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Tesi di dottorato

BEYOND MARKET PRICES

Three essays on equity and efficiency in public intervention

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Conventional economic analyses refer to inequality in terms of distribution of income and wealth, but a significant part of inequality of opportunities is due to differences in non-market outcomes like education and health (Roemer, 1998; Oliver, Mossialos, 2004; Stiglitz *et al.* 2010). Two main issues characterize the evaluation of these phenomena. Unlike the case of the commercial sector, there is no obvious criterion, like profitability, in the objective function of the suppliers. Moreover, non-market good and services are provided free of charge or at prices that are economically insignificant. Technically, these two issues are reflected in an inherent multidimensionality of the outcome, while efficiency, effectiveness, and inequality measures are defined in single-dimensioned cases (Savaglio, 2006; Ray, Chen, 2015). The synthesizing procedure is therefore the compelling step for economic analysis, decision-making, and policymaking. The orthodox synthesizing practice in the case of marketed goods and services is the weighted sum of outcomes using prices as weights. Factors' costs and goods' final prices are used in the estimates of Gross Domestic Product (GDP) and its components[1]. However, as it has been already stressed, education, health, and many relevant aspects of the economic performance and the social progress have no market prices[2].

In the absence of market prices, different strategies are usually employed to avoid technical criticisms in the evaluations. For instance, National Accounts use public expenditure as proxy of public sector contribution to growth (GDP). Regrettably, this procedure sheds little light on what the magnitude of this phenomenon is, although

[1] The underlying assumption is that the ratios among market prices are reflective of the relative appreciations among products. Based on this assumption, the weighted sum of quantities of goods and services multiplied by their prices allows capturing, in a single number, the overall economic activities, as well as the links between an economy and the rest of the world etc.

[2] For instance, when the consumption or production of goods affects society as a whole, the eventual price that individuals pay will differ from the value of those products.

performance of public sector is one of the most important factors for development (World Bank, 1997)[3].

In recent times, an increasing number of indicators are collected for non-market goods and services to overcome these criticisms (e.g., World Bank, 2013; World Economic Forum, 2016; OECD, 2016; 2017b; United Nations Development Programme, 2016; World Health Organization, 2017). The problem that remains is how to summarize the different information in one single measure of performance (Costanza *et al.* 2016).

This thesis, by means of three essays, contributes to the literature focused on equity and efficiency in sectors that are typically out of the market. The first two chapters are specifically dedicated to education and health care, and the third chapter is devoted to multidimensional well-being, as proposed by the framework of Stiglitz *et al.* (2010). Synthesis of quantitative measures of outcome without market prices is the key aspect of all the evaluations proposed here.

As far as the data is concerned, this thesis mainly relies on three different databases. The 'Programme for International Student Assessment' (PISA) survey of OECD (2017b) is used for the evaluation of education sector. The evaluation of health services relies on the 'Health for All' dataset of ISTAT (2017). The evaluation of multidimensional is executed by means of the 'Better Life Index' (BLI) of OECD (2016).

The way to collapse the multidimensionality of these phenomena into one index without recurring to market prices is the biggest challenge of this work. We can trace back this issue to the literature of Composite Indicators (Nardo *et al.* 2008; Costanza *et al.* 2016). As defined in OECD (2017a), a Composite Index (CI) compiles individual indicators into a single measure in order to summarize complex multidimensional realities. To this regard, there are different positions in the literature, and the main concerns are about the weighting process, as different weights may give rise to significant differences in the final synthetic evaluation

[3] Among the others, the government creates the environment in which companies can gain competitive advantage, provides the basic national infrastructure, holds the critical responsibilities for healthcare and education, and can stimulate and upgrade domestic demand (Porter, 1990).

(Sharpe, 2004; Saisana *et al.* 2005; Cherchye *et al.* 2008; Foster *et al.* 2009; Permanyer, 2011; Costanza *et al.* 2016; Greco *et al.* 2017). Nardo *et al.* (2008) suggest that, according to the impossibility Arrow's theorem (Arrow, 1951), there is not any perfect synthesizing procedure.

In previous works, three main solutions have been adopted for the weighting process: *a priori* weights based on economic theory; data-driven weights (such as Data Envelopment Analysis, Charnes *et al.* 1978); and a large set of random weights (such as Stochastic Multi-Objective Acceptability Analysis, Lahdelma *et al*. 1998; Lahdelma and Salminen, 2001).

The World Economic Forum in the Global Competitiveness Report 1999, as well as Annoni, Dijkstra (2013) and Annoni, Kozovska (2010) in the Regional Competitiveness Index (RCI), choose *a priori* weights. Among others, Lall (2001) strongly criticized this choice because there is not a clear economic literature focused on weights[4]. In other words, as Dijkstra *et al.* (2011, p. 16) explicitly admit, the weighted system is "the result of a long list of subjective choices".

