Similarly to cross-sectional clustering, time series clustering moves from the choice of an opportune algorithm to produce clusters. Several algorithms have been developed to carry out time series clustering and the choice of which one is more adapt depends on both the aim of the analysis itself and the typology of data at hand. We apply some of these methods to the data set of daily time series on intensive care and deaths for COVID19 stretching from, respectively, 23/02/2020 to 15/02/2022 and from 23/02/2020 to 29/03/2022. These data refer to the 19 Italian regions and the two autonomous provinces of Trento and Bolzano.

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POVERTY IN ITALY'S INLAND AREAS[1]

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1. National Strategy of Inland Areas

The National Strategy of Inland Areas (SNAI) finds its regulatory reference in the 2014 National Reform Program (PNR) and is defined in the 2014-2020 Partnership Agreement[2]. It's an important example of a policy aimed at improving the living conditions of the population residing in areas at risk of marginalization.

It was established with the declared intention of identifying homogeneous clusters of municipalities based on accessibility to the main basic services.

Then, the municipalities Polo and Inter-municipal Polo have been identified which at the same time have access to access to the three main services: transport, health facilities and schools. Depending on the distance from these municipalities, the Belt, Intermediate, Peripheral and Ultra-peripheral municipalities have been identified.

In particular, at national level according to SNAI 2014, there are 339 municipalities and inter-municipal centers in which over 24 million inhabitants reside and occupies a territorial area of 38,000 sq km.

The municipalities Pole and intermunicipal Pole, together with the Belt municipalities, represent the macro-class of municipalities defined as Centers. The three remaining classes, on the other hand, identify the Inland Areas.

The latter, and in particular the peripheral and outermost municipalities, constitute for the territory those areas most at risk of marginalization, social and economic.

Above all, the incidence of peripheral and outermost municipalities and the incidence of residents residing there can be considered as indicators of the marginality of a territory and the support policies are mainly intended for these municipalities.

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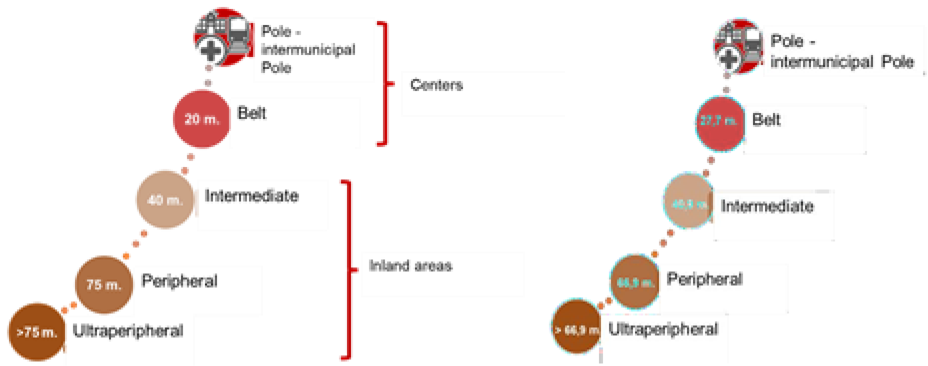
[2] Dipartimento per le politiche di Sviluppo (2013). Strategia nazionale per le Aree interne: definizione, obiettivi, strumenti e governance– Doc. tecnico collegato alla bozza di Accordo di Partenariato trasmessa alla CE il 9 dicembre 2013.

In 2014, the peripheral and outermost municipalities represented 22% of the total municipalities, 7% of the Italian population resided there and covered 9% of the national territory.

In 2022, a new mapping of the municipalities was created by the Department for Cohesion Policies and Istat[3], reshaping the definition of essential services to identify the intermunicipal poles and poles, and reviewing the minimum distance from the poles, functional to the classification of common in other clusters (Figure 1).

Figure 1 – *Spatial distribution municipalities - SNAI Classification 2014 and 2021.*



With the new classification[4], the number of pole or inter-municipal pole municipalities is 29% less, also excluding some provincial capitals that in the first definition had been included in this class, and the resident population of almost 10% less (Table 1).

On the other hand, the peripheral and ultra-peripheral municipalities, to which historically the greatest financial resources to support the territory are destined, are 8% more and in them 9% of the Italian population resides (Figure 2).

[3] Dipartimento per le politiche di coesione. 2022. Aggiornamento 2020 della mappa delle aree interne. Nota tecnica NUVAP.

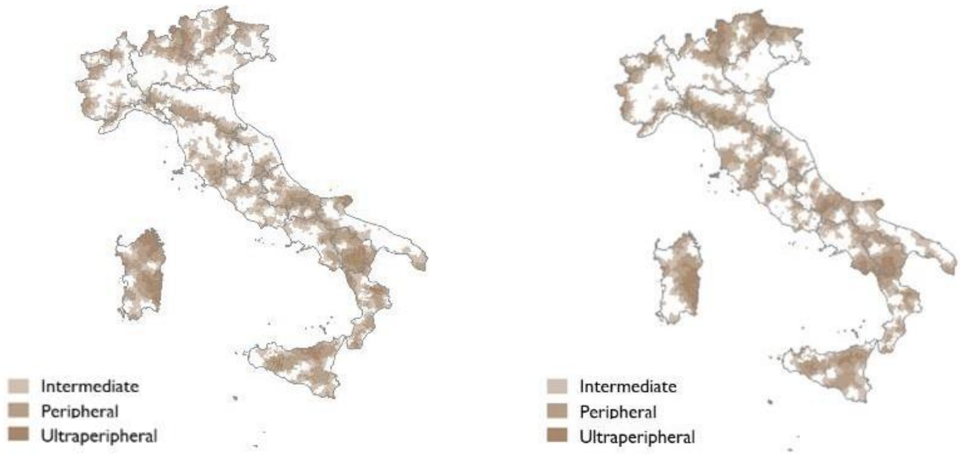
[4] Dipartimento per le politiche di coesione. 2022. Criteri per la Selezione delle Aree Interne da sostenere nel ciclo 2021-2027.

Table 1 – *Spazial distribution municipalities - SNAI Classification 2014 and 2021.*

SNAI Classification	Municipalities		Population	
	2014	2021	2014	2021
A – Pole	217	182	21.271.729	20.470.301
B - Intermunicipal Pole	122	59	2.992.749	1.576.586
C – Belt	3.509	3.828	22.248.629	23.756.465
D – Intermediate	2.288	1.928	8.495.430	8.059.454
E – Peripheral	1.475	1.524	3.585.164	4.653.355
F – Ultraperipheral	292	382	642.512	720.052
Total	7.903	7.903	59.236.213	59.236.213

The South sees an average increase in the number of municipalities at greater risk of territorial marginalization although, without prejudice to the variability at the territorial level, the regions with a greater increase of municipalities in this macro class are the Autonomous Province of Trento, Tuscany and Emilia-Romagna.

Figure 2 – *Intermediate, peripheral and ultraperipheral municipalities - SNAI Classification 2014 and 2021.*



Surely, residing in an area far from services leads to social and economic marginality that well explains the demographic decline of these areas over the last 70 years. Between 1951 and 2019, the population of the Centers grew on an annual average by 5.1% in Italy and by 4.8% in the South.

The Inland Areas of the South have lost 1.2 million residents (-2.5‰ on annual average; Italy -1.6‰) and one municipality out of three has systematically lost population since 1951.

2. Definition of poverty indicators

The official estimates of poverty mostly use the results of sample surveys, with the consequent limits of significance of the data when the level of detail, thematic or territorial, becomes very fine. For example, the official statistics produced by Istat stop at the regional detail as regards the incidence of relative poverty and the risk of poverty and the level of distribution for the estimates of absolute poverty. At the local level, therefore, there is an information gap that makes it difficult, if not impossible, to define territorial policies and evaluate their effects, and it is therefore necessary to try to take the path of using administrative sources for statistical purposes.

This work aims to extend to all Italian municipalities the study already conducted on the estimation of the incidence of poverty using the Integrated Archive of Economic and Demographic Microdata (ARCHIMEDE) project, made available by Istat. The Archimede Project uses integrated administrative sources with the aim of producing collections of elementary data useful for territorial and sectoral planning and for the evaluation of public policies also at regional and local level.

The traditional methodology to estimate absolute poverty, developed in 2005 and officially used[5], is a measure based on the monetary evaluation of a basket of goods and services considered essential to avoid serious forms of social exclusion. Starting from the hypothesis that primary needs and the goods and services that meet them are homogeneous throughout the country, account has been taken of the fact that costs vary in different parts of the country. The risk of poverty provides an assessment of the inequality in the distribution of equivalent disposable income and identifies poor households among those that are at a disadvantage compared to others. In fact, a family with a risk of poverty is defined as a family of two members with equivalent disposable income lower than or equal to the 60% of the median equivalent disposable income.

[5] ISTAT.

3. Main results

The more complex concept of social and economic marginality is associated with territorial marginality. The main indicators of absolute poverty and risk of poverty for the clusters of municipalities classified according to the National Strategy of Inland Areas 2021 are presented below.

In Italy, in 2017, there were almost 5 million families in absolute poverty, 18.9% of total families and almost 11 million individuals.

Just over 2 million families reside in municipalities classified as Poles or inter-municipal Poles, equal to about 20% of the families residing there. In the peripheral and outermost municipalities, over one in five families live in conditions of absolute poverty. The municipalities of the Belt have the lowest incidence of families in absolute poverty. The analysis of the risk of poverty-only is particularly interesting. Moving from a town in the center to towns in inland areas significantly increases the risk of both family and individual poverty.

Just over 6 families out of 100 are at risk of poverty in the poles and over 14% in the peripheral and outermost municipalities.

The distribution of non-poor households by cluster of municipalities is evidently clearer. Over 73% are non-poor families in the Polo municipalities while about 64% are non-poor families in the outermost municipalities (Table 2).

These results are the result of a great variability at the territorial level; indeed, in the Poles it is possible to speak of variability even within the city.

Table 2 – *Incidence of families in absolute municipal poverty, at risk of poverty and notpoor - SNAI classification 2021 - Year 2017.*

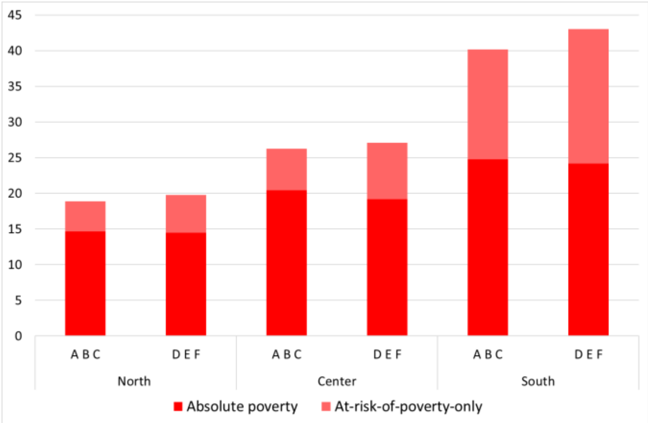
SNAI Classification	Absolute poverty	At-risk-of-poverty-only	Non-poor families
A – Pole	20,8	6,2	73,1
B – Intermunicipal Pole	19,3	9,6	71,1
C – Belt	16,2	8,6	75,3
D – Intermediate	19,7	11,9	68,4
E – Peripheral	21,4	14,3	64,2
F – Ultraperipheral	21,3	14,4	64,3
Total	18,9	8,7	72,4

By extending the analysis by division and aggregating the municipalities into only two macro-classes, Centers consisting only of Inter-municipal Poles and Poles and Inland Areas and Belts, it is noted how the incidence of families in absolute poverty is always higher in the centers while the risk of poverty is significantly higher in Inland Areas and Belts.

In the South, over 13% of families are at risk of poverty in the pole or inter-municipal pole municipalities compared to 18% of the remaining municipalities.

The municipalities of the South confirm the higher incidence of poverty and at risk of poverty only, which is even more significant for the municipalities in the Belt or Inland Areas (Figure 3).

Figure 3 – *Families in absolute poverty and at risk of poverty only by breakdown. Year 2017.*

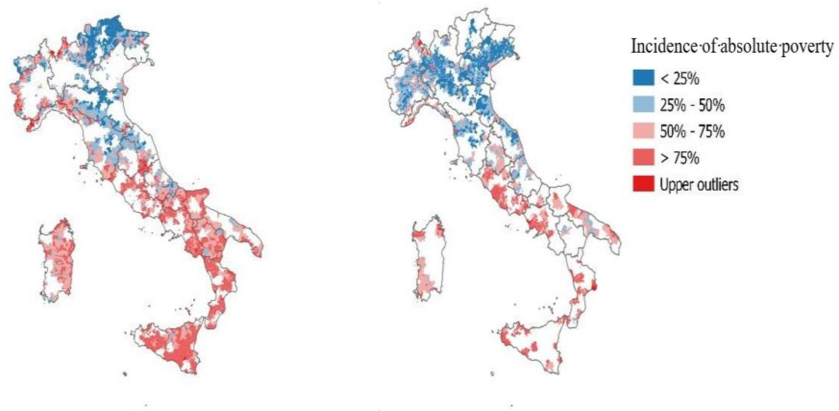


If we compare the incidence of absolute poverty in inland areas and in centers, it is observed that in the inland areas families in medium-high absolute poverty classes (in red and dark red) prevail, especially in the South.

In the Centers there is a high level of absolute poverty, especially those with a high degree of urbanization and in the Center and South (Lazio, Campania, Puglia, Calabria, Sicily) (Figure 4).

Figure 4 – *Incidence of absolute municipal poverty in inland areas - Year 2017.*

Inland areas (D, E, F) Centers (A, B, C)



To analyze the presence of any spatial associations and identify the "critical areas" of poverty in Italy, the techniques of Spatial Analysis were used. In particular, the Local Indicator of Spatial Association (LISA) proposed by Anselin (LISA) was used which allows to evaluate the similarity between each observation and the elements surrounding it.

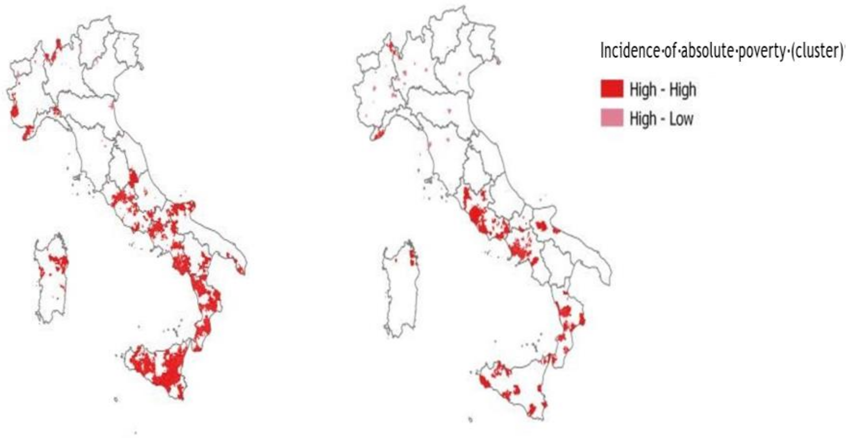
These associations can be of the High-High type (high values observed in a territorial unit and high values also in its surroundings) or Low-Low (low values observed in a territorial unit and low values also in one's own neighborhood) in the case of positive autocorrelation. Conversely, the associations will be of the High-Low or Low-High type in case of negative autocorrelation.

To facilitate the reading, only the significant associations of the municipalities of the last quartile have been reported in the cartogram, colored with a more intense shade when the association is of the High-High type, i.e. neighboring municipalities all with a high level of the indicator, and with a more tenuous tone in the case of High-Low association, i.e. a municipality with a high level of the indicator and neighboring municipalities with a low level of the indicator.

The cartogram also confirms the presence of areas of high incidence of the phenomenon distributed among Campania, Calabria and Sicily also for the absolute poverty of the Inland areas (Figure 5).

Figure 5 – *Incidence of absolute municipal poverty in inland areas. The "critical" areas.*

Inland areas (D, E, F) Centers (A, B, C)



4. Conclusions

The integration and use for statistical purposes of administrative sources allows the analysis of particularly fine estimation domains and the analysis on a municipal basis allows highlighting the strong territorial variability.

In terms of absolute poverty North-South dualism is confirmed: 1) with reference to households, the South recorded a significant increase from 2016 to 2017 (from 8.5% to 10.3%) confirming itself as the most disadvantaged area of Italy; 2) the incidence of absolute poverty also grows for individuals (from 7.9% in 2016 to 8.4% in 2017), reaching in the South the highest value (11.4%) among the divisions[6].

Absolute poverty is not unique to the Inland Areas, but it is particularly present in highly urbanized centers and the risk of poverty-only increases moving toward the Inland Areas.

Beyond the results presented, this work intends to represent a first verification of the possibility of using the databases of the ArchIMEDe project for a territorial analysis of the phenomenon of poverty. The results summarized here highlight the informative potential of the ArchIMEDe datasets. In fact, the analysis of poverty conducted on survey data and administrative sources, suitably integrated, has made it possible to deepen the level of territorial detail of the analysis, producing municipal analyzes of the incidence of the phenomenon under investigation.

[6] ISTAT. LE STATISTICHE DELL’ISTAT SULLA POVERTÀ - Statistica report - Anni 2016-2017-2018-2019.

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SUMMARY

The official estimates of poverty among Italian families mostly use the results of sample surveys, so they do not go beyond the regional detail as regards the incidence of relative poverty and the risk of poverty-only and stop at the level of breakdown by estimates relating to absolute poverty. A significant part of the inland areas has gradually undergone a process of marginalization marked by depopulation since the Second World War, an aging population, a decrease in the qualitative and quantitative level of essential services, a weakening of the training offer and degradation of the natural and cultural heritage, also favoring hydro-geological instability.

This study aims to estimate the incidence of poverty in inland areas using a statistical source, the Integrated Archive of Economic and Demographic Microdata (ARCHIMEDE) project, made available by Istat. This study shows that the integration and use of administrative sources for statistical purposes allows the analysis of particularly fine estimation domains and the analysis on a municipal basis allows, in fact, to highlight the strong territorial variability.

In terms of absolute poverty and risk of poverty-only, the North-South dualism is confirmed. Absolute poverty is not an exclusive feature of Inland Areas, but it is particularly present in highly urbanized Centers and the risk of poverty-only increases moving towards Inland Areas.

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COVID-19 AND MULTIDIMENSIONAL WELL-BEING: THE CASE OF THE ELDERLY IN ITALY

Gloria Polinesi

1. Introduction

Older adults among vulnerable groups have been disproportionately affected by COVID-19 (Mueller et al., 2020).

The COVID-19 pandemic is much more than a health crisis, as it has a fundamental impact on the societies and economies. In fact, its impact is multiple, and the analysis requires information covering different angles of individuals' life and appropriate empirical research spanning from economics to statistics, demography and computer science.

Sen (1980) has been the first treating well-being as a multidimensional concept, which depends on monetary and non-monetary variables.

In fact, initially income was suggested to properly reflect society and individual's quality of life, yet this statement has been strongly reconsidered. Most of the existing studies have shown that the concepts of quality of life and well-being cannot be exclusively defined in terms of material deprivation and must also consider subjective and objective aspects depending on non-monetary variables.

Therefore, the main goal of the paper is to understand and analyze the consequences of the COVID-19 outbreak on elderly Italian individuals by estimating the multidimensional effects of the current health emergency related to the COVID-19 pandemic on different domains of well-being. This goal is particularly relevant since the actual scientific debate is mainly focused on the macroeconomic effects of the pandemic and only some research concerning the effects of pandemic on well-being has been published (see for example Grané et al., 2021 and Atzendorf and Gruber, 2021).

Shocks that individuals experienced in the first and the following waves of the COVID-19 pandemic can be analyzed through composite indicators aimed at measuring changes in well-being before (pre-COVID period[1]) and after COVID-19 (March 2020).

[1] In the rest of the paper the author refers to pre-COVID period as regular period.

The choice of studying COVID-19 effects on well-being, and not only on the economy, is motivated by fact that many studies in this field have explored purely economic aspect, which consider only material living standards, exploiting the concept of multidimensionality (Ivaldi et al., 2016; Bleys, 2012; Gigliarano and Mosler, 2009).

European Commission's “Going beyond GDP” initiative and Stiglitz (2009) have pointed out that income alone does not reflect the multi-faceted nature of the well-being suggesting that other indicators monitoring economic and social progress should be developed to complement it.

Several initiatives have taken place proposing multidimensional well-being indicators. For instance, Human Development Index (HDI) proposed by the United Nations Development Program which offers countries' mean (or geometric mean) achievement in income, education and health dimensions (Malik, 2013), and Better Life Index (BLI) established by the Organization for Economic Cooperation and Development which aggregates achievements in 11 domains (Durand, 2015).

Following this stream of literature, an individual well-being change index has been constructed and applied to the Survey of Health, Ageing and Retirement in Europe and Israel (SHARE) data set looking at the direction (downward, upward and net overall deprivation) of well-being changes before and after COVID-19 of Italian elderly population.

Since the pandemic has a varying impact on different population groups -related to age, gender, economic and work status- analysis is carried out by subgroups.

Findings suggest that employed and richer individuals suffer greater well-being losses, while results on gender is not statistically significant. Moreover, second year of the pandemic highlights the key role of the self-perceived health on well-being leading to greater contributions of health dimension to upward and downward changes.

Following Ciommi et al. (2014), dominance criteria are introduced to compare Italian situation during the first and second year of the pandemic.

In the following sections, we describe the well-being change index, and we conclude with some results.

2. Data and methods

We consider Italian data provided by the Survey of Health, Ageing and Retirement in Europe and Israel (SHARE). This database gathers microlevel information on health, well-being, and socioeconomic characteristics for the population aged 50 or older. We focus on the longitudinal individuals of the waves

8 and 9 responding to three different surveys: wave 8 regular survey (regular), wave 8 SHARE Corona Survey (1_{st} SCS) and wave 9 SHARE Corona Survey (2^{nd} SCS)[2].

Health, employment, equivalent income, the ability to make ends meet and social connections are used to construct the well-being change indices as described in Table 1[3].

Table 1 – *Survey variables of the first and second SHARE Corona Survey used to construct the multidimensional well-being indicator.*

Well-being domain	Variables
Health	Self-perceived health change since the outbreak
Social connections	Volunteered since outbreak
Financial distress	Household's total monthly income able to make ends meet
Income	Income quantile change before and after outbreak
Work	Unemployed, laid off or business closed due to COVID-19

We compute three different measures to catch downward, upward and net overall changes in the individual multidimensional well-being for the two different time periods: regular-1_{st} SCS and regular-2^{nd} SCS.

Consider a population of individuals $i = 1, \ldots, n$ over periods of time t and $t - 1$, and denote with x_t^{ik} and x_{t-1}^{ik} the value of the k-th well-being indicator at time t and $t-1$ respectively, with $k = 1, \ldots, K$. The individual downward well-being change index is defined as:

$$d_i = \frac{\sum_{k=1}^{K} 1(\, x_t^{ik} < x_{t-1}^{ik}) v_k}{\sum_{k=1}^{K} v_k}, \tag{1}$$

where v_k is the weight of each well-being indicator such that $\sum_{k=1}^{K} v_k = K$. In what follows, we assume equal weight of the well-being indicators such that $v_k = 1/K$, for $k = 1, \ldots, K$. The downward index measures the incidence of downward changes in the individual well-being dimensions over time: moving from $t-1$ to t.

Similarly, the individual upward index u_i counting the incidence of positive well-being changes is given by:

$$u_i = \frac{\sum_{k=1}^{K} 1(\, x_t^{ik} > x_{t-1}^{ik}) v_k}{\sum_{k=1}^{K} v_k}. \tag{2}$$

[2] Data refer to October 2019-March 2020, June-August 2020 and June-August 2021, respectively.
[3] For the complete list of variables used in the analysis we refer to Polinesi et. al, 2022. The choice of the domains is based on the work of Grané et al. (2021).

From d_i and u_i the individual overall deprivation change index, considering the compensatory effect between downward and upward changes, can be defined as:

$$o_i = \max\{0, d_i - u_i\}, \tag{3}$$

when individuals experience more improvement of the well-being dimensions with respect to worsening o_i is equal to 0.

The aggregate well-being change index M, aimed to assess the intensity of the COVID-19 effects in each subgroup or country, can be defined as the weighted mean of individual changes:

$$M = \frac{\sum_{i=1}^{n} m_i^{\alpha} w_i}{\sum_{i=1}^{n} w_i}, \tag{4}$$

where the generic m_i represents the individual well-being change index defined in Eq. (1)-(3), w_i is the individual sample weight such that $\sum_{i=1}^{n} w_i = 1$ and the parameter $\alpha \geq 0$ indicates the sensitivity to changes[4]. In this paper we set $\alpha = 0{,}1$ representing the headcount ratio and the gap: the proportion and the average proportion of the population experienced a worsening/improvement or deprivation in at least one well-being dimension. All the indices considered range between 0 and 1.

3. Results

In this section, we present results of well-being change and overall deprivation indices defined in Eq. (3) separately for the two time periods. We consider total and subgroup indices across elderly Italian individuals (Fig. 1), then investigate differences between social groups (Table 2[5]).

[4] Properties of the well-being changes index are listed in Polinesi et al., 2022.
[5] Results do not change with α=0.

Figure 1 – *Headcount (α=0) and gap (α=1) of well-being changes and deprivation in Italy: first SCS and second SCS.*

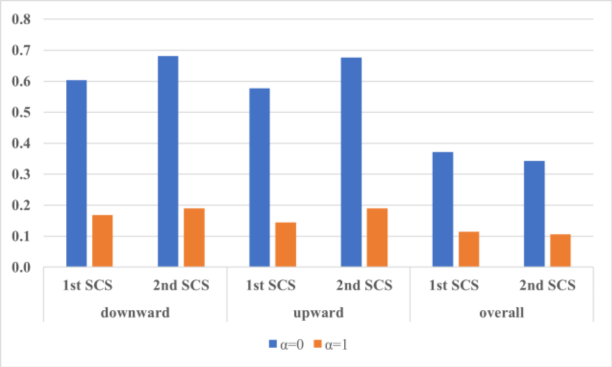


Table 2 - *Well-being change and overall deprivation indices (α=1), total and by subgroups (index and 95 % bootstrap confidence interval). 1st SCS (a) and 2nd SCS (b).*

(a)

	Downward			Upward			Overall		
	Index	95% CI		Index	95% CI		Index	95% CI	
Total	0.169	0.160	0.178	0.144	0.137	0.152	0.115	0.105	0.125
Gender									
Male	0.158	0.152	0.162	0.144	0.139	0.149	0.108	0.103	0.113
Female	0.163	0.158	0.167	0.146	0.143	0.149	0.111	0.107	0.115
Education									
≤ lower secondary	0.156	0.145	0.165	0.155	0.147	0.164	0.104	0.094	0.114
Upper secondary	0.205	0.185	0.226	0.125	0.109	0.143	0.146	0.120	0.170
Tertiary	0.152	0.123	0.177	0.128	0.101	0.160	0.094	0.070	0.117
Work status									
Retired	0.138	0.131	0.147	0.160	0.152	0.168	0.092	0.085	0.101
Employed	0.228	0.211	0.250	0.116	0.101	0.132	0.162	0.140	0.189
Other	0.134	0.116	0.152	0.158	0.144	0.172	0.084	0.066	0.102
Income quantile									
First	0.097	0.076	0.118	0.195	0.174	0.216	0.051	0.030	0.072
Second	0.100	0.087	0.114	0.228	0.213	0.242	0.053	0.042	0.065
Third	0.155	0.138	0.172	0.151	0.133	0.170	0.101	0.084	0.118
Fourth	0.201	0.185	0.218	0.133	0.117	0.146	0.130	0.109	0.155
Fifth	0.242	0.225	0.260	0.063	0.050	0.076	0.192	0.169	0.217

(b)

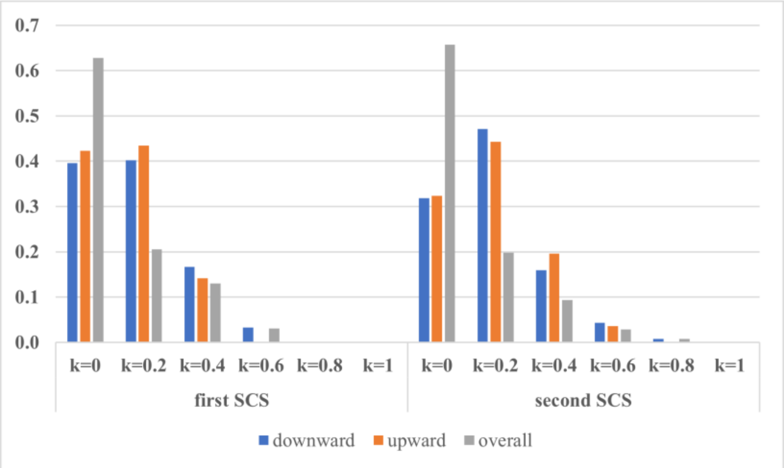
	Downward			Upward			Overall		
	Index	95% CI		Index	95% CI		Index	95% CI	
Total	0.190	0.181	0.199	0.190	0.182	0.200	0.106	0.096	0.116
Gender									
Male	0.180	0.174	0.185	0.185	0.180	0.190	0.109	0.103	0.114
Female	0.182	0.178	0.187	0.184	0.180	0.187	0.110	0.106	0.114
Education									
≤ lower secondary	0.181	0.168	0.194	0.199	0.188	0.209	0.100	0.087	0.115
Upper secondary	0.219	0.202	0.241	0.174	0.158	0.190	0.127	0.105	0.153
Tertiary	0.175	0.142	0.211	0.175	0.143	0.203	0.090	0.062	0.122
Work status									
Retired	0.171	0.164	0.178	0.207	0.199	0.217	0.092	0.084	0.100
Employed	0.249	0.223	0.274	0.153	0.133	0.170	0.159	0.130	0.189
Other	0.154	0.140	0.169	0.206	0.193	0.221	0.068	0.056	0.081
Income quantile									
First	0.122	0.106	0.140	0.257	0.237	0.275	0.032	0.023	0.041
Second	0.135	0.122	0.148	0.271	0.256	0.285	0.051	0.040	0.061
Thirth	0.207	0.168	0.238	0.183	0.165	0.203	0.138	0.099	0.169
Fourth	0.213	0.200	0.227	0.175	0.157	0.192	0.108	0.092	0.127
Fifth	0.256	0.238	0.275	0.090	0.079	0.104	0.187	0.166	0.207

Table 1 highlights a recovery effect in terms of multidimensional well-being during the second period of the analysis. In fact, moving from first year of the pandemic to the second one, downward and upward well-being changes increase differently from the overall deprivation index which decrease.