Among the data-driven methodologies, the non-parametric tools, in particular Data Envelopment Analysis (DEA, Charnes *et al.* 1978), have lately received considerable attention (Shen *et al.* 2013; Patrizii *et al.* 2017)[5]. The basic assumption of DEA evaluations is that the status-quo is a choice of the Decision Maker (Cherchye *et al.* 2007). Based on this premise, DEA compiles multidimensional metrics into one index using the combination of weights that is the most convenient for the evaluated Decision Making Unit (DMU)[6]. Formally, the optimization presented in equation (1.1) Chapter 1 ensures that each DMUs is evaluated on the bases of its own best possible weights. For this reason, decision makers

[4] "Where in the literature, for instance, weight for finance as compared to technology come from?" (Lall, 2001 p. 1516). The 'New Global Competitiveness Index GCI' (World Economic Forum, 2008) calculates weights based on a regression of the pooled dataset on country GDP per capita and tests the stability of the model by reallocating individual indicators and assessing the stability of the weights.
[5] As reported in Emrouznejad, Yang, (2017), in last four decades (1978–2016), there are 10,300 DEA-related articles in the literature.
[6] The term DMU is used to generally indicate the decision center responsible for converting inputs into outputs.

should not complain about unfair weighting, since each DMUs is put in its most favourable light, and any other weighting scheme would generate a lower composite score.

In order to explore whether the ranking system is dependent on the weights, Greco *et al.* (2017) propose to consider the whole set of feasible weights in order to rank the Italian regions in terms of multidimensional well-being[7]. Greco *et al.* (2017) use Stochastic Multi-Objective Acceptability Analysis (SMAA), proposed in Lahdelma *et al*. (1998), and generalized in Lahdelma, Salminen (2001)[8]. Formally, equations $(2.1), \dots, (2.7)$ in Chapter 2 explore the whole set of weights by means of a very large set of random extracted vectors. The arbitrariness of the weights is explicitly overcame through this procedure.

The methodological choices of this thesis follow a dynamic path from a data-driven method (DEA) to a method that embodies the representativeness in the weighting process.

In Chapter 1, we propose an innovative version of DEA in order to evaluate the educational systems in 60 countries. From a methodological perspective, the model combines the consolidated conditional procedure, proposed by Ruggiero (1996), with a non-radial version of DEA: the Slack Based Measure (SBM) model proposed by Tone (2001). The analysis is conducted on the PISA surveys for 2009 and 2012, using learning time as input, and the student achievement in the three subjects of PISA assessment (math, reading, and science) as outputs. The estimates are at student level, allowing combining micro and macro effects. With two main modifications to the standard DEA (Charnes *et al.* 1978; Banker *et al.* 1984), the model proposed in Chapter 1 (see equations $(1.1) \dots (1.13)$)allows a detailed evaluation of the additional effort the students should do when they are operating in an Economic Social and Cultural Status (ESCS) that has a comparative disadvantage.

The results show a strong and widespread effect of the ESCS on the student performances. This effect has a pervasive heterogeneity among variables, students, and countries. Part of this heterogeneity, in particular the one among the slacks in mathematics, language, and science, cannot be found by using the traditional (radial) DEA models. In many systems with

[7] They use the BES (*Benessere Equo e Sostenibile*), measure proposed by ISTAT (2015).
[8] For two surveys on SMAA see Tervonen, Figueira (2008) and Lahdelma, Salminen (2010).

pervasive inefficiencies (as in South American and South East Asian countries), a relevant part of the lacks is due to the presence of bad environments, as measured by a low ESCS. On the contrary, in many Anglo-Saxon and Middle East systems, the pervasive inefficiency is independent from the ESCS. These distinct roles of the ESCS in the presence of inefficiency in different countries clearly reveal the importance to control for environmental factors when making decisions on the education systems. Furthermore, in line with previous studies (in particular: De Witte, Kortelainen, 2013; Coco, Lagravinese 2014; Bogetoft *et al.*, 2015; López-Torres, Prior, 2015; Chetty, Hendren, 2015; Raitano, Vona, 2016; and Chetty *et al.* 2016), there is evidence that some of the problems of the education sector may not be due to the education systems themselves, but to the socio-economic gaps which determine a persistent inequality of opportunities. In average, countries with more inequality are also the more inefficient. Thus, in line with Raitano, Vona (2016) and OECD (2013), the perceived trade-off between equity and efficiency in education (Hanushek, Wößmann, 2006), is not confirmed by our analysis.

From a dynamic perspective, in the 2009-2012 interval the average improvement of students' performances has been higher in lower-medium income and upper-medium income countries than in high income countries. This catching-up phenomenon among countries may be attributed to a general improvement of the technology and to the possibility of getting information in simpler ways at lower costs, but also to the fact that students and teachers have begun to familiarize with the test. However, there is also a strong evidence showing that inequalities within countries have increased in the same years, suggesting that those improvements may not have equally spread their benefits. This last conclusion may prove particularly important for the more general issue of inequality of opportunities (Roemer, 1998), where free education should be combined with the removal of all barriers to social mobility that are imputable to the socio-economic background of students.

In Chapter 2, we propose an evaluation of the health care performances in the Italian regions over the period 1990-2013. Two main reasons make the Italian case worthy of attention: the unresolved social-economic dualism between the Northern and Southern regions (among others: Del Monte, De Luzenberger, 1989; Spadavecchia, 2007; Charron *et* *al*. 2014; Torrisi *et al.* 2015; Greco *et al.* 2017); and the important reforms of decentralization occurred in 1998-2001 (Turati 2013).

In order to get the multidimensionality of outcome, the standardized mortality rates for seventeen different diseases are used[9]. From a methodological standpoint, since the ranking of DMUs is heavily dependent on the considered weights, the research question is how the ranking changes with changes in the weights vector. In the Multi-Criteria Decision Analysis (MCDA) literature (Greco *et al*. 2005; Ishizaka, Nemery, 2013), this question was addressed with the SMAA. In order to embody unknown preferences on the weights assigned to each dimension, SMAA explicitly considers all the set of feasible weights (see equations $(2.1), \dots, (2.7)$ in Chapter 2). By means of a very large sample of randomly extracted vectors, SMAA gives the probability that each DMU has each of the position in the ranking. In other words, SMAA estimates the rank acceptability index, which is the ratio of the number of the vectors of weights by which each DMU gets each rank to the total amount of feasible weights.

In the specific case of health sector, the unprecedented use of SMAA allows to summarize the multidimensional health outcome without any assumption about the individual preferences and thus without any a priori judgement on the importance given to the different diseases. The estimates show that there is a pervasive and persistent spatial segregation in the health outcome in Italy. In particular, a bad performer area in the Southern-West side of the country (Campania and Sicily above all) and a good performer area in the Northeast are observed. Moreover, it emerges that in the period 1990-2013 there was an improvement in some Northern regions, such as Lombardy and Trentino, and a worsening in some Southern regions, Sardinia and Calabria in particular. The spatial segregation is significant both between and within regions. These results are confirmed using both the multidimensional Gini index, originally proposed in Greco *et al.* (2017), and the multidimensional generalization of Analysis of Gini (ANOGI - Yitzhaki, 1994) introduced for the first time in this thesis (Chapter 2 section 2.3.5). In spite of the constitutional right guaranteeing citizens

[9] The 17 mortality rates are: infectious disease; AIDS; tuberculosis; cancer; disease endocrine gland; diabetes mellitus; blood disorders; mental disorders; nervous system disease; disease circulatory system; disease respiratory system; disease digestive system; disease genitourinary system; complications of pregnancy; skin condition; disease muscular system; unclearly defined symptoms.

essential levels of care in the whole country, there is high inequality in the territorial performances regarding health. Some regions of the South appear to be relatively stratified with respect to the rest of the country, and some provinces converge beyond the regional borders in the Centre-North. Regional disparities are persistent over time and the decentralisation reforms that have given more organizational and spending power to the regions seem to have altered this pattern. Overall, Chapter 2 provides evidence that the general positive effect of the decentralization reforms on the regional health performance, mainly found in infant mortality rates (Porcelli, 2014; Cavalieri, Ferrante 2016), has not involved all the dimensions of health, it has not involved all the regions, and to some extent, it came at the cost of increasing the gap between the North and the South of Italy.

In Chapter 3, we focus on multidimensional well-being as proposed in the Better Life Index (BLI) by OECD (2016). Based on the framework of Stiglitz *et al.* (2010), the BLI is composed of eleven topics: Housing, Income, Jobs, Community, Education, Environment, Civic engagement, Health, Life Satisfaction, Safety, and Work-Life Balance. OECD measures country-level performances in all these topics, but synthetizing that information requires choices about weights related to the different dimensions of well-being. Our proposal is a weighting process based on the societal relative appreciations (people's priorities) of the different aspects of well-being. We argue that the relative appreciations of the different topics (i.e., societal preferences) are one of the most important factors in multidimensional well-being for at least two reasons. First, the preferences of people interested in the measurement are themselves part of the phenomenon (Helliwell, 2003; Helliwell, Barrington-Leigh, 2010), since the BLI is a metric to assess "the level of well-being of individuals with different preferences" (Stiglitz *et al.* 2010, p. 143). Second, people's preferences are eventually translated into policies by means of some mechanism of preference aggregation, so that they drive policy makers towards providing specific representations of multidimensional well-being. These issues are far more relevant in the design of a Composite Index since different weights may influence the final synthetic evaluation, and thus the ranking of countries.