Splitting the analysis by subgroups according to the gender, one may note that the difference between males and females is not statistically significant, while education, work status and income class have a significant effect. Upper secondary education implies significantly more downward changes with respect to primary and tertiary education. Employed and self-employed workers are significantly more deprived than retired (0.228 vs 0.138 and 0.249 vs 0.171, first and second SCS respectively). Moreover, poorest and middle classes (first-third income quantiles) are less affected by downward changes than individual belonging to higher income classes (fourth and fifth quantiles).

Figure 2 looks at the frequency of elderly individuals changing in the well-being dimensions (k).

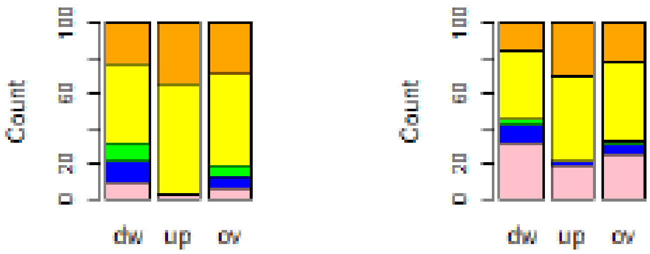
Figure 2 – *Frequency of individuals deteriorating/improving and changing according to different well-being cut-off (k). k=0 indicates individuals associated with no change, on the contrary, k=1 indicates individuals who change in all dimensions considered.*



Moving to the second year of the pandemic frequencies of upward changes associated with 1 (k=0.2), 2 (k=0.4) and 3 (k=0.6) dimensions strongly increase highlighting the recovery phase of the epidemic crisis.

Figure 3 shows the contribution of each dimension to the construction of the well-being change indices. Note that, second year of the pandemic highlights the key role of the self-perceived health on well-being leading to greater contributions of health dimension (pink bar) to downward, upward and overall changes.

Figure 3 – *Frequency of individuals deteriorating/improving and changing by well-being dimensions (k) for the 1st SCS and 2nd SCS. Health dimension (pink), social dimension (blue), work dimension (green), ability to make ends meet (yellow), income dimension (orange).*



Greater contribution of the health dimension on downward and upward changes during the second period analyzed can be explained by the fact that no changes with respect to the regular period in the health dimension sensitively decrease while worsening and improvement increase (Table 3).

Table 3 – *Frequency of individuals worsening (-1), improving (1) and not changing (0) according to each well-being dimensions: 1st SCS (a) and 2nd SCS (b). Work dimension excludes upward change by construction.*

(a)

	-1	0	1
income quantile	0.369	0.173	0.458
financial distress	0.201	0.554	0.244
health	0.080	0.907	0.012
social	0.100	0.893	0.007
work	0.094	0.906	NC

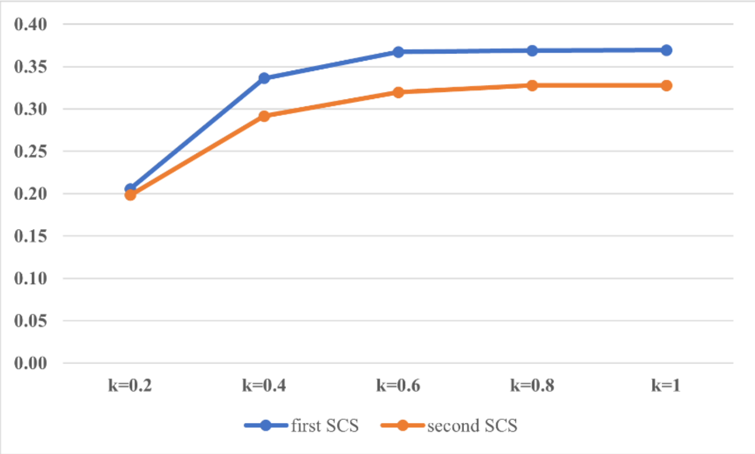
(b)

	-1	0	1
income quantile	0.376	0.157	0.468
financial distress	0.148	0.566	0.286
health	0.310	0.507	0.183
social	0.090	0.896	0.015
work	0.029	0.971	NC

The dominance criteria introduced by Lasso de la Vega (2010) guarantee reaching robust conclusions when we compare overall well-being change indices in the first and second year of the pandemic[6]. With this aim, Deprivation Curves in Figure 4 are obtained by plotting, the identification cut-off (k) against the multidimensional headcount ratio, i.e., the percentage of individuals deprived in at least k dimensions. The obtained curve shown in Figure 4 is the so-called First dimension deprivation curve (henceforth FD).

[6] Dominance conditions are based on simple graphical devices that provide a tool for checking the robustness of well-being to changes in the identification cut-off.

Figure 4 – *FD curves for the 1st SCS and 2nd SCS.*



Lasso de la Vega (2010) proves that if the FD curve associated to a country is everywhere to the left and above another FD curve associated to another country or when the curves are associated with the same country but in a different period, then the second one has lower deprivation than the first one for any multidimensional deprivation measure satisfying Focus, Monotonicity, Symmetry and Replication invariance and for any identification cut-off. Therefore, Figure 4 indicates an improvement in multidimensional well-being associated with the second year of the pandemic.

4. Conclusion

The paper contributes to the analysis of variation of well-being relatively to the elderly Italians. Specifically, we compute a multidimensional index that captures changes in the level of individual well-being during first and second year of COVID-19 pandemic.

Findings suggest that employed and richer individuals suffer greater well-being losses with higher downward changes than upward ones, while gender is not significant in discriminating against changes in individual well-being.

First dimension curve indicates an improvement in multidimensional well-being associated with the second year of the pandemic.

Further research will be aimed to include regional dimension in the study of Italy.

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SUMMARY

The aim of the study is to analyze multidimensional well-being changes in Italy at individual level between regular period end COVID-19 period using SHARE data. To this aim, we propose a well-being change index measuring negative, positive and non-directional changes. Analysis by subgroup is introduced to investigate more vulnerable groups to COVID-19 among elderly Italian population.

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PROMOTING COMMUTE ACTIVE MODES DURING THE COVID-19 PANDEMIC. WHAT IS THE ROLE OF MULTIMODAL TRAVEL MODE CHOICES?

Jurgena Myftiu

1. Introduction

In many countries, the Covid-19 pandemic has caused restrictive measures limiting the ability to get around by using transportation services and affected systematic choices, especially for commuting purposes (Bohte et al., 2009; Müggenburg et al., 2015; Schoenduwe et al., 2015). Italy witnessed a significant impact on the demand for public transport services, which suffered a severe contraction in favor of private cars but also active modes (e.g., biking and walking for shorter distances; ISFORT, 2021) which can increase social inclusion and psycho-physical well-being (Nikitas et al., 2021; De Vos, 2020; Chatterjee et al., 2019; Crotti et al., 2021; Mazziotta et al., 2022). Still, the literature about the drivers of commuting by active modes is relatively scarce. In this paper we contribute to fill that gap by focusing on university commuters and their propensity to shift towards active modes avoiding any other multimodal solutions (e.g., cars, buses, trains, etc.). To do so, we first investigate the importance of factors inducing the use of active modes to reach the college. Then, we test a logit regression model to study the impact of socio-economic variables and relevant aspects that are detected by a factor analysis. By assuming two alternative scenarios of low or medium-high health risk of contagious, this paper compares them, allowing to better understand how the perception of the Covid-19 contagion risks can affect the commute mode choice.

The paper is structured as follows. Section 1introduces the background of the study; Section 2 sets out the structure of used data; Section 3 explains the methodology approach; Section 4 highlights the results, and finally Section 5 concludes the study with policy implications.

2. Survey and data collection

The data used have been collected through a national online survey codenamed "University mobility at the time of Covid-19" by the Italian Network of Universities for Sustainable Development (RUS, 2021). The survey involved students and employees of 51 Italian universities about prospective commuting habits for the A.Y. 2020-2021. The sample is composed by 114,000 observations (students: 79.4%; faculty: 11%; technical-administrative staff: 9.6%) from the North-West of Italy (45%), the North-East (24%), the Center of Italy (16%), and from the South, and Islands (15.5%). In addition to external information on the territorial context where each university is located (e.g., the supply of public transport), the survey includes personal characteristics, mobility capital, pre-pandemic home-university travel habits, and information concerning the propensity to adopt sustainable and multimodal travel choices. Respondents were also asked to express their prospective choices and travel habits considering two alternative pandemic scenarios, i.e., optimistic, or pessimistic:

- *optimistic scenario*: the virus is almost over; new infections are reduced; social distancing and protection measures are relaxed; college activities are regular.
- *pessimistic scenario*: the virus is still dangerous; contagions have slowed down, but protection measures are still needed; college activities are not regular.

3. Methodology

In order to understand the main aspects motivating the choice to commute by active modes, an exploratory factor analysis was applied (section 3.1). This approach would allow to gain insights about the relative importance of selected nine items related to cycling, and five items related to walking to university. Then, by using the outcomes of the factor analysis, a logit regression model has been developed and estimated (section 3.2) to study the propensity to use active modes independently from the multimodal usage of other means of transport (i.e., cars, bus, train, etc.).

3.1 Factor Analysis model

The factor analysis tries to describe the covariance relationships among many variables in terms of a few underlying, but unobservable, random quantities called *factors* (e.g., see Johnson and Wichern, 2008). This method assumes that all the variables within a particular group are highly correlated among themselves, but they have relatively small correlations with variables in a different group. As a result, it is conceivable that each group of variables is represented by a factor, responsible for the observed correlations. In matrix notation, the factor analysis model is as follows:

$$\boldsymbol{AM} - \boldsymbol{\mu} = \boldsymbol{L} \times \boldsymbol{F} + \boldsymbol{\epsilon} \tag{1}$$

where the vector $\boldsymbol{AM} = (AM_1, \dots, AM_{14})$ consists of 14 observable covariates related to active mobility aspects about walking and cycling (as listed in Table A1 in the Appendix). The mean of each of those components is collected into the vector $\boldsymbol{\mu} = (\mu_1, \dots, \mu_{14})$, and the covariance matrix is $\boldsymbol{\Sigma} = Cov(\boldsymbol{AM}) = E(\boldsymbol{AM} - \boldsymbol{\mu})(\boldsymbol{AM} - \boldsymbol{\mu})'$. The factor model postulates that the vector $\boldsymbol{AM}$ is linearly dependent upon unobservable random variables, collected into vector $\boldsymbol{F} = (F_1, F_2, \dots, F_q)$, called *common factors*, whose number is determined by the related $(14 \times q)$ matrix of factor loadings $\boldsymbol{L}$ and unique variances (see Table 1). Additional sources of variation – called *errors* or, sometimes, *specific factors* – are included into the vector $\boldsymbol{\epsilon} = (\epsilon_1, \dots, \epsilon_{14})$, whose components are individually linked to active mobility variables.

3.2 Logistic regression model

In order to identify the propensity to reach the college by active modes, the respondents were asked the following question: "*Do you think it would be possible for you to go to university using active mobility (i.e., walking, cycling, e-scooter) regardless of the use of other means of transport?*". In our case, the binary response dependent variable *Y* is defined as the indicator function for modal change, taking a value of 0 if the respondent is willing to use active modes only in combination with other transport means, and 1 if that choice is independent from multimodality. In this type of classification model, the predicted probability $P = \Pr(Y = 1|\boldsymbol{X})$ is a non-linear function of independent variables, and the log of odds are a function of that probability, as in (2):

$$ln\left(\frac{P}{1-P}\right) = \alpha + \boldsymbol{X}'\boldsymbol{\beta} \triangleq P = \frac{e^{\alpha + X'\beta}}{1 + e^{\alpha + X'\beta}} \tag{2}$$

where the vector $\boldsymbol{X} = (x_1, \dots, x_{14})$ consists of 14 variables about personal characteristics (e.g., age, gender, work position, etc.), geographical contexts, transportation supply (e.g., sharing mobility and PT services), trip features (e.g., distance in km, travel times, commute weekly frequency) and pre-Covid travel habits (transport modes choice and multimodal solutions), as in Table 2, while Y indicates the binary latent utility perceived by the individual when choosing to use the active mobility independently from the joint use with other means of transport in each of the alternative pandemic scenarios. The parameter α yields the probability P when the components of $\boldsymbol{X}$ are zero, while each coefficient β_j, $j = 1, \dots, 14$ of the vector $\boldsymbol{\beta}$ is estimated using the maximum likelihood methods and adjusts how quickly the odds of changing commute mode changes with single-unit variations of the related variable into $\boldsymbol{X}$. When estimating logit models, since marginal effects are not constant in a non-linear regression, average marginal effects (AMEs), i.e., the average of marginal effects computed for each independent variable, are used (Cameron and Trivedi, 2003)[1] and they are calculated as:

$$\overline{\frac{\partial P}{\partial x_j}} = \frac{1}{14}\sum_{j=1}^{14} F'(\boldsymbol{X}'\boldsymbol{\beta})\beta_j \tag{3}$$

where F' is the first derivative of the standard cumulative logistic distribution function $F(x) = \frac{e^x}{1+e^x}$, $-\infty < x < \infty$ (Wooldridge, 2010), and β_j is the related coefficient for $x_j \in \boldsymbol{X}$.

4. Results

Before starting the analysis, from the sample we removed students declaring their intention to change own university in the A.Y. 2020-2021. This was necessary to be able to make a comparison of the responses before Covid-19 and those assuming the two pandemic scenarios considered. Table A1 in the Appendix shows the responses for each of the 14 items, measured on a 4-point Likert scale, evaluating their own perceived importance (i.e., 0 – Not at all important; 1 – Unimportant; 2 – Fairly important; 3 – Very important). The most relevant issues appear to be those linked to safety and security: a *quiet and safe pedestrian path* is considered at least fairly important by 86% of the sample, and a *path with high personal security (theft, harassment, etc.)* is likewise appreciated (84%). In the meantime, to adopt cycling both a *safe cycle path (protected from motorized traffic*), as well as a *low risk of bike theft*, are deemed relevant by 91%. Table 1 reports the main results of the above-described factor analysis. First of all, the analysis of factor loadings showed what items contribute to the definition of each factor, helping in the identification of the latent structures that factors should reveal and suggested to consider four factors. Also, the *uniqueness* values are reported, i.e., the portion of each indicator variance not explained by the first four factors that were retained and identified. Notice also that the sample size is limited to those declaring they did not use active mobility for *any* stretch of their home-to-university journey. Finally, with the aim of examining the possible identification of the four factors based on the loadings for the original items, note that, overall, the results are similar in both the scenarios, and they will be reviewed together accordingly.

Factor 1 (explaining around 37% of total variance) highlights the appreciation for itineraries rolling along parks and green environments with the purely conceptual

1 The *marginal effect at the mean*, computed at the means of all covariates, is an alternative method, but there may not be such “average” individual. Without loss of significance, the average marginal effect makes more sense.

items regarding being part of a community that cares about sustainability; thus, it could be labelled as *eco-friendly environment*.

Table 1 – *Output of factor analysis.*

Rotated factor loadings (pattern matrix) and unique variances					
Variable	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Uniqueness**
AM1. Optimistic			0.7842		0.2840
AM1. Pessimistic			0.7834		0.2847
AM2. Optimistic			0.8004		0.3024
AM2. Pessimistic			0.7962		0.3072
AM3. Optimistic			0.7364		0.3510
AM3. Pessimistic			0.7376		0.3517
AM4. Optimistic	0.7587				0.3315
AM4. Pessimistic	0.7560				0.3334
AM5. Optimistic	0.8589				0.2133
AM5. Pessimistic	0.8618				0.2094
AM6. Optimistic				0.8237	0.2340
AM6. Pessimistic				0.8273	0.2295
AM7. Optimistic		0.6984			0.3815
AM7. Pessimistic		0.7126			0.3791
AM8. Optimistic		0.7145			0.3418
AM8. Pessimistic		0.7244			0.3425
AM9. Optimistic	0.6739			0.4693	0.3100
AM9. Pessimistic	0.6730			0.4657	0.3142
AM10. Optimistic				0.6843	0.3505
AM10. Pessimistic				0.6921	0.3436
AM11. Optimistic		0.7006			0.4353
AM11. Pessimistic		0.6957			0.4490
AM12. Optimistic	0.8241				0.2268
AM12. Pessimistic	0.8254				0.2246
AM13. Optimistic		0.4843			0.5537
AM13. Pessimistic		0.4770			0.5534
AM14. Optimistic		0.6398			0.4653
AM14. Pessimistic		0.6405			0.4546

Note: After data cleaning, the final sample size is 33,092 for the optimistic scenario and 30,240 for the pessimistic one; this reduction is caused by the missing values of some covariates. For the description of questions about walking and cycling conditions see Table A1 in the Appendix.

Factor 2 (12% of total variance) combines economic and logistical aspects, involving both monetary incentives as well as technical support for multimodality and the recharging of e-bikes and e-scooters. Therefore, it can be named as the *convenience* factor. From the point of view of walking and cycling, respectively, the other two factors represent the two facets of a similar issue. They thus could be called *walking safety* (Factor 3, explaining 10% of total variance) and *cycling safety* (Factor 4, accounting for 6.5% of the overall variance). These separate factors regarding safety are due to the differing perception of the "safety" concept itself. When considering walking, safety is indeed more connected to being protected from the consequences of urban decay, such as dirtiness, petty crime, etc. As regards cycling, instead, the road safety (which implies avoiding accidents caused by motor vehicles) is of utmost importance. Table 2 reports the estimation results, both as coefficients, as well as the corresponding average marginal effects for both the scenarios. After data cleaning, the final sample amounts to 26,621 observations for the optimistic scenario and 24,345 for the pessimistic one. The binary dependent variable takes value 0 if the respondents are willing to use active modes only combined to multimodal options; and 1 if active modes are chosen independently from the use of other transport means. As we can see, the results are similar in the two pandemic scenarios. It shows that the prevailing means used before the pandemic have a negative effect on the propensity to use active mobility regardless the joint use of other means of transport. It is also highlighted that the pre Covid-19 use of multimodality is statistically and negatively related to the choice of using sole active modes for commuting purposes. Notably, this result is confirmed by controlling for the distance in km traveled, and the travel time to reach the university. Indeed, these two variables are statistically significant and negative, thus indicating that, as travel time and distance increase, the use of active modes is less likely when it is considered not combined with other means of transport. Moreover, those owning a motor vehicle are less willing to reach the university by walking or cycling: actually, this result is more accrued in the pessimistic scenario. On the other hand, as expected, it should be noted that those owning a bicycle are instead more prone to use active mobility without using other means of transport, being probably accustomed to use bikes as sustainable, but also safer and healthier, means. This result is also in line with the hometown presence of bike sharing services, that is more significantly in the optimistic scenario than in the pessimistic one. A possible motivation could concern the risk of contagion in case of the usage of bike sharing when the sanitation is inadequate.

Finally, it is interesting to note that the estimate of the *eco-friendly environment* factor (Factor 1) is not significant in the two proposed pandemic scenarios. Instead, the impact of Factors 3 and 4 are positively and significantly linked to the choice of active commuting without supporting it with other means of transport. Conversely, the Factor 2 (inherent to economic incentives) reveals a negative sign. A possible reason might depend on the fact that those who are consolidated cyclists (or, in general, people who walk or use bikes for commuting purposes) probably do not need economic incentives (e.g., to buy a bicycle or e-scooter). In fact, beyond evaluating economic incentives or nudges, even not accustomed bikers or walkers tend to consider the safety of pedestrian and cycle paths much more important in order to adopt active commuting without other transport means, as also argued by other scholars, such as Abdullah et al. (2020) and De Vos (2020).

Table 2 – *Output of logit model.*

Label variable	Optimistic scenario		Pessimistic scenario	
	Coef.	**dy/dx**	**Coef.**	**dy/dx**
Pre-Covid choice: (Active modes)				
Motor vehicles	-0.62***	-0.11***	-0.70***	-0.13***
Public Transport	-0.50***	-0.09***	-0.56***	-0.10***
Pre-Covid multi-modality of travel	-0.53***	-0.10***	-0.56***	-0.11***
Gender (Male)	-0.35***	-0.06***	-0.39***	-0.07***
Age (Scale 18 – 79)	0.01*	0.00*	0.01	0.00
Work position (Students)				
Faculty	0.08	0.02	0.12	0.02
Staff	0.02	0.00	0.05	0.01
Motor vehicles ownership	-0.19**	-0.03**	-0.21***	-0.04***
Bicycle ownership	0.52***	0.10***	0.53***	0.10***
Driving license B	0.08	0.01	0.04	0.00
Macro region (North-West)				
North-East	-0.04	-0.00	-0.07	-0.01
Center	0.03	0.00	0.03	0.00
South	0.34	0.06*	0.36	0.07*
Islands	0.01	0.00	0.03	0.00
Weekly freq. (Less than once a week)				
Once	-0.28	-0.05	-0.37*	-0.07*
Twice	-0.29	-0.05	-0.37*	-0.07*
3 times	-0.34*	-0.06*	-0.37*	-0.07*
4 times	-0.52***	-0.10***	-0.57***	-0.11***
5 or more times	-0.28*	-0.05*	-0.31*	-0.06*
Travel time (Up to 15 min)				
15-30min	-0.51***	-0.10***	-0.52***	-0.10***
30-60min	-1.02***	-0.21***	-1.05***	-0.21***
More than 60min	-1.24***	-0.25***	-1.24***	-0.25***
Distance in km covered (1-5 km)				
5–20 km	-1.14***	-0.24***	-1.12***	-0.23***
20-80 km	-1.27***	-0.26***	-1.20***	-0.25***
> 200km	-0.60***	-0.12***	-0.58***	-0.11***
Bike Sharing availability	0.23**	0.04**	0.19*	0.04*
Public Transport Service (Poor)				
Acceptable	0.17***	0.03***	0.20***	0.04***
Good	0.10	0.00	0.03	0.01
Excellent	0.10	0.00	0.05	0.01
Factor 1: eco-friendly environment	0.00	0.00	-0.00	-0.00
Factor 2: convenience	-0.10***	-0.02***	-0.90**	-0.02**
Factor 3: walking safety	0.10***	0.02***	0.12***	0.02***
Factor 4: cycling safety	0.15***	0.03***	0.15***	0.03***
Constant	2.25***		2.43***	

*Note: dy/dx for factor levels is the discrete change from the base level. *** p<0.01, ** p<0.05, * p<0.1.*

5. Concluding remarks

Besides allowing more protection from pandemics (De Hartog et al., 2010) and helping to limit the shift from public transportation to motorized private vehicles (Myftiu et al., 2022), the recourse to active mobility has even greater positive implications for people health and wellbeing. In this paper, some indications are derived to study potential drivers of active modes for commuting purposes. By considering university contexts, safety and security are invoked almost unanimously as relevant aspects. The applied factor analysis also suggested (i) an economic/logistic dimension - linked to cycling only - involving monetary incentives for bicycle commuting and, conversely, higher fees for car parking – and (ii) a more “psychosocial” side related to the wellbeing entailed by being part of an eco-friendly urban community. Chatterjee et al. (2020) state that:” […] *people who walk or cycle to work are generally more satisfied with their commute than those who travel by car and especially those who use public transport*”. Similarly, our policy implications include: quality and safety of walking and biking paths; economic incentives for cycling; and the creation of an eco-friendly environment, both culturally (i.e., people feel part of a “greener” community) and materially (i.e., urban landscape are healthier and far from the nightmare of congestion and constant air pollution).

Appendix

Table A1 *– Active mobility factors (walking)*

	Optimistic	**Pessimistic**
AM1. A quiet and safe pedestrian path with respect to motorized traffic:		
Not at all important	4.41	4.46
Unimportant	10.11	10.23
Fairly important	36.70	37.09
Very important	48.78	48.22
AM2. A path with high personal security (theft, harassment, etc.):		
Not at all important	4.42	4.60
Unimportant	11.35	11.66
Fairly important	31.10	31.36
Very important	53.13	52.38
AM3. A non-bumpy path (existence of spacious pavements, clean, not invaded by parked cars or other obstacles, absence of potholes, etc.):		
Not at all important	3.62	3.66
Unimportant	10.39	10.48
Fairly important	38.84	39.30
Very important	47.15	46.56
AM4. A pedestrian path with more greenery:		
Not at all important	6.96	7.07
Unimportant	30.89	31.28
Fairly important	37.40	37.28
Very important	24.75	24.36
AM5. I feel part of a community that considers it important to reduce its environmental impact:		
Not at all important	8.99	9.27
Unimportant	19.18	19.22
Fairly important	37.77	37.81
Very important	34.06	33.70

Table A1 (cont.) *– Active mobility factors (cycling).*

	Optimistic Scenario	Pessimistic Scenario
AM6. A safe cycle path (protected from motorized traffic), continuous and not bumpy:		
Not at all important	4.22	4.18
Unimportant	4.82	4.74
Fairly important	24.30	23.91
Very important	66.66	67.16
AM7. An economic incentive to move to this mode (e.g., incentive km, vouchers, etc.):		
Not at all important	7.48	7.54
Unimportant	19.41	19.76
Fairly important	31.41	31.14
Very important	41.70	41.56
AM8. A significant bonus for buying a bicycle or scooter:		
Not at all important	8.22	8.34
Unimportant	18.90	19.11
Fairly important	29.87	29.62
Very important	43.00	42.94
AM9. A cycle path with more greenery:		
Not at all important	7.78	7.85
Unimportant	26.58	26.59
Fairly important	36.96	36.58
Very important	28.67	28.97
AM10. Availability and security from stolen university parking:		
Not at all important	3.70	3.70
Unimportant	4.18	4.13
Fairly important	22.03	22.10
Very important	70.10	70.07
AM11. Absence/elimination/pricing of car parking available at the university:		
Not at all important	16.14	16.77
Unimportant	21.08	21.61
Fairly important	25.84	25.48
Very important	36.93	36.14
AM12. I feel part of a community that considers it important to reduce its environmental impact:		
Not at all important	10.63	11.00
Unimportant	20.12	20.17
Fairly important	36.52	36.21
Very important	32.74	32.62
AM13. Facilities for bicycle transport on public transport (train/bus):		
Not at all important	8.10	8.34
Unimportant	14.06	14.17
Fairly important	33.50	33.23
Very important	44.34	44.27
AM14. Presence of charging points for electric vehicles:		
Not at all important	12.27	12.25
Unimportant	18.15	18.26
Fairly important	33.29	32.89
Very important	36.30	36.60

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SUMMARY

This study aims at studying the effects of the Covid-19 pandemic on university commute mode choices and identifying the drivers to change usual transport means to reach college destinations. The data were collected by the Italian Network of Universities for Sustainable Development in 2020. Respondents were asked about their own propensity to switch to active commuting avoiding any other multimodal motorized modes and considering two alternative scenarios (optimistic or pessimistic) concerning the potential risk of contagion. After having identified four latent factors (related to, monetary incentives to bike commuting and psychological aspects of pro-ecological attitudes are detected), the result of a logit model suggested rather straightforward policy drivers, i.e., investing into the quality and safety of routes for walking/cycling, incentives for cycling, and the creation of an eco-friendly environment, where university users feel part of a greener community.

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PRO-ENVIRONMENTAL CONSUMPTION: EFFECTS ON SUBJECTIVE WELL-BEING AS A PROXY FOR UTILITY

Rashad Mammadli

1. Introduction

It is widely conceded that human behaviour is responsible for the main ecological problems including pollution, climate change and global warming (Swim et al., 2011), and consequently, environmental literature emphasizes that changing values and behaviours including consumption habits is essential to overcome these problems (Klöckner, 2013). But how would these changes in consumption affect the well-being of consumers? Since environmentally responsible behaviour is envisaged in self-sacrificial terms, political discourse on environmental sustainability often implies a contradiction between environmental welfare and human well-being (Brown and Kasser, 2005). Nevertheless, several empirical studies suggest that a wide range of pro-environmental consumption behaviours are associated with higher subjective well-being or life satisfaction (Brown and Kasser, 2005; Guillen-Royo, 2019; Schmitt et al., 2018; Welsch and Kühling, 2010). Still, studies reporting this relationship in specific dimensions are limited.

This paper explores the relationship between subjective well-being (SWB) and pro-environmental consumption (PEC) at individual and composite levels including the comparison of the effects of two specific dimensions of sustainable consumption using three waves of the Aspects of Daily Life dataset from Italy. The former dimension which was framed as pro-active sustainable behaviour includes attitudes and behaviours of consumers toward ecologically efficient products – the goods and services designed sustainably, and the second, framed as avoidance behaviour comprises consumption habits avoiding or reducing engagements in environmentally harmful behaviours. Through this design, the paper aims to investigate the relationship by assuming that it is stronger for more frequent pro-active behaviour rather than avoidance behaviour. Even though the classification of sustainable consumption in this way is a novelty, considering the characteristics of variables constructing the relevant composite indicators, pro-active behaviour is similar to (mostly) costlier pro-environmental consumption, while avoidance behaviour recalls behaviours requiring more effort rather than additional expenses.

In this regard, we already know that costlier consumption is strongly associated with life satisfaction compared to less costly behaviours (Schmitt et al., 2018).

In addition, we also examined whether a pro-environmental choice is a utility-maximizing decision under welfare economics, or this type of consumption is consistent with distorted preferences. With all these settings, the paper aims to provide further knowledge on the relationship between pro-environmental behaviour and well-being for facilitating policies in order to improve both ecological and human well-being.

The rest of the paper is organized as follows. Section 2 describes the data, introduces the hypotheses, and explains the methodology. Section 3 outlines the results. Finally, Section 4 recaps the main findings and concludes the report.