To this intent we use for the first time the opinions collected in the OECD website dedicated to the Better Life Index[10]. At the time of this thesis, the OECD has received and collected more than 100,000 opinions from 180 different countries. The OECD's opinions are individual vectors of weights, in which the elements are related to the eleven BLI topics. We compare the rank acceptability indices obtained by the country-level relative appreciations, with the rank acceptability indices obtained with global and random weights building upon the SMAA. Among the good performers' countries, the rank acceptability indices reveal that some systems (Australia and Switzerland in particular) show good performances with all the three different sets of weights considered. On the contrary, USA loses some ranks when real preferences of people are taken into account. On the bottom side of the rank, Mexico is considered the worst country in terms of BLI for at least the 50% of vectors in all considered the sets of weights. This signals that Mexico has the worst performance in the majority of topics included in the BLI.

The estimates in Chapter 3 produce unprecedented evidences about the relations between people's preferences and policy outcome as measured in the BLI framework, showing that the ranking obtained using the SMAA is highly consistent with the ranking produced using the real preferences according to both a local and a global perspective. In line with Greco *et al.* (2017), this result confirm that SMAA is a consistent support for decision makers interested to take into account the heterogeneity of individual preferences. Moreover, these trends are the results of a uniformity in country-level relative appreciations of people - as expressed in the OECD website - that goes beyond national borders. In addition, we find pervasive differences in the country-level performances that cannot be compensated through differences in local preferences. These results are confirmed by the high level of global inequality (as measured by the Multidimensional Gini Index of Greco *et al.* 2017), which increases when relative appreciations of people are taken into account. This reveals that good performer countries also have a proportion among the different dimensions of BLI, which is more balanced on the priorities of people. It follows that inequality in the perceived Better

[10] http://www.oecdbetterlifeindex.org/

Life Index may be higher than inequality observed in the multidimensional performances of countries.

As further research, this thesis proves that many problems related to multidimensional phenomena out of market can be studied with Multi-Criteria Decision Analysis. Policy makers dealing with collective choices need tools to manage the multidimensionality of phenomena and the heterogeneity of individual preferences. The new tools proposed in this thesis combined with the new source of big data that are nowadays increasingly available (see Laney, 2001; Maynard *et al.* 2017; di Bella *et al.* 2017), can certainly be a valid support for better-informed decisions and policy formulations. A holistic approach beyond market prices can help in understanding and managing the Market/Government relationships.

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1. Estimating the effect of Economic Social and Cultural Status to the efficiency of educational attainments by Conditional SBM. A student-level analysis on PISA[11]

Abstract

This chapter aims at investigating the effect of Economic Social and Cultural Status (ESCS) on the education performances of students, using the latest available waves of Programme for International Student Assessment (PISA) survey of OECD (2009, 2012). The analysis is conducted at student level for all countries included in the PISA sample. The estimates are based on the Conditional Data Envelopment Analysis (DEA), applied for the first time in the Slack Based Measure (SBM) version. This method allows a detailed evaluation of the additional effort the students should do when they are operating in an ESCS that has a comparative disadvantage. The unprecedented use of a conditional non-radial model of efficiency, provides evidences of a significant effect of the ESCS on performances, with a strong heterogeneity among variables, students, and countries. It follows that some problems with the education sector may not be due to the education systems themselves, but to the economic, social and cultural gaps, which determine a persistence of inequality of opportunity.

JEL Codes: C14, I24, I28.

Keywords: Data Envelopment Analysis; Efficiency; Education; Inequality of Opportunity.

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1.1 Introduction

Over the last decade, the availability of detailed international surveys on cognitive achievement tests like the Programme for International Student Assessment (PISA) of OECD, has favoured many comparative analyses of the different educational systems[12]. PISA in particular has led to the proliferation of international rankings and comparative analysis published in newspapers, technical reports and scientific studies (on pros and cons of PISA see Hopfenbeck, 2016).

Several works aimed at investigating the efficiency of educational systems have benefited from these data producing a voluminous literature on the subject. More specifically, some studies have attempted to analyse the efficient use of public expenditures looking at the PISA outcome (see Afonso and St. Aubyn, 2006; Afonso *et al*., 2010; Sutherland *et al*., 2009; Sibiano and Agasisti, 2011; Agasisti, 2014). Other empirical works have investigated the effects of institutional variables on the performance of pupils and the differences in PISA test between different types of school (Schütz *et al.* 2007; Cherchye *et al.* 2010; Agasisti, 2011; Perelman and Santin, 2011; Agasisti and Cordero-Ferrera, 2013; Crespo-Cebada *et al*., 2014; Aparicio *et al.* 2017). Finally a relevant amount of papers have been focussed on the importance of environmental factors on students' achievement (De Witte and Kortelainen, 2013; Coco and Lagravinese 2014; Bogetoft *et al*., 2015; López-Torres and Prior, 2015).

The latter studies, in line with microanalysis based on different datasets (e.g. Chetty and Hendren, 2015; Chetty *et al.* 2016), clearly show that rankings of educational systems may have limited value when the socio-economic background is not considered in the analysis.

In order to measure the family background at pupils' level, the PISA survey carried out a composite measure of background characteristics: the index of Economic, Social and Cultural Status (ESCS), which includes the occupation and education level of parents and

[12] Others international surveys on cognitive achievement are: Trends in International Mathematics and Science Study (TIMMS); Progress in International Reading Literacy Study (PIRLS); and Program for the International Assessment of Adult Competencies (PIAAC).

indicators of cultural and educational resources at home (e.g. number of books, laptop, own room etc…).

OECD (2013) employed this variable in order to estimate the equity of the educational systems in terms of the slope of the regression line that links the values of the ESCS index and the pupil performance. This is called "the socio-economic gradient" and suggests how much the score would increase when the ESCS index increases by one unit. The larger the increase, the more dependent the outcome of the ESCS index and, therefore, the less equitable the educational system (Villar, 2013).

Despite the extensive literature on efficiency in education, and the recognised effect of the socio-economic background on the education performances, it lacks a global perspective on equity and efficiency using the whole PISA sample and looking at ESCS as the main driver of score gap among different students.

In this respect, the aim of this work is to extend and improve the literature about equity and efficiency in education, along two lines. First, the chapter investigates how the Economic Social and Cultural Status (ESCS) background affects the efficiency of educational attainments using micro-data of all countries analysed by the PISA survey. PISA test is particularly suitable for the purpose of this chapter, since the survey is carried out on a representative sample of the population aged 15 years, in which the socio-economic background may still affects the outcome of the education process. This conditioning role of the ESCS, if any, should therefore be compensated when it represents inequality of opportunity (Roemer, 1998)[13].

Second, from a methodological perspective, the chapter includes the consolidated procedure to embody environmental factors into Data Development Analysis (DEA)[14] - the conditional model of Ruggiero (1996) -, in a non-radial version of DEA: the Slack Based

[13] According to the Roemer's seminal proposal (1998), inequalities in outcomes are the result of two sources: inequalities due to circumstances beyond individual control, which should be compensated for as they are unfair; inequalities due to factors for which people can be held responsible (sometimes called "efforts"), which may instead be considered acceptable.
[14] DEA originates from the work of Farrel (1957) and further developed by Charnes *et al.* (1978).

Measure (SBM) model of Tone (2001). Using SBM, the chapter assesses, for the first time, the effect of the ESCS on the overall Pareto-Koopmans efficiency at student level.

The analysis finds a significant effect of the Economic Social and Cultural Status on student performances, with a strong heterogeneity among variables, students, and countries. Some of these trends, in particular the heterogeneity among variables, cannot be examined by using the traditional (radial) DEA. This is because the radial models can only estimate an index of overall efficiency, and they ignore what happens to the specific-variables considered. More in general, the different role of the ESCS in different aspects of education clearly reveals the importance to control for environmental factors when making decisions on the education systems.

The chapter is organised as follows: section 1.2 presents the data; section 1.3 deals with problems related to efficiency evaluation with environmental factors and it introduces the model; section 1.4 shows the results of the efficiency evaluations and inequality analysis; section 1.5 concludes and discusses policy implications.

1.2 The data

The analysis is conducted using micro data collected by the PISA survey. This survey assesses the knowledge and skills of 15-year old, in an increasing number of countries, on three different subjects: mathematics, reading and scientific literacy. The survey, first carried out in 2000, has been repeated in 2003, 2006, 2009, and 2012[15]. The analysis of this chapter considers the last two available waves (2009 and 2012), in order to capture possible changes of the environmental conditions and performances during a period characterized by a global economic recession.

In selecting variables, the reference has been made to previous studies estimating the efficiency at student level on the PISA database (De Witte and Kortelainen, 2013; De Witte and Lopez Torres, 2015). This leads to using the total sum of learning time as an input (the

[15] OECD repeated the survey in 2015, but the micro data for the 2015 survey were not yet available at the time when we wrote the chapter.

sum of learning time in language, mathematics, and science), while three separate outputs are considered, given by the students' attainments on mathematics, language and sciences[16]. The database contains 373,908 students in 2009, 237,411 students in 2012, and covers 60 different countries. A summary descriptive statistic of the main variables is reported in table 1.1.