2. Methodology

2.1. Data

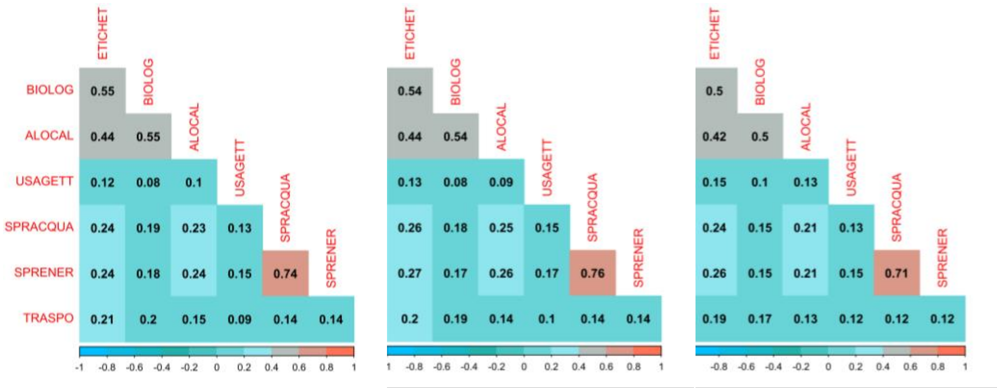
This paper employs the data based on the three waves (2014, 2019, 2020) of the Aspects of Daily Life (AVQ) survey from Italy. It is an annual multipurpose survey conducted by the Italian National Institute of Statistics (ISTAT) since 1993 by interviewing about 50,000 people from 20,000 households on the trends and patterns of the individuals' and households' daily life activities, behaviours, and problems. The data includes information about family composition, employment, education, health status, perceptions of public services, technology use, housing conditions, food consumption, lifestyle, and social engagement.

Starting from 2010, the AVQ survey also includes a couple of questions regarding the life satisfaction of individuals. This paper measures subjective well-being based on the question asking "currently, how satisfied are you with your life as a whole?" on a 0-10 rating scale in which 0 means "not satisfied at all" and 10 means "very satisfied". The average life satisfaction of people aged over 14 first decreases from 7.2 in 2010 to 6.8 in 2012, later remains its value until 2015 and then starts to rise and reach 7.2 in 2020 again (ISTAT, 2021). The average grade is the highest in the North and the lowest in the South of the country.

To investigate pro-environmental consumption behaviours, several sustainable habits including reading labels during shopping, purchasing organic food, purchasing local food, saving water, saving electricity, using disposable products, preferring alternative transportation means to private vehicles, carpooling and throwing paper in streets are measured based on the frequency scale ranging between 1 (never) and 4 (habitually). These variables are present in the 2014, 2019 and 2020 waves. Furthermore, waste sorting habits with 9 domains[1] are examined on the 3-ratings frequency scale where 1 is “never”, 2 is “sometimes”, and 3 is “always” starting from 2017.

Only the individuals who are at age of 16 and more were considered for the analysis. The maximum percentage of missing values (4.41%) for an individual variable was for the variable representing “Alternatives to a private car” in the 2014 survey (it was around 2% for all remaining variables across three years). To deal with missing data, kNN, random forest and hot-deck imputation techniques were implemented; from which the data with kNN imputation was employed.

Figure 1 – *Correlation between the pro-environmental consumption variables.*



Note: ETICHET = Reading labels, BIOLOG = Organic food, ALOCAL = Local food, USAGETT = Disposable products, SPRACQUA = Saving water, SPRENER = Saving electricity, TRASPO = Alternatives to a private vehicle.

Four composite indicators illustrating sustainable behaviour were constructed as an arithmetic mean of the same scale variables. 7 variables - reading labels during the shopping, purchasing organic food, purchasing local food, saving water, saving electricity, using disposable products, and preferring alternative transportation means to private cars, were employed to build the PEC Index. Throwing paper in streets and carpooling were excluded because of negative effects on the total scale. Cronbach's alpha is 0.68 for the 2020, 0.69 for the 2019, 0.67 for the 2014 datasets meaning that the internal consistency is moderate. Moreover, two different indices were built to include pro-environmental consumption (1) aiming to reduce negative ecological footprint through avoiding harmful behaviours and (2) employing pro-

[1] It includes sorting habits for paper, glass, medicine, battery, metals, plastic, organic, textile and other materials.

active behaviours such as consuming products with better environmental efficiency.

Table 3 – *Descriptive statistics for the selected variables and composite indicators.*

Variables	2020		2019		2014	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Life satisfaction[a]	7.18	1.60	7.09	1.70	6.80	1.79
Reading labels[b]	2.94	1.06	2.95	1.07	2.84	1.11
Organic food	2.49	0.99	2.41	1.00	2.15	1.00
Local food	2.85	0.97	2.77	1.01	2.54	1.06
Throwing paper in streets	3.79	0.63	3.75	0.66	3.72	0.68
Saving water	3.55	0.81	3.50	0.85	3.54	0.81
Saving electricity	3.59	0.77	3.55	0.80	3.63	0.73
Disposable Products	2.62	0.96	2.67	0.97	2.68	0.98
Alternatives to a private car	2.19	1.14	2.17	1.15	2.23	1.16
Income[c]	2.67	0.56	2.64	0.58	2.48	0.64
Proportion of Females	0.52		0.52		0.52	
Composite Indicators						
PEC Index	2.89	0.56	2.86	0.58	2.80	0.57
Avoidance Behaviour Index	2.73	0.69	2.70	0.70	2.55	0.72
Pro-Active Behaviour Index	3.11	0.66	3.08	0.68	3.14	0.65
Waste Sorting Index[d]	2.73	0.69	2.70	0.70	2.55	0.72

[a] 0 (not satisfied at all), 10 (very satisfied)
[b] 1 (never), 2 (rarely), 3 (sometimes), 4 (habitually): for all the PEC variables and Indices
[c] 1 (absolutely insufficient), 2 (scarce), 3 (adequate), 4 (excellent)
[d] 1 (never), 2 (sometimes), 3 (always)

Three variables - habits of saving water, saving electricity, and using alternative transportation means to private vehicles, are included to calculate the former composite indicator with an arithmetic mean technique (Cronbach's alpha for 2020 is 0.54; for 2019 is 0.55; for 2014: 0.50 – weaker internal consistency compared to other indicators). The same method was applied for the latter composite indicator with four components – reading labels during shopping, buying organic food, buying local food, and preferring disposable products (Cronbach's alpha for all three years is 0.64). The last composite indicator for sustainable behaviour was set with waste sorting habits excluding "other waste". Waste Sorting Index has Cronbach's alpha of 0.82 and 0.84 respectively in 2020 and 2019 which demonstrate high internal consistency. Along with Cronbach's alpha, correlation analysis between the pro-environmental variables was also performed (Figure 1) in which the results provide that there is a moderate correlation rate among the components of Pro-Active Behaviour Index (excluding consuming disposable products) or Avoidance Behaviour Index (excluding using alternative transportation means rather than private vehicles). Since all the composite indicators are formative in this study (the construct gets its meaning from the components (Diamantopoulos et al., 2008)), low correlations are acceptable (Bollen, 1984). Therefore, both the consumption of disposable products and alternative transportation means were remained in the constructs to prevent a restriction in the domain of the indices (MacKenzie et al., 2005).

Several socio-demographic characteristics such as gender, age, civil status, income, education, occupation, health status and region of residency are included in the set of control variables which are considered important and widely used covariates in well-being and happiness studies.

Table 1 provides summary statistics for life satisfaction (dependent variable), income, gender and pro-environmental consumption behaviours as individual variables and composite indicators.

2.2. Empirical Models

Existing evidence suggests that there is a positive relationship between pro-environmental consumption and subjective well-being, and the former is explained under the distorted choice models rather rational choice model. From a theoretical point of view, using life satisfaction as a proxy for experienced utility allows testing the discrimination between competing theories (Frey and Stutzer, 2002). Obtaining positive and significant coefficients for the pro-environmental consumption in the estimation of subjective well-being would provide evidence for distorted choice models since under the rational choice theory, net marginal utility of quality should be zero for optimal choice as marginal utility of quality is balanced with marginal disutility of quantity foregone (because the quantity is not observable in the dataset, semi-reduced experienced utility function was used where quantity is represented as a function of income and price (F(p,Y)); for theoretical and detailed empirical framework, see Welsch and Kühling (2010)). This model construction enables us to examine whether pro-environmental consumption decision is subject to the rational choice or the distorted choice (Hypothesis 1). To test this approach, the following model was investigated:

$$W_i = \alpha + \beta_i X_i + \gamma Y_i + \theta_i C_i + \delta R_i + \varepsilon_i \tag{1}$$

where W_i denotes life satisfaction as an ordered categorical variable (0-10), X_i is the environmental friendliness (quality) of the consumption, Y_i is income[2], C_i is the set of control variables including gender, age, civil status, education, occupation, and health status, and R_i is the region of residency.

[2] It was employed for deriving semi-reduced experienced utility function to examine whether pro-environmental consumption decision is subject to the rational choice or the distorted choice.

Model 1 also investigates the direct effects of pro-environmental consumption on subjective well-being in which this paper assumes that individuals with more frequent pro-environmental consumption would experience higher life satisfaction compared to those who engage in the same behaviours less frequently.

To compare the levels of the influences of the avoidance behaviour and pro-active environmental behaviour on subjective well-being, the following model was examined:

$$W_i = \alpha + \beta_a X_{a_i} + \beta_p X_{p_i} + \theta_i C_i + \delta R_i + \varepsilon_i \quad (2)$$

where X_{a_i} and X_{p_i} respectively denote Pro-Active and Avoidance Behaviour composite indicators. Model 2 enables us to test Hypothesis 2 assuming that the relationship is stronger for more frequent pro-active behaviour rather than avoidance behaviours since the former (usually) have either higher financial costs (such as purchasing more expensive organic and local food) or require additional effort (such as reading labels).

Considering the characteristics of the variables of interest and also previous research, ordered probit regression was employed to report the results.

3. Results

The results regarding the sign of coefficients of the socio-demographic control variables in relation to life satisfaction are consistent with the common findings in the pertinent literature. Moreover, when single PEC regressor models controlling socio-demographic variables and region of residency is considered, the coefficients for each domain of sustainable consumption become significant in all the models (results are not reported in this paper). However, in this section, only the results of multiple PEC regressors models are reported.

Table 2 provides the results of ordered probit estimations for Models 1. Two different groups of regressors were considered for this empirical model. The first one includes only composite indicators to represent sustainable consumption, while the second one includes individual domains of PEC behaviours and Waste Sorting Index (a composite indicator). As can be seen in the table, both the PEC Index (2020: 0.19, $p<0.01$; 2019: 0.23, $p<0.01$; 2014: 0.18, $p<0.01$) and the Waste Sorting Index (2020: 0.10, $p<0.01$; 2019: 0.10, $p<0.01$) positively predict life satisfaction across three years. The former has a significantly stronger effect on life satisfaction compared to the latter both in 2019 and 2020; while it is not estimable for 2014 since waste sorting habits were not collected in this year. Considering specific domains of pro-environmental consumption, only organic food and using alternative transportation means instead of private vehicles remain insignificant (at 95% significance level) across three years. Saving electricity is positively and significantly associated with life satisfaction in 2019, while its effect becomes insignificant in the 2014 and 2020 datasets. Conversely, using disposable products has a positive and significant effect on subjective well-being in 2014 and 2020, and an insignificant effect in 2019 (significant at 90% significance level, p=0.0582). All the remaining PEC variables and Waste Sorting Index positively and significantly correlated with life satisfaction controlling socio-demographic attributes and region of residency across three years. Furthermore, according to the specification 1, positive and significant coefficients for the pro-environmental consumption range provide evidence for distorted choice models which is consistent with existing evidence in social sciences that individuals underestimate future utility from intrinsic attributes (Frey and Stutzer, 2002). These results support Hypothesis 1.

Table 2 – *Life satisfaction as a function of pro-environmental consumption (Model 1).*

Composite Indicators & Variables	2020		2019		2014[a]	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Model with only CI's						
PEC Index	0.190***	0.010	0.225***	0.009	0.176***	0.010
Waste Sorting Index	0.104***	0.012	0.102***	0.011		
Income	0.358***	0.010	0.372***	0.009	0.344***	0.009
Pseudo R^2 (Nagelkerke R^2)	0.137		0.148		0.160	
Model with Variables						
Waste Sorting Index (CI)	0.099***	0.012	0.097***	0.011		
Reading labels	0.041***	0.006	0.063***	0.006	0.054***	0.006
Organic food	0.009	0.007	-0.002	0.007	0.002	0.007
Local food	0.058***	0.007	0.057***	0.006	0.039***	0.006
Throwing paper in streets	0.058***	0.009	0.066***	0.008	0.055***	0.008
Saving water	0.053***	0.010	0.042***	0.009	0.041***	0.009
Saving electricity	0.014	0.011	0.041***	0.010	0.014	0.010
Disposable Products	0.015***	0.006	0.011*	0.006	0.027***	0.006
Alternatives to a private car	-0.006	0.005	0.002	0.005	-0.010***	0.005
Income	0.355***	0.010	0.373***	0.009	0.344***	0.009
Pseudo R^2 (Nagelkerke R^2)	0.140		0.148		0.163	

Control variables: gender, age, civil status, education, income, occupation, health status, region

***p < 0.01, **p < 0.05, *p < 0.10

[a] the results of the 2014 survey cannot be directly compared with 2019 and 2020 since the 2014 dataset does not include waste sorting habits.

To test Hypothesis 2, the Avoidance Behaviour Index and the Pro-active Behaviour Index were used as simultaneous predictors in Model 2 (Table 3). The results provide that both indices are positively and significantly associated with life satisfaction across three years. However, the Pro-active Behaviour Index (2020: 0.133, p<0.01; 2019: 0.142, p<0.01; 2014: 0.126, p<0.01) has considerably higher coefficients compared to the Avoidance Behaviour Index (2020: 0.061, p<0.01; 2019: 0.088, p<0.01; 2014: 0.045, p<0.01), meaning that pro-environmental consumption with preferences for the products with higher environmental efficiency has a stronger effect on subjective well-being compared to sustainable choices aiming to avoid or less frequently engage in consumption decisions having negative ecological externalities (Figure 2). The results support Hypothesis 2. To our knowledge, this is the first study investigating the association between subjective well-being and pro-environmental consumption concerning the comparison of these two dimensions. However, if we consider pro-active sustainable behaviour costly and avoidance behaviour less costly, then our findings confirm the previous findings emphasizing that costlier consumption is strongly associated with life satisfaction compared to the less costly behaviours (Schmitt et al., 2018).

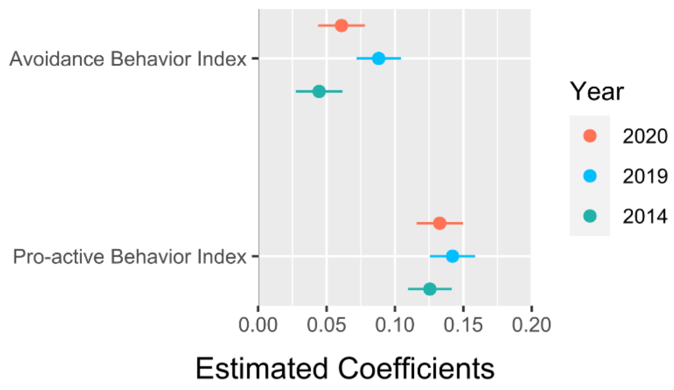
Table 3 – *Life satisfaction as a function of the Avoidance and Pro-active Behaviour Indices (Model 2).*

Composite Indicators	2020		2019		2014	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Avoidance Behaviour Index	0.061***	0.009	0.088***	0.008	0.045***	0.009
Pro-active Behaviour Index	0.133***	0.009	0.142***	0.008	0.126***	0.008
Pseudo R^2 (Nagelkerke R^2)	0.135		0.146		0.161	

Control variables: gender, age, civil status, education, income, occupation, health status, region

***p < 0.01, **p < 0.05, *p < 0.10

Figure 2 – *Coefficients of Avoidance and Pro-active Environmental Behaviour Indices.*



4. Concluding Remarks

This study implies that people systematically make imprecise predictions about the utility obtained from pro-environmental consumption, and this type of behaviour leads to higher subjective well-being. Several model constructions were built to test various assumptions in these regards by using three waves of a multipurpose survey from Italy. Findings show that individuals who more frequently engage in various types of sustainable consumption report higher life satisfaction, which was used as a proxy for utility, than those who less frequently behave environmentally friendly or who do not, controlling a wide range of socio-demographic variables and the region of residency. So, these results allow to argue that people may systematically mispredict, more precisely, underestimate the possible outcomes of their pro-environmental consumption and consequently, they fail to maximize their utility, which is evidence of the distorted choice theory. Considering the domains of sustainable consumption, results provide that life satisfaction is positively and statistically significantly associated with most of PEC variables and composite indicators in all three waves of Italian Aspects of Daily Life survey. So, these findings suggest that more frequent engagement in most domains of sustainable consumption associated with higher satisfaction with life, while a few of them have no significant impact on well-being, and furthermore, none of them causes a deterioration in life satisfaction.

4.1. Contribution and Limitations

These results are not new in pertinent literature, however, examining this relationship in two specific dimensions of sustainable behaviour contributes new findings to the literature. To my knowledge, this is the first study that implies satisfaction with life is differentially influenced by pro-active sustainable behaviour, representing the consumption of ecologically efficient products and avoidance behaviour representing avoiding or less frequently engaging in environmentally harmful consumption. Indeed, our findings show that the former has a considerably stronger effect on life satisfaction compared to the latter. However, it should be noted that if we consider pro-active sustainable behaviour costly (three of four variables constructing the Pro-Active Index imply higher costs for consumers) and avoidance behaviour less costly (all three variables constructing the Avoidance Index require more effort rather than additional expenses), our results confirm the previous results instead of being novelty in the pertinent literature.

Using life satisfaction as a proxy for utility allows studying problems empirically such as testing discrimination between competing explanations for empirical findings in human behaviour (Frey and Stutzer, 2002). So, data on life satisfaction or happiness help to tackle important questions in economics; however, still, the results obtained from this type of survey should be treated critically and cautiously (Di Tella and MacCulloch, 2006). Here both pro-environmental consumption and life satisfaction are measured based on the self-reports which may constitute the main limitation of this study. On one hand, there is evidence that individuals incline to report their sustainable behaviours higher than their actual behaviour because of the social desirability effect (Tarrant and Cordell, 1997); while on the other hand, other research provides that this effect does not influence the accuracy of the measurement of the environmentally friendly behaviour (Kaiser, 1998). In this regard, the results are consistent with the findings of previous studies which support their robustness (Guillen-Royo, 2019). Another limitation is endogeneity because of omitted variable bias and reverse causality. As an example of the former, in the AVQ dataset, it was not possible to measure how the ecological concerns of respondents affect both sustainable consumption and life satisfaction. Indeed, perceived environmental threats and other unobserved factors may influence the variables of interest which may cause the omitted variable bias, however, employing a wide range of socio-demographic variables gave some confidence that this limitation was controlled in the best feasible way (Guillen-Royo, 2019; Schmitt et al., 2018; Welsch and Kühling, 2010). Considering reverse causality, on one hand, several studies provide that more happiness leads to less consumption (Guven, 2012), while others demonstrate that happiness causes improvements in consumption expenditures both in rural and urban areas (Zhu et al., 2020). On the other hand, there are studies providing that consumption has a positive effect on subjective well-being as well (Noll and Weick, 2015). Considering pro-social characteristics of pro-environmental behaviour (Schmitt et al., 2018), previous experimental and longitudinal research demonstrate that pro-social behaviour positively affects well-being (Dunn et al., 2014). However, the lack of this type of studies concerning sustainable behaviour limits the plausibility of this interpretation and gives rise to a necessity for future research with a longitudinal or experimental design to identify the direction of the causality (Guillen-Royo, 2019; Schmitt et al., 2018).

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SUMMARY

This paper contributes to the growing empirical evidence that engaging in pro-environmental consumption has positive consequences on satisfaction with life as well as strengthens the idea that this type of behaviour is subject to systematic deviations from utility-maximizing choices that consumers underestimate extra utility from sustainable consumption. Moreover, the results imply that pro-environmental consumption preferences for the products with a higher environmental efficiency has a stronger effect on subjective well-being compared to the sustainable choices characterized as to avoid or less frequently engage in consumption decisions having negative ecological externalities. The findings were obtained through using three waves (2014, 2019 and 2020) of Aspects of Daily Life dataset, an annual multipurpose sample survey in Italy; however, they are consistent with the results of similar studies in other countries including Germany, China, and the United States, and therefore, as Luechinger (2009) suggests in an equivalent situation in a different context, this approach may also be transferred to other countries.

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QUALITY OF GOVERNMENT AND ENVIRONMENTAL WELLBEING ACROSS EUROPEAN REGIONS

Andrea Vaccaro, Carlotta Montorsi

1. Introduction

As stated in the United Nations General Assembly resolution 66/288 (UN 2012: 2), “to achieve our sustainable development goals, we need institutions at all levels that are effective, transparent, accountable and democratic”. Simply put, we need *quality of government* to foster human wellbeing. The vast majority of cross-national comparative studies on the relationship between institutions and wellbeing supports this view, yet extant research has focused primarily on the economic and social aspects of wellbeing. Given that wellbeing is commonly conceived as a tri-dimensional concept consisting of three main pillars – economic, social, and environmental (e.g., Ciommi *et al.*, 2020) – the current literature has neglected the environmental dimension of wellbeing. Furthermore, the few existing studies on the relationship between quality of government and environmental wellbeing remain inconclusive. Depending on the study, this association has been described as positive (e.g., Ríos and Picazo-Tadeo, 2021), negative (e.g., Cole, 2007), or non-significant (e.g., Peiró-Palomino *et al.*, 2020).

This study contributes to the literature on the relationship between institutional quality and human wellbeing, by filling the above gap in the literature. Ultimately, our goal is to investigate if quality of government – defined as “the extent to which states perform their required activities and administer public services in an impartial and uncorrupt manner” (Charron *et al.*, 2015) – is a significant predictor of common dimensions of environmental wellbeing. To shed light on the institutions-environment nexus, we address three major shortcomings in the existing body of scholarship on the topic. We argue that these three limitations may have played an important part in prior inconclusiveness of results.

First, a lion’s share of studies has focused on institutional quality and environmental wellbeing at the country-level, disregarding subnational variation within countries. Experts however have recently demonstrated that both quality of government (Charron *et al.*, 2015; Charron *et al.*, 2019) and human wellbeing (Iammarino *et al.*, 2019; OECD 2014) vary significantly within countries. Therefore, we investigate the relationship between quality of government and environmental wellbeing at a subnational level. We focus on NUTS 2 regions in the European Union (EU) because, in the last decades, within-country territorial differences have increased especially in Europe (Iammarino *et al.*, 2019).

Second, present knowledge on the institutions-environment nexus is based on an excessively narrow understanding of the environment. Even some of the most sophisticated studies measure environmental wellbeing through exposure to air pollution by particular matter (Peiró-Palomino *et al.*, 2020) or by a combination of multiple air pollutants (Halkos *et al.*, 2015). Nevertheless, it is self-evident that one or more air pollutants cannot represent environmental wellbeing in its entirety. In the same way that human development is much more than GDP/capita, environmental wellbeing is much more than air pollution. Therefore, we take a multidimensional approach to environmental wellbeing measurement. Following the Italian National Institute of Statistics (ISTAT 2021), we identify six main dimensions, and measure four of them with multiple representative indicators. Specifically, we look at: (1) air quality, (2) water quality, (3) soil quality, and (4) energy and climate change.

Third, somewhat related, instead of using simple indicators to proxy these four dimensions, we construct composite indices to represent each of them as comprehensively as possible. To do so, we take a Bayesian approach to composite indicator construction, which has some important advantages compared to frequentist methods. In particular, our Bayesian latent variable approach, through the incorporation of prior knowledge, results in estimates that are more precise and informs on the uncertainty of these estimates. Moreover, since scholars have shown that regional wellbeing tends to be spatially interdependent (Peiró-Palomino *et al.*, 2020), we assess the magnitude of environmental wellbeing's spatial correlation in EU regions and take into account this information in the newly developed composite indicators. Finally, we use these composite indicators as dependent variables in our subsequent regressions of environmental wellbeing on quality of government.

This paper proceeds as follows. First, we present the data we use in the analysis. Second, we explore the methods. Third, we present and discuss our empirical results. Finally, in the conclusive section, we briefly summarize our main findings.

2. Empirical Approach

2.1. Main Data

Frequently used cross-national measures of environmental wellbeing and quality of government capture these two concepts at the country-level without making any difference among territorial discrepancies within countries. Recently, however, as scholarly interest in subnational development has increased, new subnational data on institutional quality and environmental wellbeing has been published.

To measure subnational quality of government in EU regions, we use arguably the most widely used and well-constructed dataset on the topic: the *European Quality of Government Index Survey Dataset* (Charron *et al.*, 2019). The dataset, published by the Quality of Government Institute at the University of Gothenburg, provides subnational data for EU countries in four years – 2010, 2013, 2017, and 2021. Its *European Quality of Government Index* (EQI) is constructed by first aggregating individual survey question scores into three dimensions of quality of government, and then by synthesising these three component indicators – *Quality*, *Impartiality*, and *Corruption* – into an aggregate index. EQI captures institutional quality at the NUTS 2 level in 238 subnational territories across EU countries. The index runs from low to high on a z-score scale (mean of 0; standard deviation of 1).

As for environmental wellbeing, no comprehensive measure at the subnational EU level exists at the time of this writing. As already stressed, to cope with the lack of subnational data on the environmental pillar of wellbeing, most scholars tend to focus only on measures of air pollution. Yet, these measures are not representative of environmental wellbeing as a whole. For instance, one of the most well-known datasets on subnational wellbeing – OECD's *Regional Wellbeing Dataset* – provides only one measure of environmental wellbeing: air pollution by particulate matter. To tackle the above problems, we (1) scrutinize and collect a battery of subnational indicators of various aspects of environmental wellbeing and (2) develop an original set of composite indicators of air quality, water quality, soil quality, and energy and climate change to comprehensively capture these aspects.

Next, before the actual empirical analysis, we discuss in detail the process of constructing our novel set of composite indicators and specify the regressions used to examine the nexus between quality of government and environmental wellbeing.

2.2. Methods

One of the shortcomings in past subnational studies on the relationship between quality of government and environmental wellbeing is the lack of a comprehensive and synthetic measure of environmental wellbeing. Hence, by means of a data-driven approach based on factor analysis, we construct four environmental composite indicators, one for each of our four environmental pillars – air, water, soil, and energy – summarizing the information of 17 elementary environmental indicators. Then, we run ordinary least squares (OLS) regressions to shed light on the link between quality of government and environmental wellbeing in EU regions.

We hypothesize the existence of spatial spillovers, so that environmental conditions in each region are partially determined by the environmental conditions of its neighboring regions. To verify this initial assumption, we test for spatial autocorrelation in the 17 environmental elementary indicators through the Global Moran I test (Moran, 1950), which provides significant results for all the indicators.

Based on these results, we follow Hogan and Tchernis (2004) and estimate a Bayesian latent factor model for spatially correlated data.

The Bayesian approach naturally adapts to the hierarchical structure of the latent factor model. Moreover, through priors' distribution specification, the Bayesian approach allows providing information on the spatial structure of the data, resulting in more precise latent factors' estimates. Finally, the Bayesian approach has the specific advantage of providing a measure of uncertainty about the latent factor scores, through the information embedded in the posterior parameters' distribution.

For each European region i, where $i = 1, \dots, 235$, let $Y_{i,p}$ denote the elementary environmental indicator p in region i and $p = 1, \dots, 17$. Hence $\boldsymbol{Y}_i = \left(Y_{i,1}, \dots, Y_{iP}\right)^T$ is the vector of the observed outcome variables for region *i*. We assume the existence of a latent variable δ_i, that fully characterizes the environmental wellbeing level, which in turn manifests itself through Y_i. Thus, we represent the model in a hierarchical form. At the first level we have:

$$\mathbf{Y}_\mathrm{i} \mid \mu_i, \delta_i, \boldsymbol{\Sigma} \sim \textit{Multivariate-Normal}\,(\mu_i + \boldsymbol{\lambda}\delta_i, \boldsymbol{\Sigma}),$$

where $\boldsymbol{\mu}_i$ is $a\ P \times 1$ mean vector, $\boldsymbol{\lambda}$ is a $P \times 1$ vector of factor loadings, and $\boldsymbol{\Sigma} = \mathrm{diag}(\sigma_1^2, \dots, \sigma_P^2)$ is a diagonal matrix measuring residual variation in Y_i. Assuming Σ diagonal implies independence among the elements of Y_i conditionally on δ_i. Writing the model compactly, let Y be the $NP \times 1$ stacked vector of manifest variable and $\boldsymbol{\mu}$ the stacked vector of mean defined analogously. Finally, let $\boldsymbol{\Lambda} = \mathrm{I_N} \otimes \boldsymbol{\lambda}$ the $NP \times N$ matrix of factor loadings where I_N is the identity matrix of dimension N.

Let $\boldsymbol{\delta} = (\delta_1, \dots, \delta_N)^T$ be the vector of regions' latent environmental wellbeing. We add spatial information to the latent factor prior distribution by assuming:

$$\boldsymbol{\delta} \sim \text{Multivariate-Normal}(0_n, \boldsymbol{\Psi}),$$

where $\boldsymbol{\Psi}$ is a $N \times N$ spatial variance-covariance matrix having 1's on the diagonal and $\psi_{i,j} = corr\left(\delta_i, \delta_j\right)$ on the off-diagonal. When $\boldsymbol{\Psi} = I_N$ the model assumes spatial independence across regions' environmental wellbeing levels. To introduce spatial correlation, the literature proposes several alternatives. We choose a marginal parametrization of the spatial variance-covariance matrix $\boldsymbol{\Psi}$, through specifications of spatial dependency based on distances between regions' centroids (Cressie, 1993). This parametrization assumes $\psi_{i,j} = \exp\left(-\xi d_{i,j}\right)$, where ξ is the spatial correlation parameter, and $\xi \geq 0$ to ensure $\psi_{ij} < 1$; $d_{i,j}$ is the Euclidean distance between the centroid of regions i and j.

The composite index of environmental wellbeing for region i is summarized by the conditional distribution of the latent factor δ_i given Y and μ, λ, Σ. Hence, the posterior distribution of $\boldsymbol{\delta}$ will be a Multivariate normal distribution:

$$(\boldsymbol{\delta} \mid \boldsymbol{Y}, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\Sigma}) \sim \text{Multivariate-Normal}(\boldsymbol{d}, \boldsymbol{D}),$$

where

$$\mathbf{D} = \{\Psi + \Lambda^{\mathrm{T}}\Sigma^{-1}\Lambda\}^{-1},$$
$$\mathbf{d} = \mathrm{D}\Lambda^{\mathrm{T}}\Sigma^{-1}(\mathrm{Y} - \mu).$$

Finally, a characteristic of the Bayesian framework is the introduction of prior distributions on all the model's parameters. In our model, we have set $\lambda_p \sim \text{Normal}(g, G)I(\lambda_1 > 0)$, $\sigma_p^2 \sim \text{Inverse-Gamma}(\alpha/2, \beta/2)$, $\mu_p \sim \text{Normal}\big(0, V_\mu\big)$. The primary scope of prior distributions is to include subjective opinions on the parameters of interest. Yet, to let the data “speak for themselves”, we use diffuse priors by choosing $g = 0$, $G = 1000$, $\alpha = 1/1000$, $\beta = 1/1000$, and $V_\mu = 1000$.

We estimate the model with a Gibbs sampling algorithm that includes Metropolis Hasting steps for the spatial parameter ξ[1].

Next, we retrieve the mean from the estimated environmental composite indicators’ posterior distributions and use it as an outcome in OLS regressions to analyse the correlation between environmental wellbeing and quality of government. Let $\hat{\delta}_{ik} = E[\delta_{ik} \mid Y, \mu, \lambda, \Sigma]$, where i indicates the European region and k the environmental dimension, i.e. $k = air, energy, water, soil$; the QoG_i is quality of government in region i. Then, our regressions take the following form:

$$\hat{\delta}_{ik} = \theta + \beta * QoG_i + \boldsymbol{\gamma}' * \boldsymbol{x_i} + \epsilon \;\; \forall\, k$$

The coefficient of interest is β, which captures the correlation between the quality of government and the observed environmental levels in domain k. We add a few region-specific controls in $\boldsymbol{x}_i$, namely GDP/capita and population density.

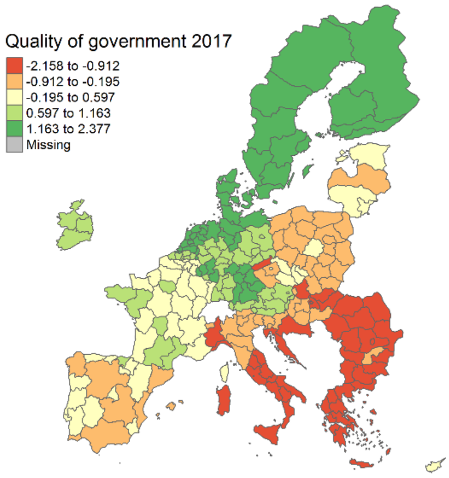
2.3. Results and Discussion

We begin the empirical part and discussion of results by drawing a map of the level of quality of government in all EU regions with available data in 2017 (Figure 1). The map shows clearly that Northern and Western European countries have more quality of government than Southern and Eastern European countries. Yet, the map confirms that there are substantial differences among regions within many countries. To give an example of the nuances that would be missed in a national level approach, let us examine the case of Italy. At the national level, according to EQI, Italy has more quality of government than Bulgaria, Croatia, Greece, and Romania. At the

[1] We have written the sampling algorithm in the R software and made it available on GitHub.

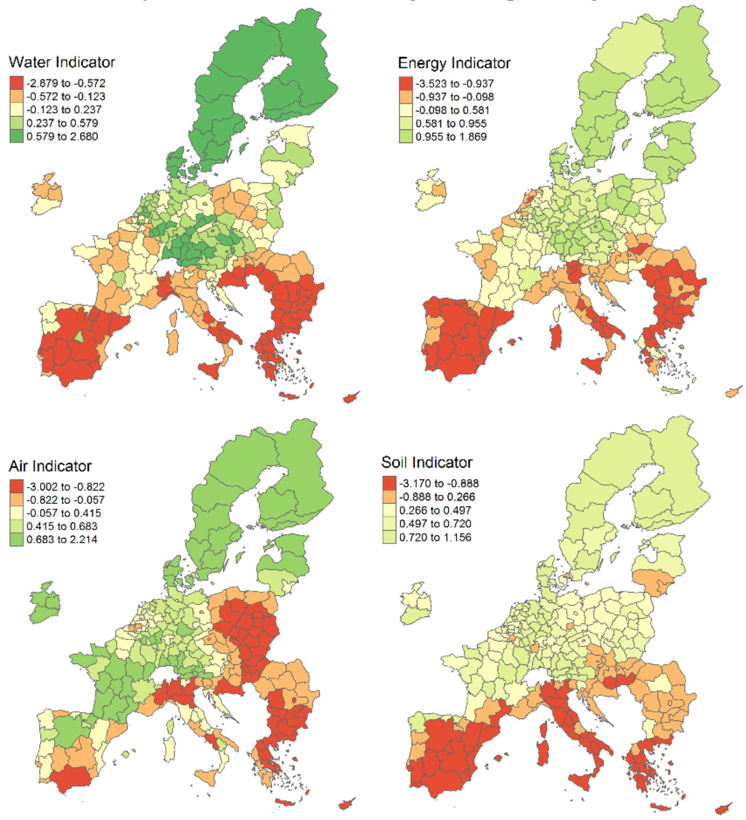
regional level, however, the South Italian region of Calabria has the second lowest level of subnational institutional quality in Europe, whereas the North Italian autonomous provinces of Trento and Bolzano have higher subnational institutional quality than regions such as Catalonia and countries such as Latvia and Poland. These details remain unseen in studies that do not dig deeper into the subnational level. Figure 1 confirms that a complete picture of the effects of quality of government requires taking into account these subnational differences.

Figure 1 – *Quality of government in EU regions.*



Next, we continue our empirical consideration by analyzing the spatial distributions of the estimated composite indicators (latent variable) for each of our four environmental domains. As illustrated by the maps in Figure 2, there seems to be a clear division in environmental wellbeing – regardless of the dimension – between countries in Northern and Western Europe and countries in Southern and Eastern Europe. Citizens of the former group of countries enjoy a considerably greater environmental wellbeing than citizens of the latter group of countries. Nevertheless, our subnational and multidimensional approach allows discovering also interesting nuances and several exceptions to this general trend. By observing Figure 2 and computing the standard deviation of regions within a given country, we can detect that within-country variation is in some cases substantial.

Figure 2 – *Dimensions of environmental wellbeing in European regions*.



As for the dimension of air, the largest within-country variation occurs in Greece (*sd* = 0.82), Italy (*sd* = 0.82), and Croatia (*sd* = 0.77). As for the dimension of water, the largest within-country variation occurs in Denmark (*sd* = 0.73), Greece (*sd* = 0.72), and Belgium (*sd* = 0.71). As for the dimension of soil, the largest within-country variation occurs in Spain (*sd* = 1.18), Portugal (*sd* = 0.98), and Italy (*sd* = 0.95). As for the dimension of energy and climate change, the largest within-country variation occurs in Portugal (*sd* = 1.28), Greece (*sd* = 0.97), and Spain (*sd* = 0.67). These results suggest that in general within-country unevenness in environmental wellbeing is higher in Southern European countries than in the rest of EU countries.

Next, in Table 1 we report the estimated factor loadings. Factor loadings with negative signs imply an inverse association between the elementary indicators and the latent dimension of environmental wellbeing. Conversely, factor loadings with positive signs imply a positive association between the elementary indicators and the latent dimension of environmental wellbeing. When the factor loading distribution is highly centered around zero, we consider the associated indicator not significant for improving wellbeing. All elementary indicators have expected signs.

As shown by factor loadings in Table 1, some elementary indicators are more strongly related to a given latent dimension of environmental wellbeing than others. Indicators of PM10 and PM2.5 based air pollution have the strongest relationships with the latent dimension of *Air*. Urban exposure to PM10 and ozone and NO2 based air pollution are moderately related to Air, whereas the capacity of urban vegetation to remove NO2 is somewhat weakly related to Air. Water productivity and the quality of drinking water instead are relatively strongly related to the latent dimension of *Water*, whereas sewage treatment and freshwater consumption are moderately related to Water. The capacity of ecosystems to avoid soil erosion has by far the strongest correlation with the latent dimension of *Soil*. Severe soil erosion by water and organic farming are moderately related to Soil. Artificial surfaces inside protected areas and land use with heavy environmental impact are weaklier related to *Soil*. Potential vulnerability to climate change instead represents well the latent dimension of *Energy*, whereas energy recovery capacity is only moderately related to Energy.

Table 1 – *Elementary indicators of wellbeing and factor loadings*.

Elementary indicator	Air	Water	Soil	Energy
NO2 Removal capacity by urban vegetation (2020)	-0.092			
Urban population exposed to PM 10 (2020)	-0.431			
Air pollution - PM2.5 (2016)	-0.974			
Air pollution - PM10 (2016)	-1.035			
Air pollution - Ozone (2017)	-0.365			
Air pollution - NO2 (2017)	-0.431			
Water productivity or use efficiency (2020)		0.642		
Drinking water quality (2020)		0.651		
Sewage treatment (2016/2014)		0.424		
Freshwater consumption per capita (2020)		-0.487		
Capacity of ecosystems to avoid soil erosion (2020)			0.976	
Severe soil erosion by water (2016)			-0.412	
Artificial surfaces inside N2000 in km² (2018)			-0.171	
Land use with heavy environmental impact (2018)			0.180	
Organic farming (2016)			0.315	
Energy recovery (R1) capacity per capita (2018)				0.321
Potential vulnerability to climate change (2071-2100)				-1.005

With our composite indicators of environmental wellbeing, we can now assess the multidimensional relationship between environment and quality of government. Table 2 reports a summary of the results of the OLS regressions on the relationship between environmental wellbeing and quality of government. In the baseline models, we do not include any control variables into the regression equation. In the second set of models, we control for potential socioeconomic confounders including GDP/capita and population density. In the third and last set of models, to exclude that the "effects" are driven by other aspects of environmental wellbeing, we control also for the different dimensions of environmental wellbeing.

Table 2 – *Environmental wellbeing and quality of government: regression results.*

	Dependent variable:			
	Air	*Water*	*Soil*	*Energy*
	(1)	(2)	(3)	(4)
Baseline models				
Quality of government	0.672***	0.562***	0.616***	0.547***
	(0.049)	(0.037)	(0.047)	(0.044)
R^2	0.49	0.49	0.38	0.31
N	233	233	233	233
Models with socioeconomic controls	(5)	(6)	(7)	(8)
Quality of government	0.594***	0.471***	0.679***	0.624***
	(0.075)	(0.049)	(0.068)	(0.068)
GDP/capita	0.336	0.322*	-0.264	-0.332
	(0.180)	(0.161)	(0.186)	(0.200)
Population density	-0.0002*	0.0002***	0.0001	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R^2	0.51	0.56	0.39	0.33
N	233	233	233	233
Models with socioeconomic and environmental controls	(9)	(10)	(11)	(12)
Quality of government	0.519***	0.143**	0.283**	0.264**
	(0.090)	(0.054)	(0.091)	(0.094)
GDP/capita	0.277	0.428**	-0.380*	-0.430*
	(0.183)	(0.150)	(0.190)	(0.181)
Population density	-0.0002**	0.0002**	-0.00004	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Air		0.073	0.054	-0.067
		(0.043)	(0.087)	(0.067)
Water	0.165		0.509***	0.547***
	(0.105)		(0.114)	(0.087)
Soil	0.052	0.216***		0.210*
	(0.082)	(0.048)		(0.081)
Energy	-0.061	0.220***	0.199*	
	(0.062)	(0.042)	(0.078)	
R^2	0.52	0.69	0.53	0.49
N	233	233	233	233

*Robust standard errors in parentheses; * p < 0.05, ** p < 0.01, *** p < 0.001.*

The baseline models (1-4) without control variables show that the quality of government is strongly related to each of our four dimensions of environmental wellbeing. The positive sign of the slope coefficients suggests that a higher level of quality of government increases environmental wellbeing. Regardless of the dimension, the result is statistically significant at the 99.9% level of confidence. Additionally, variation in the quality of government alone predicts a relatively important amount of variation in each of the four dimensions of environmental wellbeing – in particular air (R^2 = 0.49) and water (R^2 = 0.49). Nevertheless, more robust evidence on the link between quality of government and environmental wellbeing requires controlling for potential confounding factors.

This is precisely what we do in models 5-8, where we include controls for GDP/capita and population density. As shown by the estimates, adding these two common socioeconomic variables on the right-hand side of the regression equation does not alter substantively the interpretation of the results. Quality of government remains a positive and statistically significant predictor of air (β = 0.59), water (β = 0.47), soil (β = 0.68), and energy (β = 0.62) at the highest conventional level of confidence. In general, environmental wellbeing is better predicted by institutional quality than by economic development or population density. The inclusion of the two socioeconomic controls in the models generates only a negligible increase in model fit.

Finally, in models 9-12 we analyze the predictive power of quality of government on air, water, soil, and energy by controlling for the various dimensions of environmental wellbeing – excluding of course the one used as a dependent variable. At least in theory, the different dimensions of environmental wellbeing are likely to be interrelated. Models 9-12 seem to confirm these theoretical expectations at least in part. The predictive power of quality of government on water (β = 0.14), soil (β = 0.28), and energy (β = 0.26) decreases considerably compared to the previous sets of models. These three slope coefficients are also significant at the lower 99% level of confidence. Interestingly, however, our estimates show that the relationship between quality of government and air quality (β = 0.52) remains essentially unaffected by the inclusion of the controls for water, soil, and energy.

3. Conclusions

The study at hand has investigated the relationship between environmental wellbeing and quality of government across European regions through a multidimensional, comparative, and subnational approach. The main contributions of our study are manifold. First, we have detected the presence of spatial spillovers in environmental levels across EU regions. Second, accounting for this spatial correlation, we have constructed multidimensional composite indicators for four common aspects of environmental wellbeing – air, water, soil, and energy. Third, through a battery of cross-section OLS regression models, we have shown that institutional quality is a significant and positive predictor of each of our dimensions of environmental wellbeing, and it seems to be particularly important for improving air quality. This is reassuring since various measures of air pollution are often used as proxies of environmental wellbeing as a whole. Yet, we have shown that the other three dimensions of environmental wellbeing are important too, suggesting that future studies should not equate simplistically the environment with air pollution and overlook aspects related to water, soil, and energy.

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SUMMARY

Conventional wisdom holds that effective state institutions play a key role for improving sustainable wellbeing. Hence, building quality of government is one of the global targets of the UN Sustainable Development Goals. While empirical evidence indicates that quality of government is indeed crucial for social and economic wellbeing, studies on the environmental impact of effective institutions are scarce and inconclusive. Yet, considering the increasingly severe environmental threats faced by humanity, understanding whether effective institutions are associated with environmental wellbeing should be of primary importance for both researchers and policymakers. In order to shed light on the somewhat neglected institutions-environment nexus, our study addresses three major gaps in the literature. First, instead of focusing on the country level, we focus on the subnational level. Second, instead of considering only a single aspect of environmental wellbeing, our results are based on multiple domains of the environment. Third, given the lack of subnational indices on environmental wellbeing, we develop a new composite index of environmental wellbeing via Bayesian latent variable analysis that takes into account spatial correlation. Our findings show persuasively that quality of government is in general an important and positive determinant of environmental wellbeing at the NUTS 2 level the EU, though we find also that the strength of the institutions-environment nexus depends on the sphere of environmental wellbeing. Policymakers should be aware that environmental destruction can be tackled by building more effective regional institutions.

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ENVIRONMENTAL MONITORING IN ITALIAN CITIES A MULTIDIMENSIONAL ANALYSIS WITH COMPOSITE INDICES

Giuseppe Lecardane

1. Introduction

Environment quality and social well-being are closely interconnected on a collective and individual level. It is, in fact, a relationship that invests values of primary importance, such as those relating to human health and safety, heritage and resources to be passed on to future generations. Therefore, statistical information, for an in-depth knowledge of environmental issues, it is relevant for everyone. The effectiveness of any action in the environmental field implies an awareness of citizens and the choice of appropriate behaviours (Lecardane and Arcarese, 2009; Lecardane, 2013).

Complex and multidimensional nature of environmental phenomena requires the identification and measurement of indicators for the implementation of more effective and incisive information programs. Due to the number of indicators that represent the different dimensions of the state of the urban environment to be measured, it is also necessary to find a synthesis process to improve comparison and analysis of the observed phenomena. In fact, the synthesis has the advantage of performing simpler and faster analyzes especially in comparative terms and in addition of summarize heterogeneous and multidimensional phenomena.

In this paper, we will proceed to experimental comparison of some main weighting approaches for the composite indicator-construction methods referring to the data on urban environmental quality on issues such as water, air, energy, noise, waste, mobility and urban green for 110 provincial capitals (Istat, 2020).

The aim of this work is not to establish which approach is preferable to another but to analyze the robustness and sensitivity of the results from the different composite methods used. Analysis of the state of the urban environment therefore provides useful measuring tools with the appeal to an awareness of the need for a change of course towards planning a more urban sustainability.

The paper is structured as follows: description and application of the main composite methods used; comparison of the results obtained through cograduation matrices of the rankings, correlation matrices and dispersion matrices of the values obtained with the different methods; summary conclusions.

2. Methodology

The multidimensionality of the environmental phenomenon and its measurability through a system of elementary indicators allows the targeted construction of a composite technique which is able of acquiring the multiple aspects (OECD, 2008). Therefore, there is a need to experiment composite methods of elementary data to improve the measurement and communicability of the results.

Table 1 – *Environmental indicators selected, survey Istat "Environmental data of cities". 2020.*

Environmental Issues	Environmental indicators and polarity (+/-)
Water	a1(-). Household water bill per capita *(liters per day).* a2(-). Household water bill total per capita *(liters per day).* a3(-). Water network losses *(%).*
Air	b4(+). Fixed air quality monitoring stations *(per 100,000 inhabitants).* b5(-). Composite indicator of atmospheric pollution *(average values exceeding threshold limit concentration of PM10, PM2,5, NO2 and O3).*
Energy	c6(+). Extension of the thermal solar panels installed on the municipal buildings *(m^2 per 1,000 inhabitants).* c7(+). Total power of photovoltaic solar panels owned by the municipal administration *(kW per 1,000 inhabitants).* c8(+). Charging columns for electric cars by type *(per 10 km^2).*
Mobility	d9(-). Motorization rates for cars by municipality *(vehicles in circulation per 1,000 inhabitants).* d10(+).Electric vehicle circulating by municipality *(per 1.000 vehicle circulating).* d11(-).Pollution potential index of vehicle circulating by municipality *(high/medium pollution potential vehicle per 100 medium/low pollution potential vehicle).*
Municipal waste	e12(+).Door-to-door municipal waste collection for households *(%).* e13(-).Municipal road waste collection for households *(%).*
Noise	f14(+).Complaint presented by citizens on noise pollution by municipality *(per 100,000 inhabitants).*
Urban green	g15(+). Tree cadastre by municipality *(Tree per 100 inhabitants).* g16(+). Density of urban green in the municipalities *(% on the municipal area).* g17(+). Urban green in the municipalities *(m^2 per inhabitants).*

Source: Istat

Regarding the latest data on the urban environmental (Istat 2020), a set of elementary indicators on environmental themes (water, air, energy, noise, waste, mobility, and urban green) were selected (Tab. 1).

These indicators have a high variability and little correlation with each other, characteristics suitable to achieve the aims. It's the basis for the aggregation process through the construction and comparability of some main composite methods.

Elementary indicators have been normalized and standardized to obtain data purified from units of measurement and comparison process.

Standardized deviation in the composite index allows the construction of a robust measure and not very sensitive to remove a single elementary index (Mazziotta and Pareto, 2013).

In addition, *polarity* (positive or negative) of the relationship between indicator and phenomenon was specified. Finally, standardized indicators were aggregated. Following, steps to calculate composite index by comparing the following methods.

Given the matrix $X=\{x_{ij}\}$ with n rows (units) and m columns (indicators), composite methods have the following mathematical properties:

Mean Z-scores *(MZ)*

$Mz_i = \frac{\Sigma_{j=1}^{m} z_i j}{m}$ $Z=\{z_{ij}\}$ transformed matrix for unit *i* and indicator *j*

with $z_{ij} = \pm \frac{(x_{ij} - M_{xj})}{s_{x_j}}$ if the indicator *j* has positive or negative polarity.

M_{xj} e S_{xj} arithmetic mean and deviation standard of indicator j.

The *MZ* allows transformation of indicators j into standardized deviations and aggregation with the arithmetic mean.

Mean R-Indices *(MR)*

$Mz_i = \frac{\Sigma_{j=1}^{m} r_i j}{m}$ $R=\{r_{ij}\}$ transformed matrix for unit i and indicator j

with $r_{ij} = \begin{cases} \frac{(x_{ij} - Min_{xj})}{(Max_{xj} - Min_{xj})} \\ \frac{(Max_{xj} - x_{ij})}{(Max_{xj} - Min_{xj})} \end{cases}$ Min_{xj} e Max_{xj} indicator j

The *MR* allows standardization with min-max method of the j indicators and aggregation with the arithmetic mean.

Adjusted MPI *(AMPI)*

$$MPI_{ci}^{\pm} = M_{ri} \pm S_{r_i} cv_i$$

$$\text{with } r_{ij} = \begin{cases} \frac{(x_{ij} - Min_{xj})}{(Max_{xj} - Min_{xj})} 60 + 70 & \text{if the indicator } j \text{ has positive polarity} \\ \frac{(Max_{xj} - x_{ij})}{(Max_{xj} - Min_{xj})} 60 + 70 & \text{if the indicator } j \text{ has negative polarity} \end{cases}$$

$$M_{r_i} = \frac{\Sigma_{j=1}^{m} r_{ij}}{m} \quad S_{r_i} = \sqrt{\frac{\Sigma_{j=1}^{m} \left(r_{ij} - M_{ri}\right)^2}{m}} \quad cv_i = \frac{S_{ri}}{M_{r_i}}$$

The *AMPI* is a non-compensatory (or partially compensatory) composite index and allows min-max standardization of the indicators j and aggregation with the arithmetic mean penalized by the "horizontal" variability of the indicators themselves. Normalized values are approximately in the range (70; 130), where 100 is the reference value[1].

3. Results

From the exploratory data analysis, indicators show a pronounced variability (many CV values are close to 1) and little correlated with each other (-0.55 and 0.47), characteristics suitable to achieve the aims (Tabb. 2 and 3).

To identify a composite index that represents multidimensionality of the urban environment, some main methods were compared using the transformation of the indicators to obtain data purified from units of measurement and their variability (Tab. 4). Figure 1 shows cartograms of the four approaches used in 110 provincial capitals. Result of the analysis is almost uniform for all methods, with the subdivision of decreasing territorial trialism Northern, Center and Southern Italy.

However, some exceptions with good environmental performance occur in some central and southern areas. In fact, appreciable values are recorded in Sardegna (Nuoro and Oristano), Marche (L'Aquila), Puglia (Brindisi and Lecce), Basilicata (Matera) and Sicily (Messina).

[1] In the Bienaymé-Cebycev theorem, terms of the distribution within the interval (70; 130) constitute at least 89 percent of the total terms of the distribution.

Table 2 – *Average and variability measures of environmental indicators. Provincial capitals. 2020.*

	a1	a2	a3	b4	b5	c6	c7	c8	d9	d10	d11	e12	e13	f14	g15	g16	g17
Arithmetic mean	206,9	150,8	37,3	2,7	19,4	4,4	259,3	2,4	668,1	1,5	129,0	72,0	47,0	12,2	14,8	14,0	42,7
Standard deviation	37,5	27,8	15,2	2,0	19,8	18,4	261,7	5,7	69,9	0,8	18,8	34,4	40,4	20,5	14,3	14,7	61,0
Coefficient of variation	0,2	0,2	0,4	0,7	1,0	4,2	1,0	2,4	0,1	0,5	0,1	0,5	0,9	1,7	1,0	1,1	1,4

Source: Istat data processed

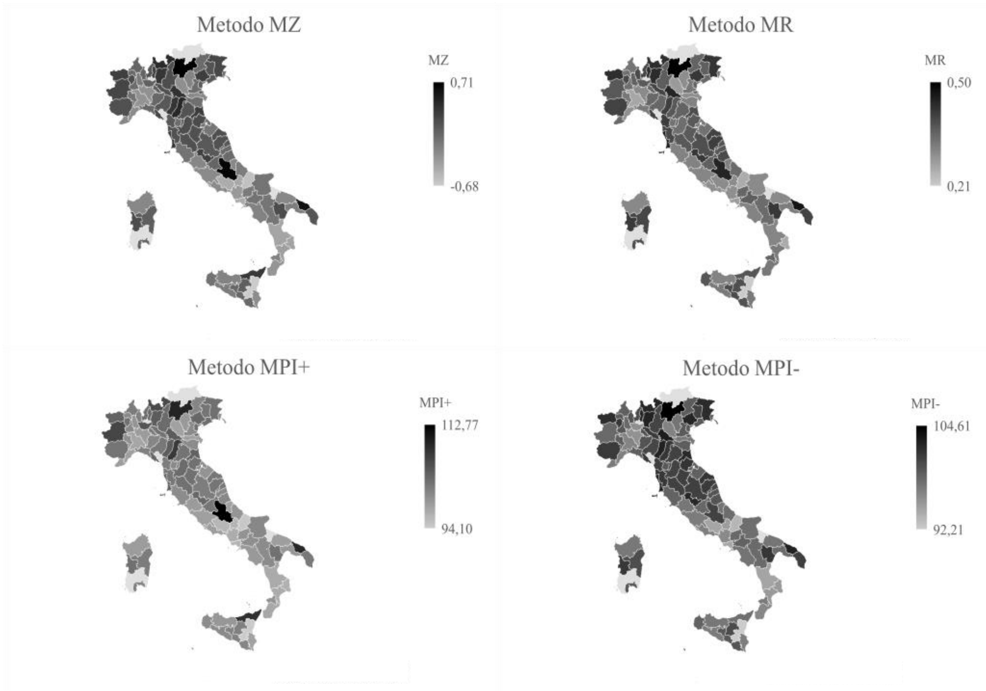
From the ranking of the four composite indicators, it is possible to observe the positioning of the Italian municipalities based on the state of environment which decreases towards the higher ranks. Trento has the best urban environmental performance while Catania is the city with the highest negative impact.

Table 3 – *Correlation matrix of environmental indicators. Provincial capitals. 2020*.

	a1	a2	a3	b4	b5	c6	c7	c8	d9	d10	d11	e12	e13	f14	g15	g16	g17
a1	1	0,38	-0,23	-0,05	0,38	-0,01	-0,27	0,34	-0,19	0,33	-0,12	0,21	-0,10	0,05	-0,01	0,09	0,05
a2		1,00	-0,16	-0,10	0,33	-0,06	-0,32	0,39	-0,16	0,23	-0,02	0,24	-0,18	0,08	-0,05	0,06	0,00
a3			1,00	0,09	-0,42	0,07	-0,02	-0,20	0,24	-0,30	0,31	-0,20	-0,01	0,07	-0,35	0,02	-0,03
b4				1,00	-0,09	0,09	0,15	-0,16	0,14	-0,05	0,00	0,26	-0,09	-0,12	-0,05	-0,10	0,15
b5					1,00	-0,12	-0,14	0,35	-0,33	0,47	-0,51	0,13	0,10	0,04	0,38	0,07	0,01
c6						1,00	0,05	-0,05	0,20	-0,03	0,03	0,03	-0,02	-0,04	-0,09	0,19	-0,01
c7							1,00	-0,24	0,24	-0,20	0,05	0,02	-0,06	-0,18	-0,02	-0,17	-0,05
c8								1,00	-0,33	0,30	-0,15	0,03	-0,12	0,08	0,10	-0,03	-0,07
d9									1,00	-0,27	0,27	0,20	-0,31	-0,10	-0,10	-0,24	0,05
d10										1,00	-0,55	0,13	0,02	0,09	0,28	0,08	0,30
d11											1,00	-0,03	-0,21	-0,07	-0,37	-0,02	-0,12
e12												1,00	-0,42	-0,10	0,01	-0,05	0,14
e13													1,00	0,19	0,18	0,08	0,04
f14														1,00	0,07	0,32	0,02
g15															1,00	-0,02	0,08
g16																1,00	-0,11
g17																	1,00

Source: Istat data processed.

Figure 1 – *Map of composite indicators. Provincial capital. 2020 (*).*



Source: Istat data processed.
(*) Chromatic provincial areas refer to their provincial capitals.

In ranking of the top five cities with low environmental impact, Bolzano, Sondrio, Mantova and Bergamo are also distinguished, cities of small and medium population size in Northern Italy.

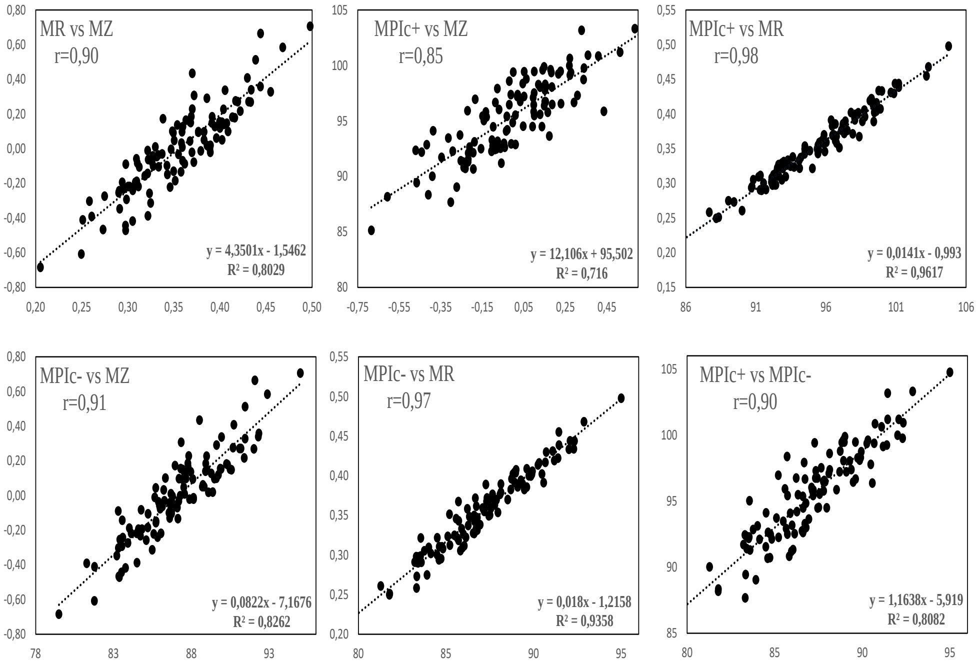
At the bottom of the ranking with a greater environmental pressure Isernia, Napoli, Frosinone and Campobasso in Southern Italy (Tab. 5).