Table 1.1 – Descriptive statistics

Variable	2009				2012			
	Min	Aver.	Max.	S. Dev.	Min.	Aver.	Max.	S. Dev.
ESCS	-6.62	- 0.23	3.53	1.13	-5.66	- 0.18	3.69	1.09
Learn. time* (x)	120	661.65	2,250	203.74	135	649.29	2,420	210.44
Math score (y_1)	87.87	476.77	916.19	100.64	96.05	484.35	962.23	99.43
Language score (y_2)	70.20	477.21	871.12	96.23	86.59	487.05	904.80	96.17
Science score (y_3)	104.20	482.47	868.65	98.78	130.31	490.24	903.34	96.42

Source: OECD PISA database (2009, 2012). Note: *minutes per week

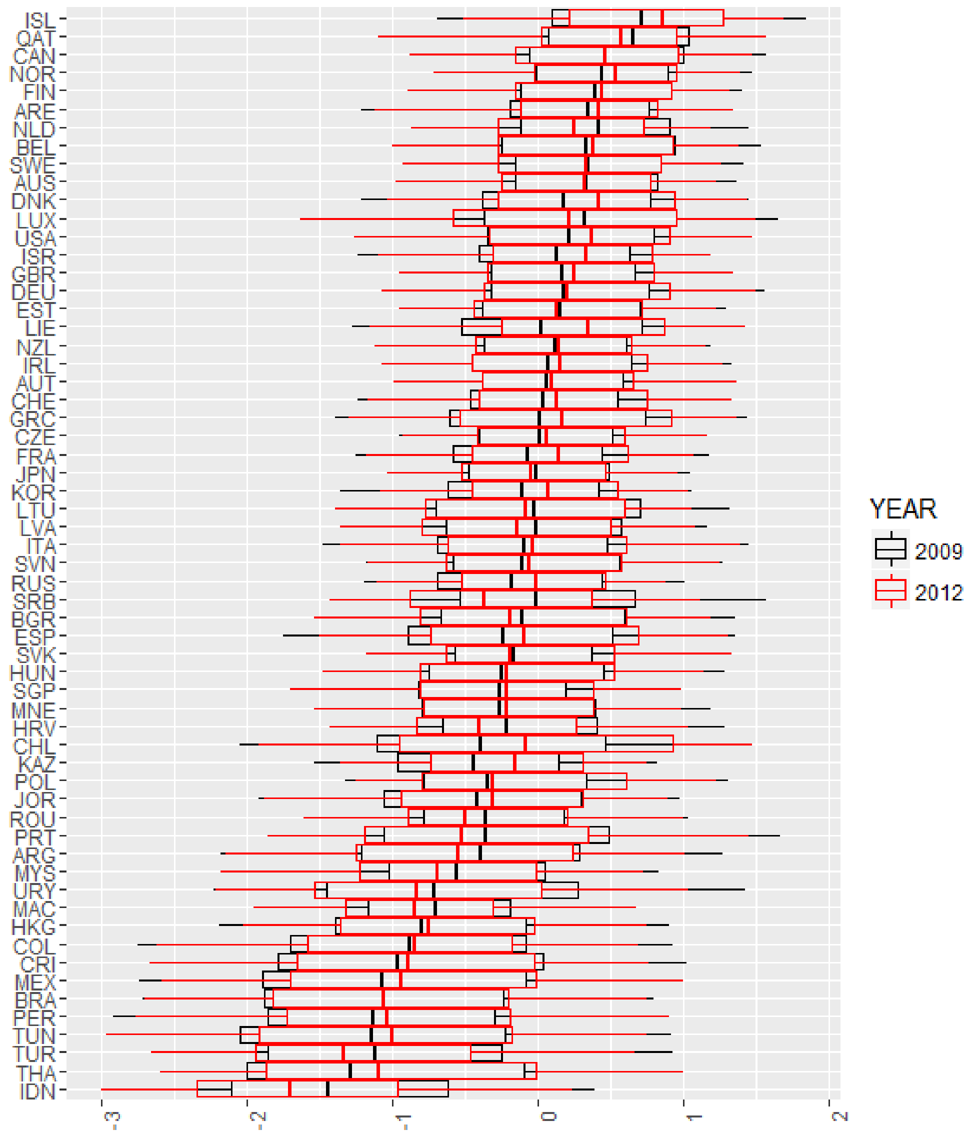
Particularly important for the analysis is that the database provides a measure of the Economic, Social and Cultural Status (ESCS index), which can be used as a good approximation of inequality of opportunity among students, and – more in general – of all different backgrounds that may affect their educational performance. Indeed, the ESCS index is based on information on the students' status provided by themselves and calculated as the first Principal Component of three variables: a) the highest occupational status of parents; b) the highest educational level of parents; c) the home possessions[17]. The final ESCS index is normalized to have mean zero and variance one in the OECD student population[18].