Table 4 – *Syntetics methods matrix - Provincial capital. 2020.*

Provincial Capital	MZ	MR	MPIc+	MPIc-	Provincial Capital	MZ	MR	MPIc+	MPIc-	Provincial Capital	MZ	MR	MPIc+	MPIc-
Agrigento	-0,14	0,32	95,03	83,56	Foggia	-0,09	0,30	92,43	83,30	Pistoia	-0,04	0,33	94,09	85,89
Alessandria	-0,30	0,26	87,68	83,32	Forli	0,19	0,37	96,50	87,77	Pordenone	0,13	0,36	95,61	87,57
Ancona	0,15	0,40	97,79	90,48	Frosinone	-0,47	0,30	92,35	83,38	Potenza	-0,10	0,34	94,47	86,62
Andria	0,14	0,40	99,61	88,91	Genova	-0,01	0,32	92,93	85,64	Prato	0,10	0,36	95,84	87,21
Aosta	0,27	0,43	100,63	91,09	Gorizia	-0,05	0,33	93,00	86,79	Ragusa	-0,01	0,38	97,37	88,13
Arezzo	0,16	0,37	96,75	87,32	Grosseto	-0,08	0,31	92,48	84,77	Ravenna	0,29	0,39	96,68	89,61
Ascoli Piceno	-0,02	0,37	96,47	87,88	Imperia	-0,22	0,35	95,93	85,58	Reggio di Calabria	-0,31	0,32	93,47	85,48
Asti	-0,08	0,33	93,18	85,99	Isernia	-0,44	0,30	92,19	83,51	Reggio nell'Emilia	0,34	0,41	98,74	89,94
Avellino	-0,09	0,36	96,67	86,73	La Spezia	0,23	0,40	99,47	88,97	Rieti	0,01	0,36	95,53	87,56
Bari	-0,22	0,30	91,55	84,49	L'Aquila	0,18	0,44	101,20	92,08	Rimini	-0,06	0,32	92,53	86,14
Barletta	0,03	0,36	96,76	86,22	Latina	-0,24	0,29	91,30	83,59	Roma	-0,24	0,31	90,82	85,83
Belluno	-0,03	0,36	95,43	87,19	Lecce	0,12	0,40	98,28	89,73	Rovigo	-0,23	0,30	90,72	84,72
Benevento	-0,13	0,35	95,37	86,61	Lecco	0,27	0,43	99,99	92,02	Salerno	-0,19	0,31	93,13	84,02
Bergamo	0,34	0,43	99,77	92,29	Livorno	0,33	0,46	103,17	91,44	Sassari	-0,22	0,30	92,11	84,13
Biella	0,19	0,39	98,06	88,92	Lodi	0,05	0,35	94,53	87,51	Savona	-0,25	0,29	91,41	83,41
Bologna	0,14	0,35	94,49	87,96	Lucca	0,10	0,41	99,47	89,61	Siena	0,15	0,37	96,75	87,43
Bolzano-Bozen	0,51	0,44	101,20	91,45	Macerata	0,15	0,41	99,88	89,00	Siracusa	-0,26	0,32	93,73	85,10
Brescia	0,17	0,36	95,77	87,78	Mantova	0,36	0,44	100,93	92,33	Sondrio	0,41	0,43	100,85	90,72
Brindisi	0,18	0,47	103,32	92,87	Massa	-0,10	0,33	92,75	86,56	Taranto	-0,16	0,32	92,50	85,72
Cagliari	0,02	0,39	97,22	89,09	Matera	0,18	0,42	99,62	90,31	Teramo	-0,02	0,39	98,60	88,13
Caltanissetta	0,00	0,39	99,41	87,28	Messina	0,11	0,37	97,30	87,34	Terni	0,27	0,42	99,14	91,18
Campobasso	-0,61	0,25	88,17	81,77	Milano	0,04	0,37	98,38	85,71	Torino	0,23	0,37	96,57	87,82
Carbonia	0,05	0,40	99,45	88,82	Modena	0,44	0,37	95,87	88,52	Trani	-0,39	0,26	90,02	81,27
Caserta	-0,35	0,29	91,72	83,21	Monza	-0,07	0,36	96,03	87,10	Trapani	-0,08	0,37	97,92	86,67
Catania	-0,68	0,21	85,14	79,49	Napoli	-0,47	0,27	89,44	83,33	Trento	0,71	0,50	104,76	95,00
Catanzaro	-0,39	0,32	94,12	84,50	Novara	-0,13	0,36	95,81	87,14	Treviso	0,28	0,42	99,38	90,67
Cesena	0,10	0,38	97,52	87,65	Nuoro	0,06	0,40	98,79	88,74	Trieste	-0,11	0,31	92,26	85,22
Chieti	-0,15	0,34	95,43	85,73	Oristano	0,18	0,41	99,36	90,25	Udine	0,22	0,42	99,25	91,39
Como	0,13	0,39	98,05	89,28	Padova	-0,04	0,33	92,62	86,61	Varese	0,02	0,39	97,38	89,37
Cosenza	-0,42	0,31	92,86	83,77	Palermo	-0,19	0,31	92,13	84,83	Venezia	0,09	0,35	94,49	87,45
Cremona	0,16	0,40	98,11	89,85	Parma	0,10	0,35	95,49	86,33	Verbania	0,01	0,33	92,89	86,69
Crotone	-0,41	0,25	88,35	81,78	Pavia	-0,29	0,30	92,29	83,54	Vercelli	-0,03	0,34	94,20	86,27
Cuneo	0,15	0,40	98,31	89,90	Perugia	0,10	0,38	96,44	89,47	Verona	-0,27	0,27	89,05	83,92
Enna	0,05	0,38	97,22	88,70	Pesaro	-0,10	0,33	93,29	86,72	Vibo Valentia	-0,18	0,35	96,96	85,20
Fermo	0,10	0,38	97,10	88,09	Pescara	-0,22	0,31	91,32	86,04	Vicenza	-0,19	0,29	90,67	84,60
Ferrara	-0,06	0,31	91,19	85,95	Piacenza	0,00	0,35	94,85	86,79	Viterbo	-0,21	0,31	92,65	84,62
Firenze	0,17	0,34	93,64	86,95	Pisa	0,15	0,39	96,38	90,57					

Source: Istat data processed.

Figure 2 – *Linear relationship compared between composite methods used.*



Source:Istat data processed

Table 5 - *Ranking of the five best and worst environmental performances - Provincial capital. 2020.*

Provincial capital	MZ		MR		MPIc+		MPIc-	
	N.	Rank	N.	Rank	N.	Rank	N.	Rank
Better environmental performance								
Trento	0,71	1	0,50	1	104,76	1	95,00	1
Bolzano-Bozen	0,51	2	0,44	6	101,20	5	91,45	7
Sondrio	0,41	3	0,43	10	100,85	7	90,72	12
Mantova	0,36	4	0,44	5	100,93	6	92,33	3
Bergamo	0,34	5	0,43	7	99,77	11	92,29	4
Worse environmental performance								
Isernia	-0,44	106	0,30	98	92,19	92	83,51	100
Napoli	-0,47	107	0,27	105	89,44	105	83,33	103
Frosinone	-0,47	108	0,30	97	92,35	89	83,38	102
Campobasso	-0,61	109	0,25	109	88,17	108	81,77	108
Catania	-0,68	110	0,21	110	85,14	110	79,49	110

Source: Istat data processed.

Table 6- *Sum of ranking differences between composite methods used.*

Measures	Ranking differences					
	MZ-MR	MZ-MPIc+	MZ-MPIc-	MR-MPIc+	MR-MPIc-	MPIc+-MPIc-
Absolute average rank diff.	11,60	14,35	10,44	5,19	6,36	11,29
Cograduation index ρ	0,89	0,83	0,91	0,98	0,96	0,89

Source: Istat data processed.

Table 6 shows rank differences compared by means of the absolute difference and Spearman's rank correlation coefficient.

Sensitivity analysis shows similar results in the comparison between MR-$MPIc_{+}$ method and the MR-$MPIc_{-}$ method with absolute average rank differences 5.19 and 6.36 positions respectively with a strength of the relationship directly proportional and close to 1 (0.98 and 0.96).

Linear relationship with R-values is very high too (fig. 2).

4. Conclusions

The (provisional) conclusions focus on the methodological assumptions useful for developing the research, reflecting on how to produce increasingly "refined" indicators and comparison systems to satisfy two of the basic functions of benchmarking in environmental policies: providing knowledge and opportunities for understanding of many variables on territorial performance; facilitate the task of local administrations in the decision-making processes of intervention on the actual territorial gaps.

Study on the multidimensional aspects of the urban environmental through comparison of some composite methods offer an important contribution to the interpretation of the phenomenon.

The work offers a critical vision in the universe of synthetic indexes and has been prepared according to a "journey in itinere" scheme with the aim of creating conditions for research to evolve and improve knowledge to develop increasingly effective and sustainable to offer to policy maker.

The construction of a synthetic index is a delicate task and there are no consolidated solutions.

This study tries to concretely emphasize that, regardless of the methodological choices, if one pursues the sole objective of seeking a summary indicator, sometimes, one loses sight of the dimension of reality.

However, synthetic indices are widely used and are a current and evolving analysis tool. In the implementation phase of the indices, an attempt was made to limit arbitrariness by focusing, for the standardization of elementary indicators, on simple and understand statistical tools to eliminate units of measurement and variability. Therefore, with purely exploratory purposes, 4 principal synthetic indices were compared and the results responded similarly in the synthesis of a set of elementary indicators at the territorial level. In addition, a high concordance between the rankings obtained from the application of the synthesis methods with a cograduation index (between 0.83 and 0.98) and shifts in the ranking between one application and the other on average very content.

This conclusion is relevant because, starting from the assumption that for the study of a multidimensional and complex phenomenon such as the environmental one, the comparison of several weighting techniques is necessary, the nature and information content of the elementary indicators analyzed are so strong and decisive that they condition practically the uniformity of the results at a territorial level in the 4 different synthesis methods applied. In this case not one but 4 methods gave similar answers.

A good result for those who have to deal with a study of the phenomenon and must give an interpretation that is as representative as possible of the environmental reality.

Geography of the environmental state and urban anthropic pressure highlights an unbalanced and negative configuration for most of the southern cities.

At the other end of distribution, higher environmental performances are recorded, especially in the northern small and medium-sized urban areas where investments in environmental projects are constantly growing.

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SUMMARY

The consequences of climate change, depletion of water resources, urban pollution and other aspects of environmental crisis of environmental crisis negatively interact with human life and activity.

In this work, some main statistical methods are compared for the synthesis of indicators representative of environmental phenomena. A multidimensional study through a territorial comparison on the state of environmental health in the urban area.

The proposed approach normalizes the indicators by a specific criterion that deletes the unit of measurement and the variability effect (Method of the average of values standardized MZ, Method of mean of relative indices MR and Corrected MPI index method). The obtained index is easily computable and interpretable or comparable. As an example of application, we consider a set of indicators on urban environmental quality such as water, air, energy, noise, waste, mobility, urban green in the 110 provincial capitals (Istat, 2020).

The results show that the negative impact on the environment is in all Italian regions but is stronger in southern Italy. In addition, the result of the analysis is almost uniform for the methods used, returning the decreasing territorial subdivision of North, Central and Southern Italy.

The analysis of the environment in the urban context therefore provides useful tools for measuring the phenomenon and development policies and environmental sustainability.

The paper is structured as follows: description and application of the main synthesis methods used; comparison of the results obtained through cograduation matrices of the rankings, correlation matrices and dispersion matrices of the data with the different methods; conclusions.

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VARIANCE-BASED SENSITIVITY ANALYSIS: NON-PARAMETRIC METHODS FOR WEIGHT OPTIMIZATION IN COMPOSITE INDICATORS

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1. Introduction

Composite indicators are basically computational models used to measure the performance of objects or individuals in complex concepts which are not able to judge based on a single aspect. The role of composite indicators is to provide a proper aggregation that combines the conduct of objects in different dimensions into only one scalar. On the one hand, composite indicators are useful to support decision makers in capturing multidimensional realities and comparing object performance straightforwardly. On the other hand, synthetic indices might provide incorrect benchmarks and misleading policy messages if they are poorly constructed (OECD, 2008; Saisana and Tarantola, 2002).

While the choice of sub-indicators or inputs mainly depends on the definition of the phenomenon, the composite model, including the setting of weights and the aggregation function, is much in the hands of developers. Conceptually, weights refer to the explicit importance of inputs to a composite indicator, and the relative importance (trade-off) between these inputs (OECD, 2008). However, a weight can be directly interpreted as a measure of importance for each input only if several conditions are satisfied: normative weighting, constant variances, and no correlations among variables (Becker *et al.*, 2017). Decancq and Lugo (2013) also pointed out that only under the circumstance of using the weighted arithmetic aggregation and a proper transformation of variables, the ratio of weights becomes equal to the trade-off between input factors. Most composite indicators cannot meet all such requirements, and hence recruiting a measurement of variable importance that is not subject to any model constraints is requisite for weighting.

Given a computational model, there are two main approaches to assess the importance of input variables to the model output: local sensitivity analysis and global sensitivity analysis. This paper focuses on the global approach using variance-based sensitivity measures (Sobol', 1993; Homma and Saltelli, 1996; Saisana *et al.*, 2005). In detail, the article introduces a non-parametric estimation procedure for measuring the importance of input factors, which is developed from the original work of Mara *et al.* (2015) and integrated with the Monte Carlo estimator of Martinez

(2011). The selection of optimal weights is hence carried out by solving a minimization problem in which the weight vector is tuned to achieve the minimum difference between itself and the normalized importance of inputs.

2. Measuring Importance

2.1. Importance Measures for Independent Inputs

Let Y denote a composite indicator obtained from a square integrable function $f(X)$ where the input $X = (X_1, X_2, \dots, X_n)$ is a random vector. Assume that X is defined by a joint probability density function p_X. The variance of the conditional distribution of Y given X_i is denoted by $\mathrm{Var}_{X_{\sim i}}(Y|X_i)$, where the term $X_{\sim i}$ is the vector X without X_i. We can establish a measure of importance for X_i as

$$\mathrm{Var}(Y) - \mathrm{E}\left(\mathrm{Var}_{X_{\sim i}}(Y|X_i)\right) = \mathrm{Var}\left(\mathrm{E}_{X_{\sim i}}(Y|X_i)\right), \quad (1)$$

which is the expected variance reduction in composite indicator scores if the factor of variation X_i is fixed. According to the ANOVA representation of Sobol' (1993), $f(X)$ can be decomposed into summands of different dimensions:

$$f(X) = f_0 + \textstyle\sum_{i=1}^{n} f_i(X_i) + \sum_{1\le i<j\le n} f_{ij}\left(X_i, X_j\right) + \cdots + f_{1\dots n}(X_1, \dots, X_n) \quad (2)$$

This expression is always existent and unique if the integrals of the summands with respect to any of their own variables are zero (Sobol', 1993). The condition results in all the individual terms in (2) being pairwise orthogonal, implying that all X_i's are mutually independent. The orthogonality leads to the variance decomposition

$$\mathrm{Var}(Y) = \textstyle\sum_{i=1}^{n} \mathrm{Var}(f_i) + \sum_{1\le i<j\le n} \mathrm{Var}\left(f_{ij}\right) + \cdots + \mathrm{Var}(f_{1\dots n}). \quad (3)$$

Sobol' (1993) introduced his measurement of importance, known as Sobol' indices, which is derived from dividing both sides of (3) by $\mathrm{Var}(Y)$ to acquire

$$\textstyle\sum_{i}^{n} S_i + \sum_{1\le i<j\le n} S_{ij} + \cdots + S_{12\dots n} = 1, \quad (4)$$

where

$$S_i = \frac{\mathrm{Var}(f_i)}{\mathrm{Var}(Y)} = \frac{\mathrm{Var}(\mathrm{E}_{X_{\sim i}}(Y|X_i))}{\mathrm{Var}(Y)}, \; S_{ij} = \frac{\mathrm{Var}(f_{ij})}{\mathrm{Var}(Y)} = \frac{\mathrm{Var}(\mathrm{E}_{X_{\sim ij}}(Y|X_i,X_j))}{\mathrm{Var}(Y)} - S_i - S_j, \quad (1)$$

and so on. The term $X_{\sim ij}$ denotes the vector X without X_i and X_j. S_i is a first-order Sobol' index that captures the main contribution of X_i to the output variance. S_{ij} is a second-order Sobol' index that gauges the contribution caused by the interaction between X_i and X_j, and analogous formulas can be applied to higher-order indices.

Homma and Saltelli (1996) established another measure called a total Sobol' index that captures the total contribution of X_i and all its interactions, defined by

$$ST_i = S_i + \sum_{j \neq i} S_{ij} + \cdots + S_{1 \ldots i \ldots n} = 1 - \frac{\mathrm{Var}(\mathrm{E}_{X_i}(Y|X_{\sim i}))}{\mathrm{Var}(Y)} = \frac{\mathrm{E}(\mathrm{Var}_{X_i}(Y|X_{\sim i}))}{\mathrm{Var}(Y)}. \quad (2)$$

While S_i indicates the expected proportion of variance reduction that would be obtained if X_i was fixed, ST_i indicates the expected proportion of variance that would be left if all inputs were fixed except X_i. Therefore, a large value of either S_i or ST_i implies that X_i is an important contributor and vice versa.

2.2. Importance Measures for Independent Inputs

The application of the Sobol' ANOVA representation to dependent inputs is not prohibited but might lead to incorrect computation and wrong interpretation (Mara and Tarantola, 2012). In Mara *et al.* (2015), the authors proposed a strategy to estimate importance indices that account for the dependency of inputs, using the Rosenblatt (1952) transformation (RT). It transforms $X \sim p_X$ into a random vector $U \sim \mathcal{U}^n(0,1)$ with independent and uniformly distributed entries:

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_k \\ \vdots \\ X_n \end{bmatrix} \xrightarrow{RT} \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_k \\ \vdots \\ U_n \end{bmatrix} = \begin{bmatrix} F_{X_1}(x_1) \\ F_{X_2|X_1}(x_2|x_1) \\ \vdots \\ F_{X_k|X_1,\ldots,X_{k-1}}(x_k|x_1,\ldots,x_{k-1}) \\ \vdots \\ F_{X_n|X_1,\ldots,X_{n-1}}(x_n|x_1,\ldots,x_{n-1}) \end{bmatrix}, \quad (7)$$

where $F_{X_k|X_1,\ldots,X_{k-1}}$ is the cumulative distribution function (CDF) of X_k conditioned by $X_1,\ldots,X_{k-1}$.

Let $U^i = (U_1^i, U_2^i, \ldots, U_n^i)$ be the random vector obtained from RT of X with the order $(X_i, X_{i+1}, \ldots, X_n, X_1, \ldots, X_{i-1})$. Because RT is bijective, there exists an inverse transformation such as $X = RT_i^{-1}(U^i)$ and the aggregation function can be written as $Y = f(RT_i^{-1}(U^i)) = g^i(U^i)$. This establishes a one-to-one mapping

$$(F_{X_i}, F_{X_{i+1}|X_i}, \dots, F_{X_1|X_i, X_{i+1}, \dots, X_n}, \dots, F_{X_{i-1}|X_{\sim(i-1)}}) \leftrightarrow (U_1^i, U_2^i, \dots, U_n^i). \tag{8}$$

Since $U_1^i, \dots, U_n^i$ are independent, the variance of Y can be decomposed into the Sobol' indices of U^i instead of X. The first-order index of U_1^i indicates the expected proportion of variance that would be reduced if X_i was fixed and the other factors varied conditionally on X_i. In other words, it quantifies the main contribution of X_i to the output variance, taking into account its dependency with the other inputs. The total index of U_1^i specifies the expected proportion of variance that would remain if all the inputs but X_i were fixed conditionally on X_i, measuring the total dependent contribution of X_i and all its interactions. These two measures are so-called the full Sobol' indices of X_i, denoted by S_i^{full} and ST_i^{full} respectively.

As can be seen from the mapping (8), the first-order index of U_n^i is the main contribution of X_{i-1} that does not account for its dependence on all the other inputs. Therefore, this value is called the independent first-order Sobol' index of X_{i-1}, denoted by S_{i-1}^{ind}. Analogously, the total index of U_n^i is called the independent total Sobol' index of X_{i-1}, denoted by ST_{i-1}^{ind}, that specifies the independent contribution of X_{i-1} and all its interactions. The formulas of full and independent Sobol' indices, and their relationship with the original indices are given as follows:

$$\begin{aligned}
S_i^{full} &= \frac{\mathrm{Var}(\mathrm{E}_{U_{\sim 1}^i}(Y|U_1^i))}{\mathrm{Var}(Y)} = \frac{\mathrm{Var}(\mathrm{E}_{X_{\sim i}}(Y|X_i))}{\mathrm{Var}(Y)} = S_i, \\
ST_i^{full} &= \frac{\mathrm{E}(\mathrm{Var}_{U_1^i}(Y|U_{\sim 1}^i))}{\mathrm{Var}(Y)} = \frac{\mathrm{E}(\mathrm{Var}_{X_i}(Y|(X_{\sim i}|X_i)))}{\mathrm{Var}(Y)}, \\
S_i^{ind} &= \frac{\mathrm{Var}(\mathrm{E}_{U_{\sim n}^{i+1}}(Y|U_n^{i+1}))}{\mathrm{Var}(Y)} = \frac{\mathrm{Var}(\mathrm{E}_{X_{\sim i}}(Y|(X_i|X_{\sim i})))}{\mathrm{Var}(Y)}, \\
ST_i^{ind} &= \frac{\mathrm{E}(\mathrm{Var}_{U_n^{i+1}}(Y|U_{\sim n}^{i+1}))}{\mathrm{Var}(Y)} = \frac{\mathrm{E}(\mathrm{Var}_{X_i}(Y|X_{\sim i}))}{\mathrm{Var}(Y)} = ST_i.
\end{aligned} \tag{9}$$

In terms of measuring importance, S_i^{ind} points out the expected proportion of variance decline caused by fixing X_i conditionally on all the other inputs while ST_i^{ind} indicates the expected proportion of variance that would remain if all the inputs except X_i were fixed and X_i was set to vary conditionally on them. Overall, a great value of either full or independent Sobol' indices implies that the input factor is important in explaining the variance of composite indicator scores.

3. Estimation Methods and Sampling Strategies

The estimation of full and independent Sobol' indices can be performed using the "pick and freeze" strategy (Saltelli *et al.*, 2008). Only two independent samples of

$U \sim \mathcal{U}^n(0, 1)$ with N rows are sufficient to estimate all four importance measures of each input factors. The first step is to generate two random samples $A \sim \mathcal{U}^n(0, 1)$ and $B \sim \mathcal{U}^n(0, 1)$ with the same size $N \times n$. Then two samples B_1 and B_n are formed by all columns of B except the first (1-st) and the last (n-th) column taken from A respectively. Finally, the indices are calculated using the Martinez (2011) estimator with ρ symbolizing the Pearson correlation coefficients:

$$\begin{aligned} \widehat{S_i^{full}} &= \rho(g^i(A), g^i(B_1)), & \widehat{S_i^{ind}} &= \rho(g^{i+1}(A), g^{i+1}(B_n)), \\ \widehat{ST_i^{full}} &= 1 - \rho(g^i(B), g^i(B_1)), & \widehat{ST_i^{ind}} &= 1 - \rho(g^{i+1}(B), g^{i+1}(B_n)). \end{aligned} \quad (3)$$

Since the composite scores are computed from the samples of U, the inverse Rosenblatt transformation is required to calculate the output $Y = g^i(U^i)$ and the importance indices. If p_X is known, this transformation can be derived from conditional CDFs in X. In practice, p_X is often unidentified and only a representative sample S_X of X is available. The question here is how can we establish a bijective mapping from S_X, which satisfies the property of the inverse Rosenblatt transformation, to provide a sufficiently large number of trials for the Monte Carlo estimation?

A simple solution is to assume a multivariate normal distribution in X then applying Gaussian inverse transform sampling. The distribution parameters Σ and μ can be estimated from S_X, and they in turn are used to construct the conditional inverse CDFs (conditional quantile functions). The second solution for sampling is the Iman-Conover method (Iman and Conover, 1982), which is designed to generate a random sample based on a given correlation structure and known marginal distributions. Because p_X is unknown, the Pearson correlation matrix and the empirical marginals of S_X will be employed instead. The last potential technique is copula sampling based on Sklar's theorem. Having a proper copula model fitted on S_X, one can totally use the inverse copula and empirical marginals to simulate the inverse Rosenblatt transformation.

4. Weight Optimization

With respect to the variable X_i, denote w_i as the weight and I_i as the importance measure using one of the four Sobol' indices. The importance measures for all the variables are normalized by $\widetilde{I_i} = I_i / \sum_{k=1}^{n} I_k$ to make them comparable to the value of weights. Denote a loss function

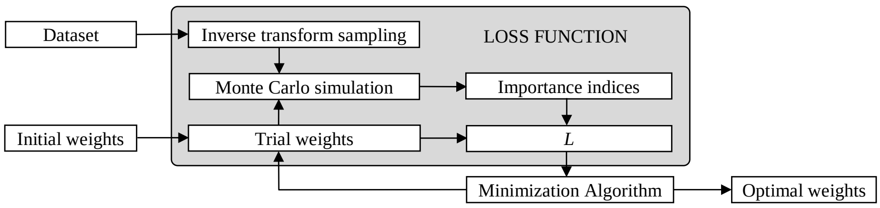
$$L = d^2(w, \tilde{I}) = \sum_{i=1}^{n} \left(w_i - \tilde{I}_i\right)^2, \tag{11}$$

which is the squared Euclidean distance between two vectors $w = (w_1, \dots, w_n)$ and $\tilde{I} = \left(\tilde{I}_1, \dots, \tilde{I}_n\right)$. The optimal set of weights is defined by

$$w^* = \underset{w_1,\dots,w_n}{\operatorname{argmin}} L \quad \text{s.t.} \quad w_i \in (0, 1),\ \sum_{i=1}^{n} w_i = 1 \tag{12}$$

At $L_{\min}$, the distance between the two vectors is minimal and hence we attain the set w^* as close as possible to $\tilde{I}$. In case $L_{\min} = 0$ that is equivalent to $w^* \equiv \tilde{I}$, the weights obtained are exactly proportional to the measures of importance. For the general case, L can be always expressed as a function of w and p_X. Thus, we can reach the global minimum if two conditions are satisfied: the joint probability distribution of inputs is given; and the loss function is convex in its domain. Figure 1 gives an illustration of the optimization procedure. At the beginning, a sample of X and an initial set of weights are fed into the loss function to estimate the distance L. The trial weights are then calibrated using a minimization algorithm based on the estimated values of L until the loss function achieves its minimum, which indicates the best course of action.

Figure 1 - *Diagram of the weight optimization procedure.*



5. Empirical Analysis

5.1. Test Case 1: Multivariate Normal Distribution

Considering the composite indicator $Y = w_1X_1 + w_2X_2 + w_3X_3 + w_4X_4$, where $X = (X_1, X_2, X_3, X_4)$ follows a multivariate Gaussian distribution $\mathcal{N}(\mu, \Sigma)$ with the parameters $\mu = (0, 0, 0, 0)$ and

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \rho_{12} & \rho_{13} & \rho_{14} \\ \rho_{21} & \sigma_2^2 & \rho_{23} & \rho_{24} \\ \rho_{31} & \rho_{32} & \sigma_3^2 & \rho_{34} \\ \rho_{41} & \rho_{42} & \rho_{43} & \sigma_4^2 \end{bmatrix} = \begin{bmatrix} 1 & 0.8 & 0.2 & 0.4 \\ 0.8 & 1 & 0.6 & 0.5 \\ 0.2 & 0.6 & 1 & 0.3 \\ 0.4 & 0.5 & 0.3 & 1 \end{bmatrix}. \tag{13}$$

Let ST_i^{full} be the measure of importance. Since the composite model is purely additive, the importance of X_i can be computed as

$$I_i = ST_i^{full} = S_i^{full} = \frac{\mathrm{Var}(\mathrm{E}_{X_{\sim i}}(Y|X_i))}{\mathrm{Var}(Y)} = \frac{\left(w_i + \sum_{j\neq i} w_j \rho_{ji}\right)^2}{\sum_{k=1}^{4} w_k^2 + 2\sum_{1\leq p<q\leq 4} w_p w_q \rho_{pq}} \tag{14}$$

which is a single-argument function of w as the correlation coefficients are predefined. Hence, $L = d^2(w, \tilde{I})$ is also a function of w and the optimal weights can be achieved by solving $L = 0$, obtaining $w^* = (0.304, 0.387, 0.143, 0.167)$.

The purpose of this test case is to assess how accurate the weighing procedure could be if only working with the samples of X. Denote $\widehat{w^*}$ as the sample estimate of w^*, the error

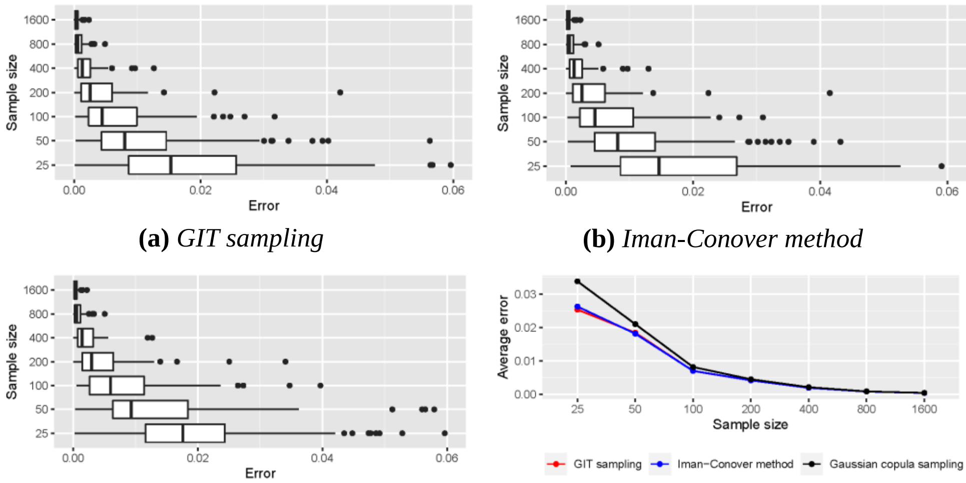
$$E = d^2(w^*, \widehat{w^*}) = \sum_{i=1}^{n} (w_i^* - \widehat{w_i^*})^2 \tag{15}$$

is a useful gauge to evaluate the similarity between the estimated weights and the true optimal weights. A small E implies that the procedure performs well on the sample, and the expression $\sqrt{E/n}$ measures the average deviation of estimated values from the true ones.

Figures 2a, 2b and 2c describe the boxplots of the error E when applying the procedure with $N = 10^4$ to seven groups of sample sizes, using three sampling methods: Gaussian inverse transform (GIT) sampling, the Iman-Conover method, and Gaussian copula sampling[1]. Each group contains 100 random samples with the same size drawn from $\mathcal{N}(\mu, \Sigma)$. In all three methods, the variation in errors tends to decline as the number of observations in samples increases. At the sample size of 400 onward, we start to acquire sufficiently low and highly stable errors, meaning that the solution derived from samples with more than 400 observations is steady and close to the true optimal weights. Figure 2d illustrates the mean of errors obtained from the three sampling methods. Although there is no clear difference between the techniques across large samples, GIT sampling and the Iman-Conover method seem to outperform Gaussian copula sampling on small samples with less than 100 observations.

[1] The Gaussian copula is chosen among other copulas based on the Akaike information criterion.

Figure 2 - *Errors by three sampling methods for samples from multivariate normal distribution.*



(a) *GIT sampling* **(b)** *Iman-Conover method*

(c) *Gaussian copula sampling* **(d)** *Average errors*

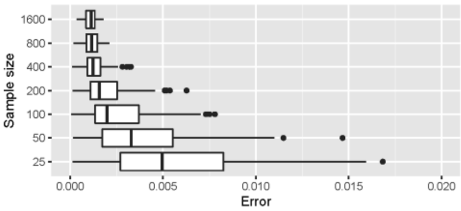
5.2. Test Case 2: Multivariate Mixed Distributions

The second test case uses the same setting as in the first one but performs on multivariate mixed distributions with a more complex model. The composite indicator is defined as $Y = w_1X_1 + w_2X_2 + X_3^{w_3}X_4^{w_4}$, where $X_1, X_2 \sim \mathcal{N}(0,1)$, $X_3 \sim \mathcal{U}(0,1)$, and $X_4 \sim \text{Pois}(4)$. The dependency structure in X is measured using the same correlation matrix as in Equation (13).

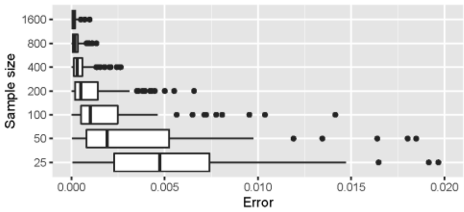
In this case, the genuine optimal weights are difficult to calculate directly from distribution parameters because of model complexity and non-normal distributions. An alternative way is employing the inverse Rosenblatt transformation with the true marginal CDFs to produce a huge number of Monte Carlo trials ($N = 10^6$, replicate 1000 times), which in turn is used to estimate an asymptotically true value of w^*. Using this strategy and choosing ST_i^{full} as the measure of importance, the optimal weight is defined as $w^* = (0.243, 0.317, 0.095, 0.345)$.

Figures 3a, 3b and 3c show the variation of error using the optimization procedure with $N = 10^4$ to seven groups of samples. Each group includes 100 equal-sized random samples from the mixed distributions. The accuracy of GIT sampling does not improve after a certain sample size while the other two methods continue lowering the errors toward zero. More evidence of this is shown in Figure 3d, where the average error by GIT sampling seems steady at around 0.001 from the sample size of 400 while the other two methods are constantly improving.

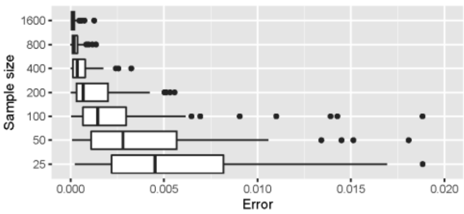
Figure 3 - *Errors by three sampling methods for samples from multivariate mixed distributions.*



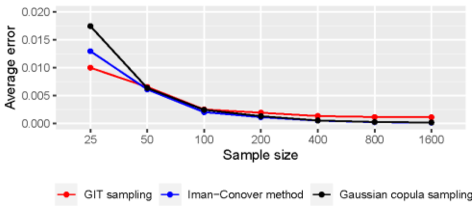
(a) *GIT sampling*



(b) *Iman-Conover method*



(c) *Gaussian copula sampling*



(d) *Average errors*

5.3. Practical Case: Human Development Index 2018

The Human Development Index (HDI) is constructed from three sub-indicators including life expectancy, education, and income, and aggregated by the geometric mean with equal weights. The data for the HDI 2018 used in this section is provided by the UNDP Data Center (https://hdr.undp.org/data-center). Using the Iman-Conover method with $N = 10^4$, the contribution of equal-weighted inputs to the HDI 2018 is given in Table 1. In case ST_i^{full} is selected as the importance index, the total contribution of each input and its interaction, considering its correlation with other inputs, is roughly equal $1/3$. This corresponds to a small loss value, indicating that the original model of the HDI can nearly satisfy the condition of importance weighting based on the full total Sobol' index.

However, if ST_i^{ind} is considered as the importance index, the independent contribution to the output variance is dissimilar between the sub-indicators, leading to a huge loss when comparing the normalized importance indices and the original weights. Since the correlation in the HDI components $\rho = (0.82, 0.84, 0.87)$ is high, one might be interested in a composite indicator that imposes the uncorrelated contribution of each input on the corresponding weight. This indicator can be achieved using the optimization procedure based on the independent total Sobol' index. The optimal weights from the Iman-Conover method with $N = 10^4$ are $\widehat{w^*} = (0.584, 0.177, 0.239)$ for life expectancy, education, and income.

Table 1 - *Importance measures for the HDI components in 2018 using equal weights*.

	Life expectancy	Education	Income	L
Normalized $\widehat{ST}_i^{full}$	0.312	0.344	0.344	0.0007
Normalized $\widehat{ST}_i^{ind}$	0.150	0.487	0.363	0.0580

Figure 4 - *Greatest shifts in the HDI ranking using the optimized weights based on ST_i^{ind}.*

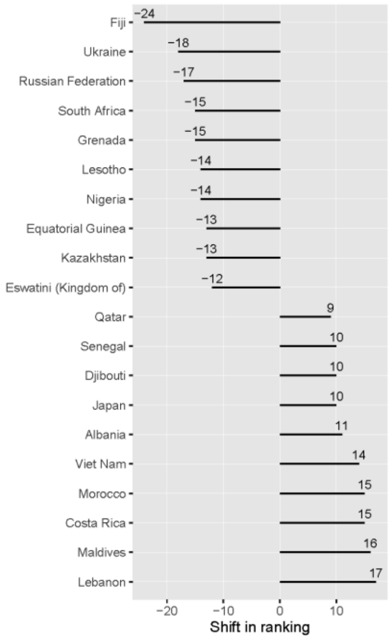


Table 2 - *Ten countries with the highest and lowest HDI rankings using the original weights and the optimized weights.*

Rank	Equal weights	Optimized weights
1	Norway	Hong Kong (+5)
2	Switzerland	Switzerland (+0)
3	Ireland	Norway (−2)
4	Germany	Singapore (+8)
5	Iceland	Australia (+2)
6	Hong Kong	Iceland (−1)
7	Australia	Ireland (−4)
8	Sweden	Sweden (+0)
9	Netherlands	Netherlands (+0)
10	Denmark	Japan (+10)
180	Eritrea	Guinea-Bissau (−2)
181	Mozambique	Burkina Faso (+2)
182	Sierra Leone	Mozambique (−1)
183	Burkina Faso	Mali (+2)
184	Burundi	Burundi (+0)
185	Mali	South Sudan (+1)
186	South Sudan	Niger (+3)
187	Chad	Sierra Leone (−5)
188	CAR	Chad (−1)
189	Niger	CAR (−1)

Note: The numbers in parentheses denote the place changes from the original ranking.

Figure 4 describes the most increases and declines in the HDI ranking when applying the optimized weights compared to the original weights. The countries that have the highest promotion in ranking are Lebanon and Maldives while Fiji, Ukraine, and Russia occur the most ranking reductions. Table 2 compares the proportion of ten countries with the highest and lowest rankings on the original HDI table with the same proportion derived from the new index. In the upper part, the positions of Switzerland, Sweden, and the Netherlands remain unchanged. Hong Kong jumps from sixth place to first place while Singapore and Japan make a significant leap to present in the top ten countries. In the lower part, despite several slight disturbances in positions, the bottom ten countries are quite similar between the two ranking tables.

6. Conclusion

This paper introduces a new weighting method for composite indicators based on a measure of importance and Monte Carlo simulations. The full and independent Sobol' indices (Mara *et al.*, 2015) and the Martinez estimator (Martinez, 2011) are two key factors used to establish a complete procedure for optimizing weights given a sample of inputs and a predefined aggregation model. The procedure allows developers to obtain a solution in which the magnitude of weights coincides with the dependent or independent contribution of inputs to the variance of composite scores. The method can be widely applied to all composite models since it works with any single-valued function regardless of complexity.

During the optimization procedure, sampling strategies play a vital role in the precision of estimation results. Three sampling techniques were tested on different data structures and model configurations. Gaussian inverse transform sampling is the simplest approach, but it is only suitable for data from the multivariate normal distribution. The Iman-Conover technique and copula sampling show greater effectiveness as they can handle samples from mixed distributions and produce near-maximum accuracy with a sufficiently large sample size. In the case of small sample sizes, checking for outliers before sampling is required because they might distort the simulation and result in inaccurate estimates of importance indices.

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SUMMARY

This paper presents an optimization procedure that helps composite indicator developers achieve the most plausible choice of weights without being restricted as the complexity of synthetic models escalates. Given a predefined aggregation function, variance-based sensitivity analysis and Monte Carlo simulations are employed to establish non-parametric methods for measuring the importance of each input to the output uncertainty. Utilizing the computational power of these methods, the weights are calibrated by an optimization procedure to attain the best fit with the estimated measures of importance. The procedure has been tested in two artificially created examples and in one practical case of well-being measurement to confirm its accuracy and efficiency in building composite indicators.

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THINGS YOU SHOULD KNOW ABOUT THE GINI INDEX

Alessio Guandalini

1. Introduction

The Gini index (Gini, 1914) is the most famous and widely used inequality measure. It is an important measure for forecasting the wealth of a country and is available for almost every country in the world from various international organizations' datasets (Decancq and Lugo, 2012).

Its importance has been immediately made clear. Since its first proposal, the Gini index has been the subject of numerous publications, both theoretical and applicative. Some of the reasons for its success and longevity are simplicity, fulfilment of general properties, interesting interpretations, useful decomposition, links with the Lorenz curve (Lorenz, 1905) and the mean difference (Gini, 1912) (see Giorgi, 1990, 1992, 1993, 1999, 2005, 2011a; Giorgi and Gubbiotti, 2017 for more details). Moreover, its use is not only restricted to economics and, every year, many applications in different and unthinkable fields continue to pop up (Giorgi, 2019). The present paper aims to retrace some lines of research related to the Gini index, pointing out the most important results and the reference works, as well as some errors several times published and re-published in the immense literature on the Gini index.

The paper is organized as follows. In Section 2, the definition of the Gini index is recalled. In Section 3, some aspects related to its origin are clarified. In Section 4, the Gini index decomposition is tackled, while its inferential aspects are treated in Section 5. Finally, in Section 6, brief conclusions are outlined.

2. The Gini index

The Gini index is a measure of the degree of inequality in the distribution of a non-negative variable X, most of the time income[1]. It is defined between 0 and 1. Where 0 marks equidistribution (or minimum concentration) of income, that is when all the recipients earn the same amount of income. Instead, it is equal to 1 when all the individuals except one have 0 income, while one earns the total amount of the income. In this case, we refer to maximum concentration. There are several equivalent ways of writing the Gini index[2]. Some of these, which will be useful in the following of the paper, are:

$$R = \frac{2\ \sum_{i=1}^{N} x_i(i-1)}{(N-1)\ t_X} - 1 = \tag{1}$$

$$= \frac{2\ \sum_{i=1}^{N} i\ x_i}{(N-1)\ t_X} - \frac{N+1}{N-1} \tag{2}$$

where N is the population size, x_i is the income earned by the i-th recipient which occupies the i-th position in the ranking of incomes arranged in a non-decreasing way, and $t_X = \sum_{i=1}^{N} x_i$ is the total income in the whole population.

Another expression for R, equivalent to (1) and (2), has been derived as a function of the covariance, $cov()$, by De Vergottini (1950) and Piesch (1975)[3]:

$$R = cov\left(\frac{i}{N}, \frac{x_i}{N}\right). \tag{3}$$

Furthermore, the Gini index can be obtained also through the Lorenz diagram (Gini, 1914). In particular, R is twice the area between the Lorenz curve and the egalitarian line (for more details see Nygård and Sandström, 1981).

3. The origin of the Gini index

Despite the fame of the Gini index, sometimes there is still confusion about the year of its first appearance in literature. It is not uncommon to find papers that place it in 1912. But indeed, Corrado Gini (1884-1965) proposed R in 1914 (Gini, 1914) as the final result of a series of studies on the measurement of the concentration of wealth and income he started in the early twentieth century.

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[1] Besides income, the Gini index can be computed also on other variables, such as wealth, expenditure, revenue, etc. However, for the sake of comodity, in the following, we will assume that it is applied to the income.

[2] See Yitzhaki (1998) for the continuous case, Giorgi and Gigliarano (2017) for the discrete case and Giorgi (1992) for a more general discussion.

[3] The corresponding expression in the continuous case has been proposed by Lerman and Yitzhaki (1984).

The main reason for this mistake is that in his 1914 paper, Gini showed, as a corollary, that R can be written also as a function of the mean difference, Δ, introduced by himself in 1912. Then, several scholars wrongly thought that R and Δ were the same index, so they started to quote the paper of 1912 as a reference for the Gini index. In reality, R and Δ are different measures with different aims useful in different contexts. The former is a concentration measure, while the latter is a variability measure. Of course, the two concepts although related are different.

Furthermore, to complicate matters even more and to contribute to the propagating of the mistake in literature it is the fact that both the papers (Gini1912, 1914) – as well as most of the literature produced by the Italian school of statistics in those years – were written in Italian, so not easily understandable by non-Italian speakers and, moreover, not even easily available. However, after a careful reading of the two papers, it looks clear that the Gini index had been unequivocally proposed for the first time in 1914. Furthermore, any possibility of doubt about this issue is eliminated by Gini himself who stated "… in 1914 I proposed the concentration ratio showing contemporarily the relations between this index and the Lorenz curve and the mean difference" (Gini, 1931 p. 305). Moreover, from the quotation, it is curious to notice that Gini refers to R as the concentration ratio. The other names by which the index is actually known in literature, that explicitly refer to the namesake author, such as Gini index, Gini ratio and Gini coefficient, have only been used later and by Italian scholars to pay homage to Corrado Gini.

4. The Gini index decomposition

The decomposition is a common and recurring practice in the study of inequality measures. According to the structure of the data and the research objectives, it is mainly possible to distinguish decomposition by sources and by population subgroups (for a comprehensive survey on the subject see, e.g., Giorgi 2011b).

The general aim is to determine how much of the inequality is due to each income source or population subgroup. Then, the results of the decomposition are very useful to better understand the inequality and bring out where it lurks.

4.1. Decomposition by sources

When data enables us to decompose the total income by different income sources (for instance, wages, salaries, capital incomes, etc.), it is possible to decompose inequality measures and, of course, the Gini index by the contribution of each income source to the inequality.

The Gini index is additively decomposable by income sources, that is, the overall inequality can be broken up into the contribution of each income source (Rao, 1969):

$$R = \sum_{j=1}^{k} F_j = \sum_{j=1}^{k} q_j R_j \, E_j.$$

The contribution of each income source ($j = 1, \ldots, k$), F_j, is given by the product of three factors:

- q_j, the ratio between the mean income of the source j and the population mean;
- R_j, the Gini index computed only on the incomes of the source j;
- E_j ($-1 \leq E_j \leq 1$), the ratio between the inequality index calculated with (3) for the source j in accordance with the ranking established on the basis of the total income and the Gini index calculated for the source j in accordance with its own internal ranking, R_j. It is equal to 1 only when the ranking within source j coincides with the total income one. E_j plays a crucial role and occurs in several studies on the decomposition by income sources of the Gini index. It provides a measure of the "disequalizing effect" induced by the source j in the income distribution. It has been independently obtained by several scholars, such as Fields (1979a, 1979b) that proposed the Factor Inequality Weights (FIW) and named it "relative coefficient of variation" and by Lerman and Yitzhaki (1985) and Schechtman and Yitzhaki (1987) who named it "Gini correlation". Furthermore, since q_j and R_j are not negative, E_j provides the sign of the contribution of the source j. When it is negative, the source j reduces the total inequality. On the contrary, when it is positive it contributes to increase the total inequality.

4.2. Decomposition by sub-population

When income data are gathered together with individuals characteristics such as age, sex, level of education, geographical area, etc., it is possible to explore the contribution of each population subgroup – identified by these features – to total inequality (see for more details, Deutsch and Silber 1999; Mussard *et al.* 2006).

Bhattacharya and Mahalanobis (1967) were the first to try decomposing R by population subgroups. They attempted to decompose the Gini index as in the ANalysis Of VAriance (ANOVA), that is, into the sum of within (w) and between (b) components. However, they discovered that R cannot be additively decomposed in this way. This overshadowed the Gini index with respect to other indices that instead are additively decomposable in terms of the analysis of variance, such as the Theil index and the entropy index, at least till Mehran (1975) showed that R can also be decomposed additively. In order to do so, it is necessary to take into account the within component (w) and the across component (a) defined as $a = b + i$, where i is the interaction,

$R = w + b + i.$

The interaction component is “a measure of the extent of income domination of one group over the other apart from the differences between their mean incomes” (Mehran, 1975, p.148).

From that moment on, different methods for additively decomposing the Gini index have been proposed. Frick *et al.* (2006) exploiting the results by Mehran (1975) and by Yitzhaki (1994), proposed the ANalysis Of the Gini Index (ANOGI). according to which the Gini index is decomposed by between (b), within (w), overlapping between (ob) and overlapping within (ow) components:

$R = w + ow + b + ob$

The two additional elements, ow and ob[4], are functions of the overlapping, a measure and a concept introduced in the literature on the Gini index by Yitzhaki and Lerman (1991). The overlapping represents the extent by which one subgroup is overlapped by the other. When there is no overlapping, a population is stratified, that is, there is a kind of “segregation” between the subgroups with respect to the income distribution. Therefore, this measure has very important and practical economic implications. In fact, a stratified society, in which the membership of a group automatically precludes certain incomes to its members, can bear less inequality and takes more the risk of instability. Stratification is both the cause and the consequence of inequality. Furthermore, this type of information cannot be captured by the inequality measures that are additively decomposable. In the end, what initially looked like a drawback for the Gini index is one of its strengths. However, to be precise and exhaustive, the concept of overlapping is close to the concept of “transvariation” already grasped by Gini (1916) (see also Pittau and Zelli, 2017).

It is possible to obtain an interesting decomposition of the Gini index also applying the concept of Shapley value in cooperative game theory (Shapley, 1953). The Shapley value provides the marginal impacts of some components, suitably chosen, which play in determining a profit function. Deutsch and Silber (2007) in their work put down the Gini index as the profit function and consider the components within (w), between (b), ranking (r) and the relative size in each population subgroup (n) (see also Shorrocks, 1999). So, they additively decompose R as:

$R = w + b + r + n.$

Finally, another interesting result, that goes by the name of Balance Of Inequality (BOI) decomposition, has been proposed by Di Maio and Landoni (2015). The

[4] In general, ob is negative because the overlapping reduces the differences between subgroups.

interest in this work is twofold. First, they demonstrate that R in (2) coincides with the normalized barycenter of the income distribution, the BOI. This provides, if additional proof were needed, the extraordinariness of the Gini index which also has a physical interpretation. Then, they propose a decomposition that, besides the components within (w) and between (b), consider the asymmetry ($asym$) and irregularity[5] (irr). Therefore,

$$R = BOI = w + b + asym + irr.$$

5. Inference

The study of the sampling properties of the Gini index is a very interesting and prolific research field that has remained uncharted for a long period, at least by Italian statisticians. In fact, Gini was very critical of statistical inference and the attitude of such recognized authority like him, who had a great impact on the Italian school of statistics, which for many years neglected almost completely this topic and, therefore, the study of the inferential aspects of the Gini index (Piccinato, 2011). Then, the first attempts of studying the sampling properties of R were by non-Italian scholars. Furthermore, inference on the Gini index is a tricky problem and this generated a large number of publications and a large number of mistakes, often even re-published in the literature. For the sake of brevity, parametric inference and finite population inference are here considered.

5.1. Parametric inference

Parametric inference aims to express the Gini index as a function of parameters in theoretical distributions. This is useful for facing inferential problems but also the problem of missing data, especially at the top of the distribution, and, then, for imputing the data and improving the estimates.

The expression of the Gini index has been already determined under several continuous theoretical distributions, such as Pareto (Michetti and Dall'Aglio, 1957; Girone, 1968), exponential (Cicchitelli 1968), lognormal (Langel and Tillé, 2012). Giorgi and Nadarajah (2010), in a very extensive work, determined the expression of R under thirty-five continuous distributions.

Under discrete distributions, Conti and Giorgi (2001) suggested using a kernel estimation for filling the gap between observations. They proposed a two steps procedure: in the first step, the unknown population distribution is estimated via a kernel method; in the second step, the kernel estimate of the density is used to produce an estimate of the Gini index.

[5] The income distribution is regular if the distance between two adjacent recipients in the population or in the subgroup is constant.

5.2. Finite population inference

Finite population inference deals with the sample surveys commonly carried out for collecting income data on which the Gini index is usually computed.

The Gini index is a non-linear statistic, since it is based on rank statistics, therefore its variance is not straightforward, especially under complex sampling designs. Three main lines of research can be distinguished in the finite population framework: (i) asymptotic theory, (ii) linearization methods, (iii) resampling methods.

In the asymptotic theory, the properties of an estimator are studied for n that going to infinity. The first attempt of studying the inferential properties of the Gini index is framed within this framework and traced back to Hoeffding (1948). There were also prior attempts in the same framework, but they had focused on the numerator of the Gini index, the mean difference (such as Nair, 1936). Instead, Hoeffding showed, as part of an application of his general results, that the Gini index is a ratio of two U-statistics and that under certain conditions, it is asymptotically normal. The same result has been obtained with different procedures by other scholars (see Giorgi and Gigliarano 2017 for further details).

Linearization methods include a range of techniques (such as Taylor series expansions, estimating equations, influence function, indicator variables). The basic idea of these techniques is to approximate the variance of a non-linear statistic, like R, through the variance of the total of a linear function of the observations, i.e., a linearized variable. All the linearization techniques have been applied to the Gini index, but with mixed success (see Langel and Tillé, 2013). The method, currently used by Eurostat in the estimation procedure for computing the sampling error of the Gini index on Eu-Silc[6] income data, has been developed by Osier (2009). This method uses the influence function, already known in the field of robust statistics, as artificial variables for approximating the variance of non-linear statistics (Deville, 1999) and, therefore, also of the Gini index. However, the linearized expression of R obtained with the influence function and used by Osier (2009) was not new and was initially determined by Monti (1991). Vallée and Tillé (2019), used the method proposed by Graf (2011) based on the Taylor series expansion with respect to indicator variables, for dealing with the cases in which the Gini index is computed in the presence of non-response and re-weighting procedures, such as calibration. Also, resampling methods have been applied in the last fifty years for estimating the variances of the Gini index. Manfredi (1974) was the first to use the jackknife method followed by, among others, Yithzaki (1991) who proposes an estimator

[6] European Union Survey on Income and Living Conditions. For further details, please see the material on this link <https://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions>.

based on the influence function. Moreover, Dixon *et al.* (1987) were the first to use bootstrap. Most recently, Antal and Tillé (2011) derive a time-efficient bootstrap method useful under classical sampling designs.

6. Conclusions

The Gini index is the most famous and widely used inequality measure. Since its first proposal, it has been subject of numerous publications. Nowadays, after more than one century, it is still a matter of great interest. Hence, it is important to keep track of the oceanic quantity of papers already written and, moreover, be able to navigate among them.The present paper represents an attempt to clarify and resume some aspects related to the origin, the decomposition and the inferential aspects of the Gini index. Of course, the topics and the literature covered represent only the tip of the iceberg. Several interesting topics have been overlooked just for reasons of space. Anyway, this paper hopefully could be a useful starting point for scholars approaching this topic.

Acknowledgements

This paper is an attempt to resume in few pages some of the main knowledge, notions and curiosities on the Gini index that Prof. Giovanni Maria Giorgi attempted to convey to me from 2010 until the day before his departure. So, this paper is a simple way to thank him for all the teachings I received and simply a first attempt to not waste his immense knowledge on this topic.

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SUMMARY

The present paper retraces a few of the main lines of research related to the Gini index, pointing out the most important results and the reference works, as well as some errors, several times published and re-published in the literature. It can be seen as a short compendium, based on the works, teachings and discussions of Prof. Giovanni Maria Giorgi.

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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,

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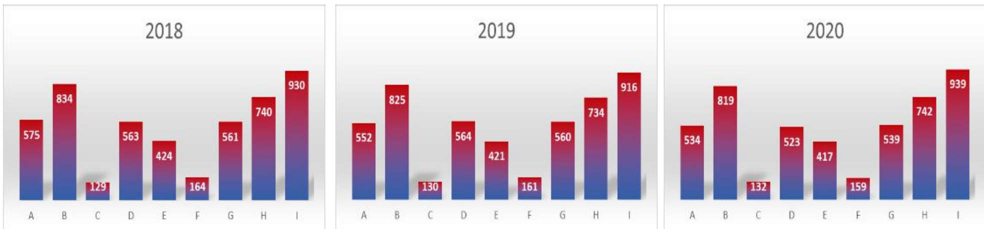
[8] For the methodology and mathematical properties of AMPI see Mazziotta and Pareto, 2016; Mazziotta and Pareto, 2020.

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	Campione 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	Campione 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	Campione 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	Mongiardino 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	Asti	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	Mongiardino 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.

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[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.

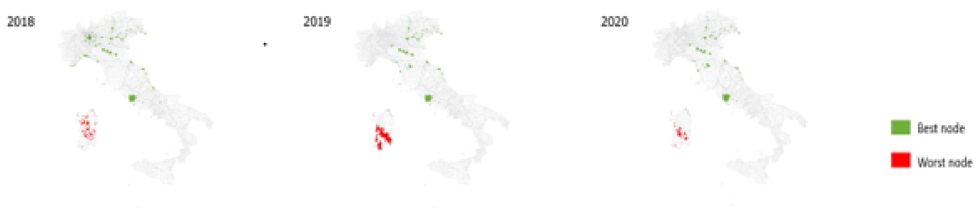
Figure 4 – *The best and worst nodes.*

	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.

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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.

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THE SOCIOECONOMIC SEGREGATION IN ITALIAN METROPOLITAN CITIES[1]

Giuseppe Cinquegrana, Giovanni Fosco

1. Introduction

During the pandemic, the gap between center and periphery inequalities widened. Recent reports indicate a further deterioration in those areas where social marginality was already high, suggesting profound differences, not only in income, between the center and the periphery.

In 2016, the "Commissione Parlamentare d'Inchiesta sulle Periferie" had just opened the discussion on the precarious security conditions and the state of deterioration of the cities and their suburbs, raising the possibility of a possible phenomenon of socioeconomic stratification at the local level.

We develop our analysis in the framework of the economics branch concerning social interactions. In particular, that explores the degree of residential socioeconomic segregation to get the interdependencies between individuals where the preferences, beliefs, and constraints faced by a person are directly influenced by the characteristics and choices of others belonging to an environment where social interactions occur (i.e., neighborhood), where individuals spend their daily lives.

The following study offers new empirical evidence regarding the phenomenon of socioeconomic stratification in Italy. In particular, using the data of the Census (2011) of the main metropolitan cities of Northern and Southern Italy, we exploit the composition of the population of the neighborhoods (or census section) pre-covid to determine the residential segregation indices used in the social economy literature (Graham, 2018; Card and Rothstein, 2007: Cutler and Glaeser, 1995) to measure socioeconomic stratification at the territorial level.

The results show that upper-class individuals self-segregate in such a way as to reduce the likelihood of interaction with more deprived classes. The two metropolitan cities follow the same pattern in terms of residential segregation.

The article is organized as follows: Section 2 provides a background of the topic. Section 3 defines residential segregation; section 4 shows the results; Section 5 concludes.

Introduction and Section 2 were written by Cinquegrana G. Sections 3, 4 and Conclusion were written by Fosco G.

2. Background

2.1. "Commissione parlamentare d'inchiesta sulle periferie"

In 2016, the "Commissione Parlamentare d'inchiesta sulle periferie" had just opened the discussion on unstable social insurance conditions regarding metropolitan cities and their suburbs, highlighting a possible phenomenon of residential socioeconomic stratification (segregation).

Metropolitan suburbs are characterized by degradation and hardship in small and large municipalities, which grew up because of uncontrolled building development, generating suburban settlements wherein lack the supply of functional and institutional public services. Therefore, these dynamics have determined peripheral areas' residential mono-functionality (dormitory-suburbs), forcing residents, who are not always adequately supported by mobility infrastructures, to commute to work.