[16] De Witte and Kortelainen (2013, p. 2407) point out that "The total sum of time devoted to the three subjects is preferred on including the three time allocations separately in the analysis, as there might arise significant measurement errors from the time devoted to each of the three subjects separately. For example, students learn languages during the math courses, and time for homework is not clear-cut in the three subjects."

[17] Home possession is a summary index of: A desk to study at; A room of your own; A quiet place to study; A computer you can use for school work; Educational software; A link to the Internet; Classical literature; Books of poetry; Works of art; Books to help with your school work; Technical reference books; A dictionary; A dishwasher; A player; Cellular phones; Televisions; Computers; Cars; Rooms with a bath or shower; Number of books at home.

[18] The ESCS index of 2012 is centred at different value, and it has some small differences in the considered variables, compared with the ESCS index of 2009. Nevertheless, OECD (2014) states that there is both cross countries and over time consistency in the comparisons.

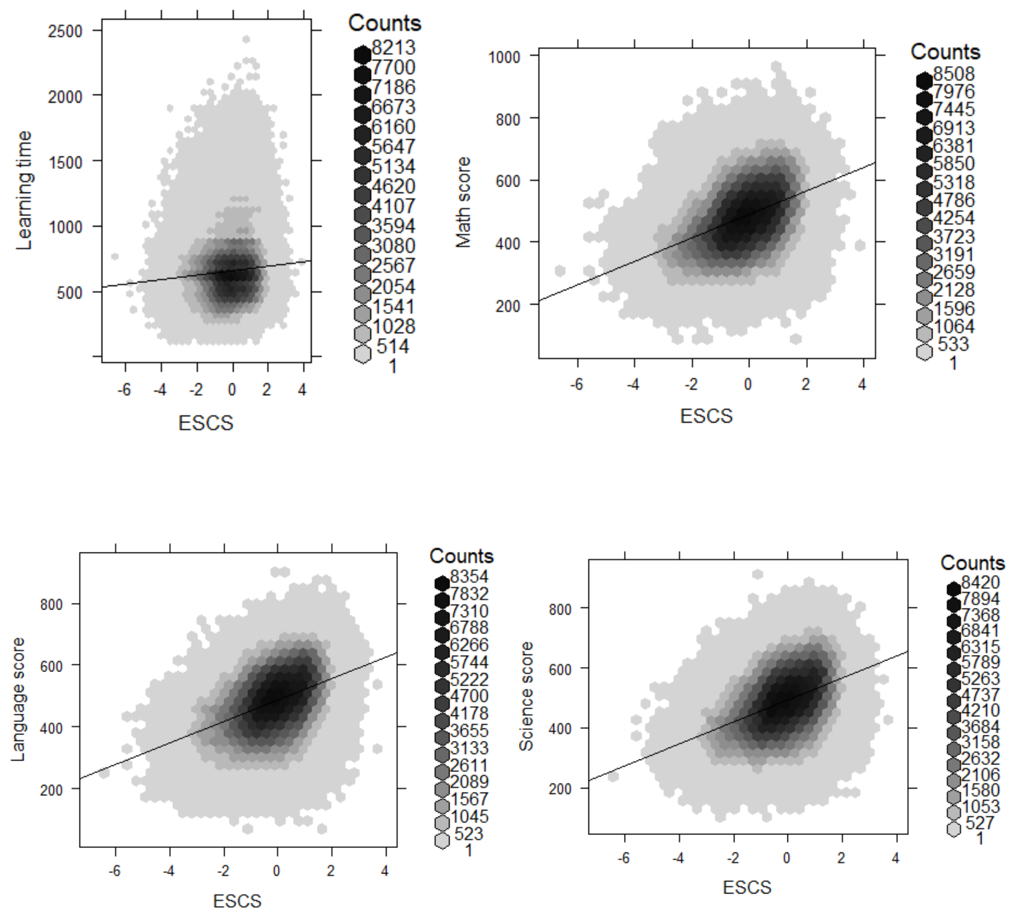
Figure 1.1 – ESCS indices 2009-2012



Source: Author's elaboration on OECD PISA database (2009, 2012). Notes: The countries are sorted by the 2009-2012 median; The 5 and 95 percentiles are the extremes of the lines.