In Italy, most of the population lives and works in the suburbs. In 2017, residents in main towns amounted to 43% of the people residing in metropolitan areas, while the remaining population was in 1260 municipalities belonging to several metropolitan hinterlands.

Italian suburbs are featured by disadvantaged households and young people outside the education and employment environments. The 38% of residents in main metropolitan towns live in neighborhoods with deprived households, which amounts to 1% and 3%, while 15% and 25% in south Italian cities.

The suburbs represent the environment wherein social phenomena such as the aging of the population, the crisis of the middle class, multiculturism, and the youth social problems drift out.

The "Commissione Parlamentare d'inchiesta sulle periferie" highlighted several inequalities between peripherical and center areas, suggesting a likelihood phenomenon of residential socioeconomic stratification (segregation). This implies that deprived and affluent people are not homogeneously spatial distributed across neighborhoods.

2.2. The Index of "vulnerabilità sociale e materiale" (IVSM)

In 2015, ISTAT published the Index of "*vulnerabilità sociale e materiale*" (IVSM) to measure risk factors that threaten welfare stability intended as the system of social integration and resource allocation by population groups. The purpose of the Index is to provide a synthetic measure of the social and material vulnerability at the level of Italian municipalities.

ISTAT defines social and material vulnerability as the exposition of some population groups to economic and local social uncertainty. Therefore, it measures several degrees of the population exposition to vulnerability conditions, which do not imply necessarily deprived situations. It takes into account five dimensions that are based on factors determining a state of vulnerability. Therefore, first, education attainment, namely the share of people who are illiterate and literate without graduation aged between 25-64. Second is the family structure, namely the share of households with six or more members, the share of single-parent families, and the share of households composed of older people (65 years and older) or with at least an octogenarian. Third, housing conditions are the percentage of people living in small houses with many members (40 sm and four members, 40-59 sm and five members, and 60-79 sm and six members or more). Fourth, labor market participation is the share of youths aged between 15-29 who are not employed and not enrolled in any education course. Fifth is the economic condition of households, the percentage of households with unemployed members and without none retired workers.

Finally, the IVSM does not consider how the population is distributed at the residential level according to their socioeconomic status (i.e., the degree of socioeconomic residential segregation), which contributes to several social risk factors related to social interactions and local inequalities reinforcement (e.g., ghettoization). In the next section, we broadly discuss residential socioeconomic segregation and its consequences.

3. Residential segregation

3.1. What is the residential segregation

Segregation refers both to a separated environment and the action of isolating. Social scientists usually define situations in which groups experience separated environments (neighborhoods, schools, firms, offices, etc.) as the phenomenon of segregation. Nevertheless, completely segregated situations are not frequent, and the term usually refers to a heterogeneous environment.

The separation between individuals has been investigated in several research frameworks, mainly residential mobility, school enrolment, and its implications in the policy design.

Our field of research addresses segregation as the uneven or non-random distribution of individuals who have in common some characteristics (income, social status, sex, and ethnicity) in a given environment. Therefore, residential segregation can be defined as the extent to which individuals who belong to different groups live in different areas (neighborhoods) characterized by different group compositions (Reardon and O'Sullivan, 2004). For example, suppose residents of city A are divided into white and blue collars. If the majority of white collars live in neighborhoods whose population consists mainly of blue collars, then we can conclude that city A is characterized by residential segregation.

3.2. Potential consequences

There are many mechanisms through which residential segregation might affect individual outcomes. The quality of public goods and local institutions is usually based on local tax burdens and community involvement in maintaining public resources. Thus, if upper-class households place within a small number of neighborhoods, they are able to generate resources that better their outcomes.

Further, residential segregation may be self-reinforcing since lower-class households are often unable to perform enough resources to disincentivize upper-class households to self-segregate.

Moreover, the ability of upper-class households to self-segregate does not affect only the current welfare and opportunities of lower-class households but also affects the opportunities for future generations (intergenerational mobility) through investment in locally financed institutions that serve children (e.g., schools).

Conversely, if high socioeconomic households are not clustered, they may help fund social services and institutions that serve lower socioeconomic populations.

3.3. How to measure segregation

A measure of residential segregation requires defining the environments within which individuals live (e.g., neighborhood, school, etc.) and dividing the reference population based on characteristics of interest (e.g., social class) in such a way to quantify the extent to which the distribution of the attribute of interest varies across neighborhoods (Reardon and O'Sullivan, 2004).

In this section, we discuss the two most relevant indices of segregation: the dissimilarity index (Duncan and Duncan, 1955) and the exposure index (Lieberson, 1981). We use the methodological notion suggested by Reardon and Firebough (2002) to operationalize the measure of segregation. Consider a region R populated by M subgroups indexed by m. The region of interest is divided into r-subregions, and π is the population proportions.

T = the total population in the area R.
t_r = the total population in the r-subarea
t_{rm} = the absolute frequency of the group m in subarea r.
π_{m} = relative frequency of group m on total population.
π_{rm} = relative frequency of group m in subarea r.

The most popular segregation extant is the Dissimilarity index (D), which can be interpreted as the proportion of minority members who should change their tract of residence to have the same minority proportion in all tracts. It is between [0,1], where [1] is the maximum segregation.

$$D = \frac{1}{2}\sum_{r\in R}\frac{t_{\mathrm{r}}|\pi_{\mathrm{rm}} - \pi_{\mathrm{m}}|}{T\pi_{\mathrm{m}}(1-\pi_{\mathrm{m}})}.$$

A different concept that measures segregation is exposure, which means the average degree members of a group are exposed to members of other groups in a neighborhood. The exposure index can be interpreted as the likelihood of interaction among individuals of different groups. It ranges between [0,1], where [1] is the full exposition (integrated neighborhood).

$${}_{m}P_{n}^{*} = \sum_{r\in R}\frac{t_{\mathrm{rm}}}{T_{\mathrm{m}}}\pi_{\mathrm{rn}}.$$

It is worth noting that the exposure index is not asymmetric. Thus, exposure of group *M* to group *N* is not complementary to exposure of group *N* to *M*.

3.4. Socioeconomic segregation in cities

How to sort individuals according to their socioeconomic status (SES) is as long as the history of urbanization (Nightingale, 2012). The pioneering study of Booth (1888) started the era of systematic research on intraurban socio-spatial division.

The present study is related to Chicago school studies, which used the biology analogy of invasion and succession to explain the residential segregation paths.

Duncan and Duncan (1955) introduced the widely used dissimilarity index claiming that higher socioeconomic groups (e.g., white collars) were most segregated from the remainder of the population.

Morgan (1975, 1980), on socioeconomic segregation in cities in England and Wales, confirmed segregation profiles toward higher socioeconomic groups. A similar trend characterizes income segregation in urban regions of the United States (Reardon and Bischoff, 2011). Our study aims to provide for the first time evidence on the socioeconomic segregation in Italian metropolitan areas, collocating on this strand of literature.

4. Socioeconomic segregation in Italian Metropolitan cities

How should quantify socioeconomic residential segregation in a metropolitan area? In this section, we measure residential socioeconomic segregation. We focus on the two main metropolitan areas in terms of the population size of North and South Italy: Milan and Naples. The sample choice is motivated by the aim of comparing different and distant realities, avoiding potential spillovers between nearby cities.

To extant socioeconomic segregation in a Metropolitan area, we use Census (2011) data, which provides detailed microdata at the local level. Therefore, we define the "sezione censuaria" as the environment where individuals live and interact to construct residential segregation indices.

We cluster the population in four socioeconomic classes (upper, middle, lower, and excluded) based on the European socioeconomic classification (ESEC, Harrison and Rose, 2006) through census variables "attività lavorativa svolta" and "condizione di lavoro classificazione Italia."

To provide a clear description of the socioeconomic segregation phenomenon in Metropolitan areas, we estimate dissimilarity and exposure indices by most populated municipalities (above 40000) and rings (distance in kilometers from the Metropolitan capital) of Metropolitan cities, which are based on information provided by the "Dossier delle aree Metropolitane."

4.1. Residential socioeconomic segregation in Naples

The metropolitan city of Naples is one of the most populated with a high population density in the European Union, and it is the third most populated metropolitan city in Italy. Its extension is on a surface of 1171 square kilometers and includes 92 municipalities.

The metropolitan city of Naples has particularities that characterize it from other metropolitan Italian towns: its territory occupies just 8.6% of the Campania area, and more than half of the entire regional population is located there. This phenomenon of overcrowding has created a strong demographic and territorial imbalance with other areas of the region, which are more extensive and less populated.

Table 1 – *Residential socioeconomic segretation by rings: Dissimilarity index.*

	D_{upper}	D_{middle}	D_{lower}	$D_{excluded}$
Core	.34	.14	.21	.14
Ring 1	.14	.09	.12	.1
Ring 2	.17	.15	.09	.13
Ring 3	.14	.11	.1	.13

Source: authors'elaboration on ISTAT Census (2011).

Table 1 shows the dissimilarity socioeconomic index for two groups at once by Metropolitan rings. It represents the proportion of individuals belonging to a given group who should change their "sezione censuria" of residence to have the same proportion in all "sezione." In the first column, it is reported the dissimilarity index for the upper class than the rest. In this way, it also reported for the other: middle, lower, and excluded groups. Instead, Table 2 shows, in the first three columns, the exposure of the upper to the other group, while in the last three, the exposition of the other classes to the upper one.

Table 2 – *Residential socioeconomic segretation by rings: Exposure index.*

	$P_{up\|mid}$	$P_{up\|low}$	$P_{up\|ex}$	$P_{mid\|uo}$	$P_{low\|up}$	$P_{ex\|up}$
Core	.52	.37	.88	.36	.39	.07
Ring 1	.69	.63	.94	.3	.32	.06
Ring 2	.69	.67	.93	.29	.27	.06
Ring 3	.65	.66	.9	.34	.32	.07

Source: authors'elaboration on ISTAT Census (2011).

The dissimilarity indices by rings of Naples metropolitan area point out a higher segregation profile for upper class (.34) and lower class (.21) located in the core than the middle class and excluded, which share more neighborhoods in the core. Both the two kinds of index highlights that a possible social phenomenon of upperclass self-segregation is relevant in the Metropolitan city.

Table 3 – *Residential socioeconomic segretation by Municipalities: Dissimilarity index.*

	D_{upper}	D_{middle}	D_{lower}	$D_{excluded}$
Acerra	.31	.24	.2	.2
Afragola	.37	.27	.19	.2
Casalnuovo di Napoli	.18	.17	.18	.16
Casoria	.25	.16	.16	.17
Castellamare di Stabia	.31	.15	.19	.12
Ercolano	.3	.21	.17	.16
Giugliano in Campania	.3	.31	.16	.27
Marano di Napoli	.23	.19	.25	.2
Napoli	.34	.14	.21	.14
Portici	.23	.14	.2	.13
Pozzuoli	.39	.21	.22	.2
Torre del Greco	.21	.11	.13	.09
Others	.13	.09	.08	.12

Source: authors'elaboration on ISTAT Census (2011).

Table 4 – *Residential socioeconomic segretation by Municipalities: Exposure index.*

	$P_{up\|mid}$	$P_{up\|low}$	$P_{up\|ex}$	$P_{mid\|uo}$	$P_{low\|up}$	$P_{ex\|up}$
Acerra	.64	.64	.93	.25	.2	.04
Afragola	.63	.63	.92	.26	.19	.03
Casalnuovo	.77	.74	.96	.2	.19	.03
Casoria	.72	.67	.94	.24	.25	.04
Castellamare	.59	.44	.92	.34	.31	.05
Ercolano	.6	.54	.94	.32	.27	.03
Giugliano	.66	.57	.88	.28	.29	.06
Marano di Napoli	.67	.57	.93	.28	.29	.05
Napoli	.52	.37	.88	.36	.39	.07
Portici	.59	.36	.9	.36	.47	.07
Pozzuoli	.6	.44	.89	.3	.27	.05
Torre del Greco	.7	.7	.95	.26	.23	.03
others	.67	.67	.91	.33	.32	.08

Source: authors'elaboration on ISTAT Census (2011).

Whereas Tables 3 and 4 propose the same indices as the previous two tables by the most populated municipalities (above 40000 inhabitants).

Socioeconomic segregation is related to municipality size, and instead, the most populated municipalities in the metropolitan area of Naples are more segregated from others. Also, in this case, the middle class and excluded share more areal units by municipalities. Comparing exposure of the upper group (most segregated) to other groups and vice-versa, we observe a higher probability that an individual belonging to the upper class met a member of different groups. In particular for the middle class and the excluded in all rings of the metropolitan area. In contrast, the exposure of other groups to the upper one is lower.

4.2. Residential socioeconomic segregation in Milan

The metropolitan city of Milan is the second most populated metropolitan city after Rome. It extends on a surface of 1575,65 square kilometers and includes 133 municipalities.The metropolitan city of Milan is one of the most important economic areas in Italy: it concentrates 42.3% of Lombardy companies and 6.6% of active Italian companies. This element allows it to generate a high productivity level since it alone concentrates the largest percentage of the national GDP and annually produces a wealth of more than 200 billion euros.

Table 5 – *Residential socioeconomic segretation by rings: Dissimilarity index.*

	D_{upper}	D_{middle}	D_{lower}	$D_{excluded}$
Core	.28	.16	.26	.16
Ring 1	.15	.12	.09	.13
Rng 2	.15	.11	.09	.13
Ring 3	.04	.04	.05	.06

Source: authors'elaboration on ISTAT Census (2011).

Table 6 – *Residential socioeconomic segretation by rings: Exposure index.*

	$P_{up\|mid}$	$P_{up\|low}$	$P_{up\|ex}$	$P_{mid\|uo}$	$P_{low\|up}$	$P_{ex\|up}$
Core	.51	.35	.81	.37	.44	.13
Ring 1	.72	.57	.86	.26	.38	.11
Ring 2	.74	.64	.87	.24	.32	.1
Ring 3	.75	.69	.84	.24	.3	.15

Source: authors'elaboration on ISTAT Census (2011).

Table 7 – *Residential socioeconomic segretation by Municipalities: Dissimilarity index.*

	D_{upper}	D_{middle}	D_{lower}	$D_{excluded}$
Abbiategrasso	.33	.27	.23	.27
Bollate	.16	.13	.12	.12
Bresso	.22	.12	.22	.13
Buccinasco	.24	.16	.21	.17
Cernusco sul Naviglio	.16	.22	.2	.24
Cinisello Balsamo	.28	.16	.21	.15
Cologno Monzese	.29	.16	.25	.16
Corsico	.33	.19	.21	.19
Garbagnate Milanese	.19	.14	.11	.13
Legnano	.17	.16	.13	.13
Milano	.28	.16	.26	.16
Paderno Dugnano	.32	.22	.23	.2
Parabiago	.14	.1	.13	.12
Pioltello	.39	.2	.23	.19
Rho	.25	.23	.21	.22
Rozzano	.45	.37	.19	.35
San Donato Milanese	.23	.24	.34	.24
San Giuliano Milanese	.36	.27	.18	.28
Segrate	.36	.2	.32	.31
Sesto San Giovanni	.26	.16	.21	.16
Others	.05	.04	.05	.04

Source: authors'elaboration on ISTAT Census (2011).

Table 8 – *Residential socioeconomic segretation by Municipalities: Exposure index.*

	$P_{up\|mid}$	$P_{up\|low}$	$P_{up\|ex}$	$P_{mid\|uo}$	$P_{low\|up}$	$P_{ex\|up}$
Abbiategrasso	.68	.56	.85	.25	.26	.08
Bollate	.74	.63	.92	.23	.32	.06
Bresso	.69	.54	.92	.25	.31	.06
Buccinasco	.67	.43	.85	.28	.41	.11
Cernusco sul Naviglio	.65	.4	.79	.33	.53	.14
Cinisello Balsamo	.74	.63	.92	.18	.2	.05
Cologno Monzese	.73	.6	.92	.2	.19	.05
Corsico	.74	.59	.91	.18	.2	.04
Garbagnate Milanese	.74	.63	.91	.24	.29	.07
Legnano	.64	.51	.88	.32	.4	.1
Milano	.51	.35	.81	.37	.44	.13
Paderno Dugnano	.7	.56	.86	.22	.25	.06
Parabiago	.74	.65	.9	.25	.31	.07
Pioltello	.67	.56	.78	.2	.16	.06
Rho	.68	.54	.88	.25	.32	.08
Rozzano	.75	.59	.81	.17	.21	.05
San Donato Milanese	.55	.31	.8	.35	.44	.13
San Giuliano Milanese	.74	.59	.81	.21	.25	.08
Segrate	.54	.3	.71	.33	.41	.14
Sesto San Giovanni	.69	.52	.9	.24	.31	.06
Others	.75	.67	.83	.24	.32	.16

Tables 5, 6, 7, and 8 are organized as follows: Dissimilarity and Exposure indices by rings and Dissimilarity and Exposure indices by the most populated municipalities (above 40000 inhabitants).

The socioeconomic segregation profile for the Milan metropolitan area follows the same pattern as the Naples metropolitan area if we consider the socioeconomic group distribution by rings and most populated municipalities, even if segregation is lower in the core than in the Naples core. The exposure of other socioeconomic groups to the upper class is higher than Naples metropolitan area, and lower group members are more likely to meet upper members. However, the exposure of the excluded group to the upper group is, in any case, low for both metropolitan areas. The main difference between the two metropolitan areas is that upper members share more areal units (neighborhoods) in Milan than in Naples.

5. Conclusion

Socioeconomic residential segregation is relevant in the main metropolitan areas (Naples and Milan). It points out that social classes with wide inequalities are less likely to interact at the local level.

The Metropolitan areas of Naples and Milan present the same pattern of socioeconomic residential segregation (how socioeconomic groups are distributed) by Rings and most populated municipalities. In particular, the indices show the likely self-segregation phenomenon of the upper class. The results for Naples are worse than Milan.

Socioeconomic segregation should be considered a social risk factor that increases social marginality. Potential consequences concerning the low quality of public goods and negative social spillovers produce worsened individual outcomes. Hence, the place may matter because expenditure per pupil, teacher quality, access to good hospitals, and proximity to well-paying jobs vary across neighborhoods. In principle, these types of neighborhood inequalities can be ameliorated by transferring resources across space. Second place may matter because the characteristics and behaviors of our neighbors directly influence key life outcomes. If employment depends partly on information and referrals from friends and neighbors, then living in a segregated city, where few people are stably employed, acquiring a job is much more challenging. If learning depends partly on being surrounded by the socioeconomic status of peers, then a child in a classroom of advantaged children should learn more quickly than the same child in a classroom of disadvantaged children. This source of inequality can not be ameliorated by transferring financial resources across space. Therefore, reducing peer group inequality requires people to move across areas (i.e., social housing policies).

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SUMMARY

During the pandemic, the gap between center and periphery inequalities widened. Recent reports indicate a further deterioration in those areas where social marginality was already high, suggesting large differences between the center and the periphery. The Parliamentary Committee of Inquiry into the Peripheries, set up in 2016, has already put on the table the precarious security conditions and the state of deterioration of the cities and their suburbs, raising the possibility of a possible phenomenon of socioeconomic stratification at the local level which has contributed to generating different inequalities in educational levels.

The analysis we are developing is part of the social economy. This type of framework focuses on social interactions, understood as the interdependencies between individuals where the preferences, beliefs, and constraints faced by a person are directly influenced by the characteristics and choices of others belonging to a set, intended as an environment in which social interactions take place, i.e., the neighborhood place where individuals live. The following study offers new empirical evidence regarding the phenomenon of socioeconomic stratification in Italy. Using the data of the Census (2011) of the main metropolitan cities of Northern and Southern Italy, we exploit the composition of the population of the neighborhoods (or census section) pre-covid to determine the residential segregation indices used to measure socioeconomic stratification. The results show that the gap between North and South is also relevant concerning this new component.

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THE SUSTAINABILITY CHALLENGES OF ISLANDS IN A EUROPEAN PERSPECTIVE BETWEEN MARGINALITY AND DEVELOPMENT

Simona Cafieri

1. Sustainability and sustainable development

Sustainable development is defined as « development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (United Nations General Assembly, 1987) [1].

This concept "provides a framework for the integration of environment policies and development strategies" (United Nations, 1987). However, long before the late 20th century, scholars argued that there need not be a trade-off between environmental sustainability and economic development.[2]

1.1 The Sustainable Development Goals

The Sustainable Development Goals (SDGs),[3] also known as the 2030 Agenda, aim to address a wide range of economic and social development issues and recognise the close link between human well-being, the health of natural systems and the common challenges faced by all countries, and have given a new impetus to global efforts to achieve sustainable development worldwide[4]. Each goal is linked to targets to be achieved by 2030. The goals are outlined below:

[1] United Nations General Assembly, Our Common Future Report. Oslo, 1987.
[2] Sachs (2015).
[3] According to the definition of the U.N, www.un.org.
[4] Emas (2015).

Figure 1 – *The 17 Sustainable Development Goals.*

Source: https://www.un.org.

1.2. Sustainability indicators

Three periods can be distinguished along the path towards the Sustainable Development Goals:

1. Sustainability Indicators 1.0 (1972 - 2015)

In the beginning it was like "The Quest for the Holy Grail": a search for ideal indicators; then various authors contributed to the subject, (Maureen Hart ,1999)[5]

2. Sustainability Indicators 2.0 (2016 - 2030)

From Agenda 2030 onwards, the question arises as to how different countries, cities and communities compare with each other.[6]

3. Sustainability Indicators 3.0 (2030 - ????)

There is a growing trend towards community-based indicators (tailored to the needs of communities)[7]

Statistical indicators are playing an increasing role as tools to guide decision-making processes: a community with a multitude of economic, social and environmental subsystems is too complex for a single indicator to provide proper information for all decisions to be made.

The first step in a process should therefore be to develop a vision of a sustainable society - a 'leitbild' - useful as a compass[8], with indicators to measure progress, gap from the goal and failures of plans or implementation. One wonders:

What is the link between indicators and sustainability? How appropriate sustainability indicators can be identified? How indicators can be used to measure progress towards sustainable development? What data sources are available for indicators? We try to answer these questions.

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[5] Haart and Farrell (1998).
[6] Hák *et al.* (2016).
[7] Mitchell (1996).
[8] Spangenberg and Bonniot (2018).

2. Focus on Islands

Island territories, repositories of outstanding cultural and biological diversity, can be used as experimental laboratories: evolutionists were the first to use this practice: Darwin tested his evolution theories on the Galapagos, Wallace conducted further experiments on the Malay Islands.

2.1 Islands and their characteristics

Islands are highly vulnerable, highly endemic ecosystems where the pressures of human activities can have devastating effects. In fact, Islands are among the places on the planet where the effects of climate change are most evident, especially with the coming threat of sea level rise. Insularity, remoteness and consequent dependence on sea and air transport, even for basic activities, lack of economies of scale and dependence on global supply chains lay specific development challenges.

Taking into account internal and external strengths, weaknesses, opportunities and threats, the matrix shown in the following Table can be built:

Table 1 – *Strengths, Weaknesses, Opportunities and Threats for the Islands.*

	FORCES	WEAKNESSES
INTERNAL ENVELOPE	• Age structure of the young population; • Increase in the Active Population, the Activity Rate and Employment; • Natural wealth, heritage and culture; • Resistance to the crisis by the agro-food sector; • Broadband internet access; • Agri-food sector with research and innovation initiatives; • Exclusive Economic Zone of great size.	• Misalignment, in the labor market, between supply and demand for skills; • Low qualification of the active population; • Water storage capacity; • Difficulty of interconnection between research and economics; • Excessive use of some spaces by tourism, with a risk to natural resources; • Few statistical data; • Transportation.
	OPPORTUNITIES	THREATS
EXTERNAL ENVELOPE	• Political Stability; • Economic growth; • Growth of the Tourism Sector; • Growth of the Digital Economy; • Tax benefits on foreign investment; • Comprehensiveness of the education and training network.	• Trend of aging of the population; • Early school leaving; • Decrease in the resident population; • Desertification of smaller islands; • Geographical dispersion and diversity of inter-island economic and social contexts; • Vulnerability to climate change.

Source: Elaboration on Ocean & Coastal Management review[9].

[9] Polido *et al.* (2014).

When exogenous shocks hit the normal dynamics of local economic systems, the negative impact on Island communities is therefore more incisive than on the mainland, given their specialisation in traditional sectors of the economy, from manufacturing to tourism. This is why, even more so after the pandemic, Islands are facing a double race: towards recovery and towards sustainability, and thus, in a constantly changing world, they are a laboratory for testing models of sustainable development.

In this study, 17 European Islands have been analysed, using Eurostat data at Nuts[10] level 2[11] :Cyprus, Corsica, Guadeloupe, Mayotte, Martinique, Reunion, Kriti, Ionia Nisia, Sardinia, Sicily, Malta, Azores, Madeira, Canary Islands, Balearics, Ireland, Iceland.

3. The SDGs indicators for Islands

An attempt was made to build tailored indicators for Islands. For each SDG, the relevant indicators[12] were taken into account.

3.1 Tailored indicators for Islands

- People living in very low labour intensity households.
- People at risk of poverty or social exclusion.
- Severe material deprivation rate.
- At-risk-of-poverty rate.

- Economic accounts for agriculture.
- Organic farming: number of holdings, areas of different crops and heads of different types of animals by farm size.
- Labour force: number of persons and agricultural work, farm size.

- Infant mortality by region of residence.
- Life expectancy at birth.
- Health workforce.

[10] Official territorial statistical nomenclature.
[11] Eurostat:Regional statistics by Nuts Classification.
[12] Available at NUTS 2 level.

- Participation rate in education and training (last 4 weeks).
- Population by level of education, by gender.
- Early school leavers by gender.
- Youth neither in employment nor in education by gender.
- Employment rate of young people not in education and training.

- Regional disparities in the gender employment gap.

- Freshwater resources per river basin district.
- Water abstraction by river basin district.
- Water use by river basin district.

- Cooling and heating degree days.

- Employment rate by gender, age.
- Long-term unemployment (12 months and over) by gender, age.
- Regional disparities in the rate of Neet[13] young people.

- R&D personnel and researchers by sector and, gender.
- GERD by performing sector.
- Employment in technology and knowledge intensive sectors.

- Household income.

- Population density.

- Real growth rate of regional gross value added (GVA).

- Estimation of soil erosion by water, by level of erosion.

- Area of marine sites designated under NATURA 2000.

- Freshwater resources per river basin district.
- Land cover for FAO forest categories.

- Police recorded crime.

[13] Neither in Employment nor in Education and Training.

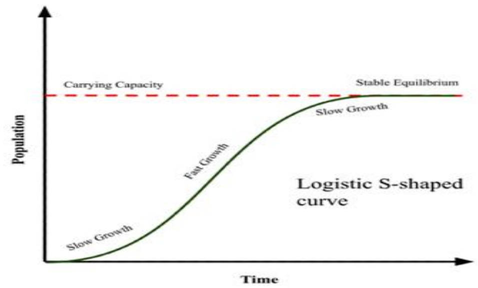
- Households with broadband access.

3.2 Island carrying capacity

Carrying capacity[14]fits, in accordance with the concept of sustainable development, into a multidimensional approach that combines several dimensions simultaneously:[15]

- Physical
- Economic
- Social
- Biophisical

Figure 2 – *Carrying capacity of the Islands.*



Source: Ecological Indicators[16].

To assess carrying capacity, an environmental and resource carrying capacity indicator (URECC) based on ecological civilisation was used in this paper, which contains 18 indicators selected from carrying capacity, water, land, air, energy and solid waste, according to the model proposed by Zang et al.(2018)[17].

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[14] The maximum number of people that can visit a tourist destination at the same time, without causing destruction of the physical, economic and socio-cultural environment and an unacceptable decrease in the quality of visitor satisfaction WTO.
[15] Kostopoulou and Kyritsis (2006).
[16] Tanguay *et al.* (2010).
[17] Zhang *et al. (*2018).

3.3. How to build a sustainability Indicator

The steps to calculating indicators are[18] :

a. Data acquisition
b. Normalization and aggregation of the normalised indicators
c. Data synthesis and validation of the composite indicator.

The proposed composite indicator[19] seeks to provide as complete as possible a representation of the sustainable development of Islands.

To build a composite indicator, a subset of elementary indicators that tend to have the same theoretical relevance (the same weight) and that are available for all Islands was selected.

The composite indicator was calculated using the AMPI[20] formula, developed by ISTAT and based on normalization with the MIN-MAX method.

The synthesis of the normalized values is based on an arithmetic mean corrected with a variability function that penalizes the Islands in proportion to the variability of the indicators.The basic idea is that all Islands should tend to be optimal, i.e. they all have high indicator values. If this condition is not met the Island is penalized.

The synthetic index chosen can be written, in generalized form, as follows**:**

$$MPI_i^{+/-} = M_{r_i} \pm S_{r_i} cv_i$$

Where, M is the mean of the matrix of r observations, S is the variance and cv is the coefficient of variation.
In the Normalization phase, given the matrix X={xij} with n rows (units) and m columns (elementary indicators), the normalization matrix R={rij} is calculated as follows :

$$r_{ij} = \frac{x_{ij} - Min_{x_j}}{Max_{x_j} - Min_{x_j}} 60 + 70 \qquad (1)$$

Where xij is the value of indicator j for unit i, Min_{x_j} and Max_{x_j} are the poles of the indicator. If indicator j has a negative polarity, the complement to (1) is calculated at 200. In the Aggregation phase, if M_{r_i} and S_{r_i} are the mean and variance respectively of the normalized values on units i, the generalized formula for the fitted MPI function is given by:

[18] OECD (2008).
[19] Mazziotta and Pareto (2016).
[20] Adjusted Mazziotta Pareto Index.

$$MPI_i^{+/-} = M_{r_i} \pm S_{r_i} cv_i \qquad (2)$$

Where $cv_i = \frac{S_{r_i}}{M_{r_i}}$ is the coefficient of variation for unit i and the sign ± depends on the nature of the phenomenon being analyzed[21].
For a positive synthetic index, we have the MPI +, for a negative index, the MPI -.

In the calculation of the synthesis index, in addition to the summary value obtained for each of the 17 goals[22], the corresponding carrying capacity value[23].

3.4. Results

The Islands have been classified according to their degree of sustainable development: in the following graph : upper quadrants contain those that have a higher value of the sustainable development indicator, while in the lower quadrants the synthetic index provides values corresponding to a low degree of sustainable development. Islands are found in the 'Marginality' or 'Development' quadrant based on the number of economic activities in marginal or innovative sectors and the number of innovative projects developed or under development[24].

The graph refers to the synthetic indicators calculated for each Island on the basis of the Sdg indicators for the last available year. By extending the calculation to the historical series of the recent years, each Island's detailed path towards sustainable development over the years can be drawn.

This can also be relevant, for example, in political decision making.

Figure 3 – *Classification of the Islands according to their sustainable development.*

[21] Mazziotta and Pareto (2012).
[22] De Muro *et al.* (2011).
[23] Obtained as described in Pamungkas *et al.* (2018).
[24] According to data provided by local Chambers of commerce.

Source: Elaboration on Eurostat data.

4. Will the theory be verified in everyday life on the Islands?

This section presents the results of the research carried out on the top 5 ranked Islands, with the purpose of checking in the real life the reliability of the built indicators and thus ensuring that these Islands are truly engaged in sustainable development.

4.1. The Azores

The Azores are involved in two projects that work for sustainable development. The first project: *Life Ip Azores Natura* make a valuable contribution to the conservation of species and habitats. In February 2020, a true hybrid renewable power plant was inaugurated on the Island of Graciosa (60.65 kmc, 4,400 inhabitants). The "Graciólica" solution reduces dependence on imported liquid fuels and reduces greenhouse gas emissions; it has the potential to eliminate approximately 190,000 liters of diesel per month.

Ife Ip Climaz is the second integrated project will encourage local communities to get involved in developing roadmaps to adapt to climate change and promote its adaptation measures in other areas, such as energy, forestry, and tourism.

4.2. Reunion Island

The Island of Reunion (2,511 kmc, 840,974 inhabitants) has set itself the ambitious goal of becoming a zero-energy Island by 2025, a particularly ambitious objective given its high population density. Several virtuous experiments are already underway on the Island, such as the « *Agrienergie 5* » project, which combines organic agriculture and solar energy.

4.3. Balearic Islands

Mallorca is the first destination certified by the « *Unwto Quest* » program, a quality certification for tourism destination management organizations.

Ibiza is a signatory of the « *Green Energy Islands Deal* » to initiate the energy transition of the Island and work to gradual elimination of single-use plastic by 2023. Another project relates to the protection of the Posidonia. It also aims to better inform people about its crucial role, in the hope of preserving it for more years.

Menorca is a United Nations Biosphere Reserve.

Formentera is a true laboratory of sustainable mobility. The number of vehicles allowed to access the Island has been limited and a digital mobility monitoring process has been implemented.

4.4 Crete

The Island of Crete (8,300 kmc, 600,000 inhabitants) has identified key actions to become a zero-emission Island by 2030.

In terms of energy supply, the Island has an isolated system and all its consumption is produced locally. A new project will work to support the increase of renewable energy. Energy efficiency solutions for hotels, buildings and street lights will be improved and an information campaign will be planned to increase the acceptance of renewable energy by the population.For water management, innovative desalination plants and systems to increase the efficiency of the water network will be studied, taking into account seasonal fluctuations in demand due to tourism.

4.5. Guadeloupe

The archipelago of Guadeloupe (1,628 kmc, 405,739 inhabitants) is partially decarbonized. In addition to the wind farm scattered throughout the archipelago on the Island of Désirade, a fleet of six electrically powered vehicles has been set up, which has also created jobs for the inhabitants.

5. Conclusion

To sum up, the Sustainable Development Goals are increasingly becoming a benchmark for national and local policies. It is therefore crucial to build appropriate tools to measure progress not only at country level, but also at a more detailed territorial level.

Statistical indicators are tools to guide decisions and can measure goals achieved towards sustainable development.

There are many indicators on sustainable communities that can be used as sources of 'inspiration', but each community is individual and the development of indicators at the local level offers an opportunity "to see" individuality in the choice of indicators, As evolutionists teach us, Islands can be considered as test laboratories for sustainable development. Therefore, by using Eurostat data at the Nuts 2 level, we can build sustainable development indicators tailored to the specific needs of Islands that preserve their local identity,

They can not only measure their path towards sustainability but also their transition from a 'traditional' to a more innovative dimension, related to the nature of the economic-social activities on the territory.

The work has shown how the results obtained from the indicators are checked in the day-to-day reality of Islands, but practical evidence suggests that any sustainable development project cannot succeed without the full involvement of local communities.

This study is still ongoing and aims to refine the analysis on the specific needs of Islands, the indicators could be applied in other territories and contexts.

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SUMMARY

Islands, repositories of great cultural and biological diversity, have historically provided situations of excellence for measuring and studying evolutionary pathways (Darwin, 1856), i.e. laboratories. These places, blending both urban and rural elements, are highly vulnerable ecosystems with high degree of endemism where pressures from human activities can have devastating effects. In fact, Islands are among the places on the planet where the effects of climate change are most evident, especially with the upcoming threat of sea level rise.

Island economies also have their own characteristics that make them vulnerable to external shocks: their insularity, remoteness and associated dependence on sea and air transport, even for basic activities, lack of economies of scale and dependence on global supply chains pose very specific development challenges. Moreover, they can be a real test case for sustainable development models.

This work, based on official statistical data, aims, on the one hand, to monitor the degree of achievement of sustainable development goals in 17 European Islands and, on the other hand, to build a system of indicators tailored to the needs of these highly specific territories.

Thanks to these indicators, Islands that had achieved some significant goals, either by taking the path of tradition or the path of innovation, will be identified. Finally, with a look at the daily life of the Islands, the correspondence of the theoretical models developed will be checked and the actions carried out on the way to sustainability will be observed. The aim is to build a tool that can be used in different contexts to measure well-being, environmental quality, the green economy and other aspects in the view of sustainable development and that can provide an integrated framework of internationally comparable quantitative information.

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THE ESTIMATION OF THE COSTS OF INSULARITY THROUGH A REGRESSIVE ECONOMETRIC MODEL APPLIED TO SICILY[1]

Gaetano Armao, Alberto Dolce, Federico Lasco, Rosario Milazzo, Domenico Spampinato

1. Premise

The geographic insular nature, which characterizes some territories and their communities determines a peculiar condition of periphery and specific accessibility problems, sometimes associated with the presence of structural delays in development processes. The wide multidisciplinary literature of reference traces the specific disadvantage of island territories compared to continental ones to many factors: the limited territorial dimension of the markets and the variety of products, the logistical dependence on air and sea transport, the amplified impact of climate change, the difficulty of actions aimed at resilience, the reduced socio-demographic dynamism (Armstrong and Read, 2004). The result is a peculiar framework of constraints on the sustainability of development processes and a specific inelasticity to economic dynamics. These factors translate into an objective condition of economic and competitive disadvantage compared to continental territories.

Due to its orographic nature, in the European Union, the insular-continental dualism is a dimension that is structurally intertwined with the debate on development and territorial cohesion, even in the presence of limited attention to the insular dimension of policies aimed at supporting precisely the processes development and cohesion in the Union. In the EU-28 it is estimated there are 2400 inhabited islands, belonging to 13 Member States. Over 20.5 million inhabitants, 4.6% of the EU population, live (data as of 2020) in NUTS 3 island regions. It is certainly true that Articles 174 and 349 of the TFEU (Treaty on the Functioning of the European Union) that islands are territories with certain geographical specificities, although the economic policies of the Union do not present specific lines for island territories.

[1] Cap. 1 Federico Lasco, Cap. 2 Gaetano Armao, Cap. 3, Cap. 4 and Cap. 5 Alberto Dolce, Rosario Milazzo and Domenico Spampinato.

Only, this year, on 21 April 2022, the Regional Development Committee of the European Parliament adopted the resolution "Islands and cohesion policy: current situation and future challenges", which will be voted on by Parliament in plenary session next June. It is the first official document of the Union which calls for the definition of a specific policy area for island territories. From a Euro-Mediterranean perspective, the insularity and sustainability of development and cohesion processes becomes central.

The cost of being an island is intertwined in the Mediterranean with the impact of the sequence of structural shocks that have hit the globalized economic system in sequence in the last three years (contractions in demand, production capacity, availability of raw materials and primary products, energy supply) by changing the real nature of economic fluctuations and medium-long term cycles. The Mediterranean, primary corridor of globalization, is deeply affected by the effects of the current crisis which could have a more drastic and profound impact on the resilience of island economic systems, characterized by factors of dependence and inelasticity that are more pervasive than continental systems (Deidda, 2015).

However, despite the strong emphasis on the economic dimension of the island question and the related debate on targeted development and cohesion policies, the number of contributions and the variety of arguments among economists are still significantly limited. Yet, the data on the gaps due to insularity, as the case of Sicily clearly shows, returns an alarming picture that highlights employment imbalances, high poverty, high costs for transport, widespread margins, reduced internationalization and a decisive infrastructural inequality.

Recently, some examples of evaluation exercises have been published aimed at estimating the socio-economic impact deriving from the condition of insularity on a given territory and it is understood that there is no univocal shared method, also due to the lack of unambiguous methodological orientation and/or political-strategic in defining insularity.

In this paper we have tried to offer a contribution to the economic debate on insularity, starting from the theme of measuring the disadvantage deriving from the state of insularity in economic terms. The relevance of the estimate of the costs of insularity for Sicily leads us to reflect on the need to extend the application of the study to other territorial contexts of the EU. This would allow, on the one hand, the definition and proposition of specific public intervention assets on a European scale, complementary or modular to those to be defined at Member State level, and, on the other hand, to base the sizing on verifiable quantitative parameters. financing of a specific investment policy aimed at cohesive action for European island territories based on trajectories of inclusive and sustainable development.

2. Reference regulatory context

A study on insularity cost in the largest European and Mediterranean island may seem an ambitious work, considering the wide dimension of regional population, wealth, goods, transport and economic target, as well as present serious economic crisis due to COVID-19 pandemic and most urgent emergency measures which are now the highest priority. The condition of insularity, pursuant to article 174 and foll. TFEU and art. 119 (revised) of the Italian Constitution, must be addressed by implementing specific rebalancing measures (territorial continuity, tax benefits, economic development measures, infrastructural improvement, aid schemes, etc.) (Fois, 1999; Frosini, 2007; Meloni *et al.*, 2015). Their goal is not only to fulfil the known principles of European and national law, but above all to implement concrete legislative measures to balance an economic gap and related "insularity cost", ensuring to Sicilian citizens equal treatment and social rights[2].

Article 174 TFEU is the main pillar of European social, economic and territorial policy of cohesion. As generally known, the first and second paragraphs state that the EU aims at reducing the economic development gap among regions by strengthening cohesion policies, while the third paragraph states that a particular attention must be paid to those regions suffering from serious and permanent geographical disadvantages, including islands (Armao *et al.*, 2016).

Unfortunately, despite several specific statements on this subject by the European Parliament (the latest was "Special situation of islands", European Parliament resolution, 4 February 2016), the European Committee of Regions ("Entrepreneurship on Islands: contributing towards territorial cohesion", Opinion of the European Committee of Regions 2017 / C 306/10, May 2017) and other less important bodies, the "condition of insularity" is still considered as a marginal aspect within cohesion policies and ESI funds' implementation[3].

In the European Document on 2021-2027 Planning, approved by the Conference of Italian Regions on 21 February 2020, it was highlighted, among other things, that post-2020 cohesion policy should consider carefully islands' situation, recognize their strategic role and create the conditions for their equal and coherent development compared to other European areas. More specifically, the

[2] It should be remembered that Italy, after Brexit, has become the European country with the largest island population, over 6.6 million inhabitants (12% of them live in Sardinia and Sicily and the latter is now the largest European island) out of the total 17 million European islanders, consequently it has to focus on the condition of insularity as of its main public policy priorities.

[3] A total of 17.7 million people live in 362 islands with over 50 inhabitants in 15 European countries (3.7 million in outermost regions and over 6.6 million in Sicily and Sardinia); in these regions GDP per capita is under 80% of EU average and a significant part of them still belong to under-developed region category.

European Institutions were formally requested to adopt regulations and planning schemes to balance territorial discontinuity, defining a specific "insularity index" depending on territorial extension, population, geographical and travel distance from the continent and most developed national areas. The final goal is to promote a islands' social, economic and environmental development in urban areas as well as inland isolated areas, with fewer population and services, according to the provisions of TFEU art.174.

With reference to national law and insularity status, despite the previous fund cancellation provided for by Article 119, third paragraph of the Constitution, later eliminated in 2001 reform text, public law recognises this disadvantage and by Law no. 42 of 2009, Article 27, guarantees the adoption of rebalancing measures like tax benefits, infrastructure enhancement and implementation of equal conditions. According to this provision, "following the failure to redefine financial relations between the State and the Autonomous Region of Sardinia in accordance with Article 27 of Law no. 42 of 2009, it should be noted that, almost ten years after the enactment of this law, the insularity issue and its disadvantages has never been taken into consideration in the definition of revenue and expenditure budgets for autonomous regions".

Therefore, this rule carries out, for the first time, a more careful interpretation of Article 27 of Law no. 42–2009, which becomes relevant for its constitutional recognition of insularity status, even without a specific quotation within the text of the Constitution itself. It will have crucial effects on financial relations between the State and islands' authorities, as it clearly recognizes "insularity cost" as a key factor to arrange these relations in a complete and appropriate manner[4].

3. Insularity as a condition of disadvantage

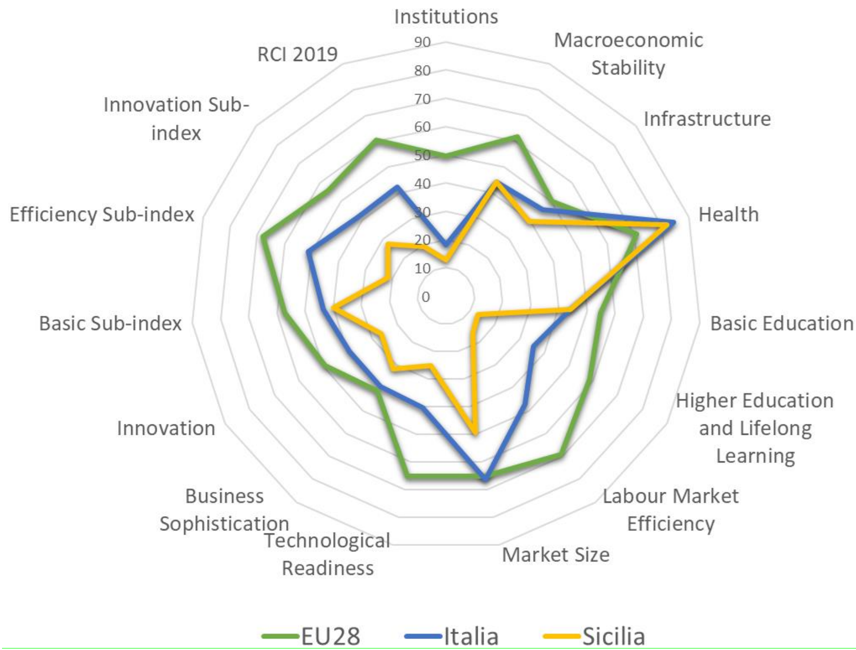
Insular regions, either nearest or furthest from the continent, have some basic features that make them different from continental regions. This derives from the incontrovertible fact that insularity, considered as territorial discontinuity, causes several economic, environmental, social, demographic and transport disadvantages to islands compared to continental areas. Insularity has become an important issue within the political, economic and social debate also in the European Union, which includes a great number of small and large islands.

[4] In line with the above-mentioned concepts, but not included in this research, it is useful to observe that the condition of insularity may be considered as a necessary and sufficient prerequisite to adopt development tax measures consistent with EU Treaties, but not considered as a State aid pursuant to art. 107 and 108 of the TFEU and of Regulation no. 2015/1589 of the EU Council of 13 July 2015.

Sicily has approximately 5 million residents (28 percent of overall island population) and is one of the largest and economically most relevant islands in Europe, with a peculiar geographical insular area including also a smaller island close district. Average GDP per capita of this population is quite modest, that is 79.2% of EU GDP average, so that a significant part of these islands is included among the least developed European regions[5]. In such context, there is a strong wealth and GDP difference among European islands. In Sicily, most of the social and economic indicators, adopted by the European Commission for spatial comparisons between the Nuts2 regions, are below the Italian and European average.

The competitiveness framework is summarized using a complex indicator called the Regional Competitiveness Index (RCI). In this context, Sicily shows negative values in some relevant sectors such as: infrastructures, human resources, innovation and institutional and administrative efficiency (figure 1).

Figure 1 – *Competitiveness Index in 2019, comparison between UE28, Italy and Sicily.*



Source: European Commission.

[5] Corsica Regional Councillor. Entrepreneurship in the islands: a contribution to territorial cohesion (2017/C306/10).

Moreover, even in a national context, Sicily has historically been characterized by a significant gap with respect to other Italian regions, as shown by the main socio-economic indicators. The main macroeconomic data show these differences: in 2018, Sicily GDP per capita was 17,721 Euro, at the penultimate position among Italian regions (followed by Calabria), with a gap of 1.266 Euro compared to the average in Southern Italian regions (figure 3). In the same year, the unemployment rate in Sicily for over 15 population was 21.5%, about 3% below Southern Italy average rate (18.4%) and twice national average rate (10.6%). With regard to gross fixed investments the values in Sicily are nearly always lower than in all Italy and Southern Italy, and tend to decrease more markedly because of its low attitude to investment, especially during 2008 financial crisis, showing its tangible effects until 2015 especially in particularly fragile economic systems, like Sicily.

3.1Estimations of insularity cost.

To start an analytical evaluation procedure, whose results may support policy decisions, the first objective was to carry out a macroeconomic estimation of insularity effects/costs in Sicily, and subsequently to create a more complex model and give a value to any "cost item". It was necessary to carry out a preliminary evaluation of insularity economic impact, which may be a reference to the institutional activity; consequently, after considering the existing studies on the subject. In this study we intend to measure, on the basis of an econometric model referring to a series of explanatory variables, the impact on GDP per capita of appropriate indicators linked to territorial wealth resources. What is obtained is an overall macroeconomic assessment, which, however, may not define the cost of any single component affected by insularity, and is also influenced by the model chosen. The approach, based on the research work carried out in 2020 by IBL Institute (Amenta *et al.,* 2020) follows quite the same econometric model, referred to economic development existing studies, to measure the average annual impact of insularity on GDP per capita and overall GDP; as noticed above, however, it may not give a value to any cost item due to insularity. This model firstly defines an island features from the economic point of view, by pointing out three factors, that must occur jointly: i) small size tendency; ii) remoteness; iii) vulnerability. Specifically, a tendency to create small size entities may cause in turn a tendency to establish a self-referent economy, a less efficient use of productive factors and a condition of structural delay; a remote distance causes a general increase in transport costs, a non-integration in neighbouring markets and related specializing opportunities, an increase in the unitary cost of locally produced and imported goods; finally, vulnerability increases the risk of suffering from the negative consequences of exogenous economic or environmental shocks. These three factors are strictly linked, so that "the limitations of small-size islands become more serious if they are vulnerable and far from the markets, the limitations of remoteness are wider for vulnerable and small islands and vulnerability has worst effects in small and remote islands. If any of these factors tends to decrease, most of the disadvantages linked to insularity are reduced" (Amenta C., Stagnaro C. and Vitale L., 2020).

3.1. Econometric estimation based on per capita GDP

The application of the econometric model is based on an econometric model used by Bruno Leoni Institute through a panel data dataset reconstructed at regional level and in historical series (2000-2018) on which one was built fixed effects regressive procedure[6] (Bontempi and Golinelli, 2006). Use of panel data, which concern observation more statistical units for two or more periods, allows you to operate using a more powerful information set than data simple as they capture greater variability on subjects and over time periods including that determined by the presence of omitted variables, reducing the risk of collinearity between the variables. The regressive model, with the goal to control the structural factors of the variables, uses the lagged term of the variable dependent within the set of variables explanatory as it assumes that the level current of the dependent variable is strongly determined by its past level. Likewise, all economic variables of the model were deflated by avoid possible distortions in the resulting estimates from different pricing structures in the time and between regions. Finally, the standards errors of the estimated coefficients were corrected for the fact that the comments do not they are independent and identically distributed since the regions appear in the sample repeatedly, an even number of times to the years observed.

The model is as follows[7]:

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[6] For econometric model analysis, GRETL software (Gnu Regression, Econometrics and Time-series Library) was used, a multi-platform package for statistical and econometric analysis written in C programming language, open source and free. A panel is a sample that contains observations on N items for T years, ie. the observations on each element are repeated over a period of time (time series data on each element). In the present case Italian regions are the elements. The fixed effects' model measures the specific effect in a deterministic way, that is, the set of specific characteristics of each element, which however remain unchanged over time.

[7] In details, we have: GDPpc is the annual gross domestic product per capita in Sicily, according to Istat regional data; Distance_continent: a variable that measures the distance from the continent. Obviously, this variable assumes a positive value only for Sicily and Sardinia – ontinent_averagereggio measures the average distance between the routes Cagliari-Rome and Sassari-Rome to Sardinia (495 km) and Palermo-Reggio Calabria and Catania-Reggio Calabria to Sicily

$$GDP_{pcit} = \beta_0+\beta_1\ Distance\_continent + \beta_2\ Interest\_active\_rateit + \beta_3\ Savings\_GDPit + \beta_4\ Highway\_supit + \beta_5\ Railways\_supit + \beta_6\ Publicspending\_GDPit + \beta_7\ Illiterateit + \beta_8\ Airportsit + \beta_9\ Interchange\_commit + \beta_{10}\ Surfaceit + \beta_{11}\ Portsit + \beta_{12}\ Tertiary\ education\ rate + \varepsilon_{it}.$$

The coefficient of interest in the model is obviously Distance_continent. This coefficient represents a kind of economic penalty on per capita income in function of the unitary increase in distance from the continent and therefore from the state of insularity, which can also be defined as one implicit tax for island residents. This penalty, multiplied by the distance from the mainland, provides a measure approximate loss of GDP per capita regional which, multiplied by the basin of reference of the regions (e.g., population resident), offers a first estimate in terms of total GDP of the cost of insularity.

The choice of model to measure the distances in kilometers is linked to a choice logistics for the movement of goods and goods people. As for the distance from Sicily, the choice focused on nearest province in terms of distance physics (Reggio Calabria), Obviously this choice, on which I am in further study course, represents a first, reasonable and prudential proxy of the concept of distance, in a broad sense, come on reference economic markets, identifying the continental point geographically closer.

The results of the application are reported in table 2. Specifically, we can observe how the distance coefficient from the peninsula both negative and strongly significant.

The model achieves a loss of GDP per capita equal to 1,246 euros, (calculated on basis of the estimate of the cost in terms of GDP per capita for every kilometer of distance, or 6.81 multiplied by the average of distances of Palermo-Reggio

(183); Interest_active_rate is the average active interest rate of regional banks, data source is the Bank of Italy; Savings_GDP is a proxy of regional savings' amount, based on the ratio between the amount of bank deposits and regional GDP, according to Bank of Italy data; Highway_sup measures the ratio between highway network kilometres and regional extent. Data source is Istat; Railways_sup measures the ratio between railway network kilometres and regional extent. Data source is Eurostat; Publicspending_GDP is the amount of regional public expenditure. Data source is Istat; Illiterates means the illitterate population rate in different regions; in particular, this variable is calculated as a ratio between the number of illiterates and the resident population according to 2011 census. This variable represents a human capital proxy. Data source is Istat; Airports means the number of airports recognized by Enac (military or inactive airports are excluded). Data source is ENAC; Interchange_comm is the variable that represents the ratio between Import and Export total amount and Gross Domestic Product in different regions. Data source is Istat; Surface means regional territorial extent; In the Variant model we have the following integrations in regressor composition: Ports means the number of ports in a region. Data source is Istat; Tertiary education rate indicates the ratio between 30-34 aged population with a 5/6 education level (Isced7) and the total amount of same aged population. Data source is Istat.

Calabria and Catania- Reggio Calabria equal to 183 kilometers). Taking into account the confidence interval 95 percent of the cost of insularity for Sicily it is in the gap between 500-2000 euros per capita. In terms of GDP overall it is possible to estimate the cost annual insularity for Sicily in about 6.2 billion euros equal to 7 percent of GDP (table 3 and 4).

Table 1 - *Regression estimates.*

Variables	**GDP_pc**	
β_1Continent_averagereggio	**-6,81**	***
β_2*Interest_active_rate*$_{it}$	-2,85	***
β_3*Savings_GDP*$_{it}$	2,99	***
β_4*Highway_sup*$_{it}$	5,09	***
β_5*Ferrovie_sup*$_{it}$	-9,07	***
β_6*Publicspending_GDP*$_{it}$	-4,76	***
β_7*Illiterate*$_{it}$	-9,10	***
β_8*Airports*$_{it}$	4,52	***
β_9*Interchange_comm*$_{it}$	-7,31	***
β_{10}*Surface*$_{it}$	-1,09	
β_{11}*Ports*$_{it}$	-9,89	***
β_{12}*Tertiary education rate*	-4,37	***
Costant	16,71	***
Observations	*380*	
R-squared LSDV	*0,8209*	
R-squared	*0,8202*	

Source: NVVIP elaborations on IBL model and Istat/Eurostat data
**** significance level at 99%*

Table 2 - *Insularity cost estimates and referring parameters.*

GDP current prices	88.843 millions of euro
GDP per capita	17.721
Resident population (2018)	4.999.981
Insularity cost (absolute value)	6.231 millions of euro
Insularity cost/GDP	7,0%
GDP lost per capita	1.246 euro

5. Some concluding remarks

The condition of a territory penalized by limiting geographical specificities such as periphery, insularity or poor accessibility, is common to many EU regions and requires the adoption of contrasting political choices which, however, must be commensurate with the extent of the disadvantages that must be mitigated or removed, but also the possible benefits that could derive from it. In particular, insularity, understood as territorial discontinuity, determines further criticalities of an economic, transport, environmental, social and demographic nature that determine an objective disadvantage compared to continental territories as noted in the extensive reference literature. In the face of growing attention on this issue both at national and at European level, there are few works of an economic nature that give results suitable for guiding policy actions.

In this work we have tried to provide an estimate of the possible costs linked to the island condition of Sicily, using an approach based on the analysis of the main elements that determine the development of an island territory identified in the factors "size", "distance" and "vulnerability". These factors were measured through some proxy variables placed in historical series and referred to the last twenty years for all Italian regions and following the application of a regressive model, an econometric estimate was obtained that quantifies the cost of insularity for Sicily. approximately 6.23 billion euros per year, equal to 7.0 per cent of regional GDP.

We need more refined estimation models, more adherent to regional specificities or based on different approaches including those based on ecosystem "pillars" or on specific compound indices which, beyond the gross domestic product, take into consideration all the dimensions of well-being. can (and must) be developed, in order to prepare further evaluation exercises. In addition to further approaches, other costs could also be investigated to complete the big picture. These include i) the costs to be incurred for an infrastructural equalization work, or for the realization of investments in public works in the logic of territorial continuity, ii) the costs to be borne centrally to create a tax advantage aimed to attract companies that have relocated abroad to the disadvantaged area by giving an incentive to back-shoring, a phenomenon particularly useful for supporting the strategies to reduce global value chains stimulated by the shock of the pandemic that is still underway, iii) costs related to impoverishment of the environment and ecosystems due to oil extraction and the product that is refined for over 40% in Sicily, certainly not compensated by royalties and finally iv) the costs related to the performance of the educational system that we can consider as a proxy of human capital since, as CRENoS has highlighted, being geographically isolated from the rest of the ter national territory constitutes a significant disadvantage in attracting students and teachers from outside[8].

To conclude, the reflections that emerged within this work lead in the direction of imagining that the convergence of island areas must be pursued following a short and long-term strategy and through targeted policies that certainly look at the more strictly growth profiles (therefore, quantitative) and development (ie also qualitative) with consequent choices that must be oriented towards respect for the territories and suited to inclusive and sustainable development. This, from a political point of view, should lead not to a simple economic claim, but rather (alongside it) to the definition of a specific finalization of the resources claimed by priority of intervention", in order to guarantee their destination to the removal of the causes of disadvantage linked to insularity, while offering greater solidity to the request for specific interventions aimed at compensating the costs of insularity because it would define a formal commitment aimed at real structural overcoming

[8] Rapporto Crenos 2020, Cuec, pp. 168-172.

of the reasons for disadvantage from insularity.

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[9] Giuseppe Nobile, Dirigente del Servizio Statistica Regione Siciliana; Carlo Amenta, Università degli Studi di Palermo; Daniela Baglieri, Università degli Studi di Messina; Luca Bianchi, SVIMEZ; Pietro Massimo Busetta, Università degli Studi di Palermo; Maurizio Caserta, Università degli Studi di Catania; Floriana Margherita Cerniglia, Università Cattolica del Sacro Cuore di Roma; Giovanni Battista Dagnino, Università LUMSA; Vincenzo Fasone, Università Kore di Enna; Michele Limosani, Università degli Studi di Messina; Vincenzo Marinello, Università Kore di Enna; Antonio Nicita, Università LUMSA; Fabio Mazzola, Università degli Studi di Palermo; Marco Romano, Università degli Studi di Catania; Carmela Schillaci, Università degli Studi di Catania; Guido Signorino, Università degli Studi di Messina.

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SUMMARY

The geographic nature of the islands determines a peculiar condition of peripherality and specific accessibility problems often associated with the presence of structural delays in development processes. Data on the gaps due to insularity, as the case of Sicily clearly shows, returns an alarming picture that highlights employment imbalances, high poverty, high costs for transport, widespread margins, reduced internationalization and a decisive infrastructural inequality.

In this work we have tried to offer a contribution to the meager debate on insularity, starting from the measurement of the disadvantage of insularity in economic terms. For Sicily, an estimate of the costs related to the insularity was drawn up using a regressive econometric approach based on the analysis of some factors that determine the development of an island territory, namely "size", "distance" and "vulnerability". The study produced an estimate that quantifies the cost of insularity for Sicily at approximately 6.23 billion euros per year, equal to 7.0 percent of regional GDP.

The relevance of the issue requires that it also be referred to other territorial contexts and to more defined methods, with the main aim of defining and proposing specific public intervention assets and basing on verifiable quantitative parameters, the financial dimensioning of a specific investment policy aimed at a cohesive action for island territories based on inclusive and sustainable development trajectories.

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