As figure 1.1 shows, the ESCS index has a widespread variability both between and within countries. On average, in the 2009-2012 higher levels of ESCS are in Northern Europe, Qatar, Canada, and Australia, while lower levels of ESCS are in South America, Mexico, Middle East and South East Asian Countries. Remarkably, countries with high indices (above all the Scandinavian) show also less variability among students. An opposite trend is instead found in countries with low indices (many Asians and South Americans), which have also more variability among scholars.

Figure 1.2 – Relation between ESCS index and learning time, math score, language score, and science score (2009-2012)



Source: Author's elaboration on OECD PISA database (2009, 2012). Notes: Hexagon binning; The hexagons with count > 0 are plotted using a colour ramp from white to black in proportion to the counts; The lines are the regressions on the data.

In figure 1.2, we show the relation between ESCS index and the variables used in the efficiency evaluation (learning time, math score, language score, and science score). Since we have a large dataset (611,319 students along two years), in figure 1.2 we show hexagon binning, that is a form of bivariate histogram useful for visualizing the structure in big datasets. The underlying concept of hexagon binning is that the (x, y) plane over the set is tessellated by a regular grid of hexagons. The number of points falling in each hexagon are counted and stored in a data structure, and the hexagons with count > 0 are plotted using a colour ramp (in our case from white to black) in proportion to the counts (Lewin-Koh, 2011).

Figure 1.2 shows that the correlations between ESCS index and the variables of our analysis are always positive. Students living in less favourable environments have also less learning time and less attainments, meaning that both the input and the ouputs of our analysis are positively correlated with ESCS. Nevertheless, given that the correlaton with ESCS is fare more high for attainments than for learning time[19], the ratio output/input is lower for students in less favourable environments.

1.3 The empirical methodology

Since education is provided either free of charge or at prices that do not reflect the market cost in many systems, two methods can be followed to measure its cross-country efficiency: i) parametric, known as Stochastic Frontier Analysis (SFA - Meeusen, van den Broek, 1977; Aigner *et al.* 1977); ii) non-parametric, called DEA (Charnes *et al.* 1978; Banker et al. 1984). So far, there is no consensus about which one has to be adopted, as these two main approaches have not only different features, but also advantages and disadvantages (Lewin, Lovell, 1990). In this study, we use DEA since, contrary to SFA, solves the problem of valuing (or weighting) non-tradable outputs and inputs, without requiring any functional form to be specified to the implicit production function.

The basic assumption of DEA evaluations is that the status-quo is a choice of the Decision Maker (Cherchye *et al.* 2007). Based on this assumption, DEA compiles multidimensional metrics into one index using the combination of weights that is the most convenient for the evaluated Decision Making Unit (DMU) [20].

[19] ESCS correlates 0.09 with learning time, 0.42 with math score, 0.40 with language score, and 0.42 with science score.

[20] The term DMU is used to generally indicate the decision center responsible for converting inputs into outputs.

Formally given n DMUs using m inputs (x_i) and producing s outputs (y_r), the basic DEA model of Charnes *et al.* (1978) estimates the index of Technical Efficiency (TE_k) of the k-th DMU by the following linear programs:

$$\begin{array}{cc}
\text{Primal Form} & \text{Dual Form} \\
TE_k = \max_{u_r, v_i} \sum_{r=1}^{s} u_r y_{rk} & TE_k = \min_{\theta, \lambda_j} \theta \\
\sum_{i=1}^{m} v_i x_{ik} = 1 & \sum_{j=1}^{n} x_{ij}\lambda_j \leq \theta x_{ik}, i = 1, \dots, m \\
\sum_{r=1}^{s} u_r y_{rk} - \sum_{i=1}^{m} v_i x_{ik} \leq 0, j = 1, \dots, n & \sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{rk}, r = 1, \dots, s \\
u_r, v_i \geq 0, r = 1, \dots, s, i = 1, \dots, m & \lambda_j \geq 0, j = 1, \dots, n
\end{array} \quad (1.1)$$

where:

- u_r is the weight given to the r-th output produced by the k-th DMU (y_{rk});
- v_i is the weight given to the i-th input used by the k-th DMU (x_{ik});
- θ is the scalar indicating the feasible radial (proportional) reduction of the input vector for the k-th DMU
- λ_j is the dual weight given to the j-th DMU (j-th element of the intensity vector).

The above linear programs (primal or dual form), are computed separately for each DMU. A DMU is considered to be best performing if it obtains a score of one in the optimal solution of program (1.1). A score less than one implies that the DMU is underperforming, the lower the index, the lower the efficiency. The weights in the objective function are chosen automatically with the purpose of maximizing the score of the k-th DMU. The optimization (1.1) ensures that each DMUs is evaluated on the bases of its own best possible weights, in this way Decision Makers could not complain about unfair weighting, since each DMUs is put in its most favourable light, and any other weighting scheme would generate a lower score.

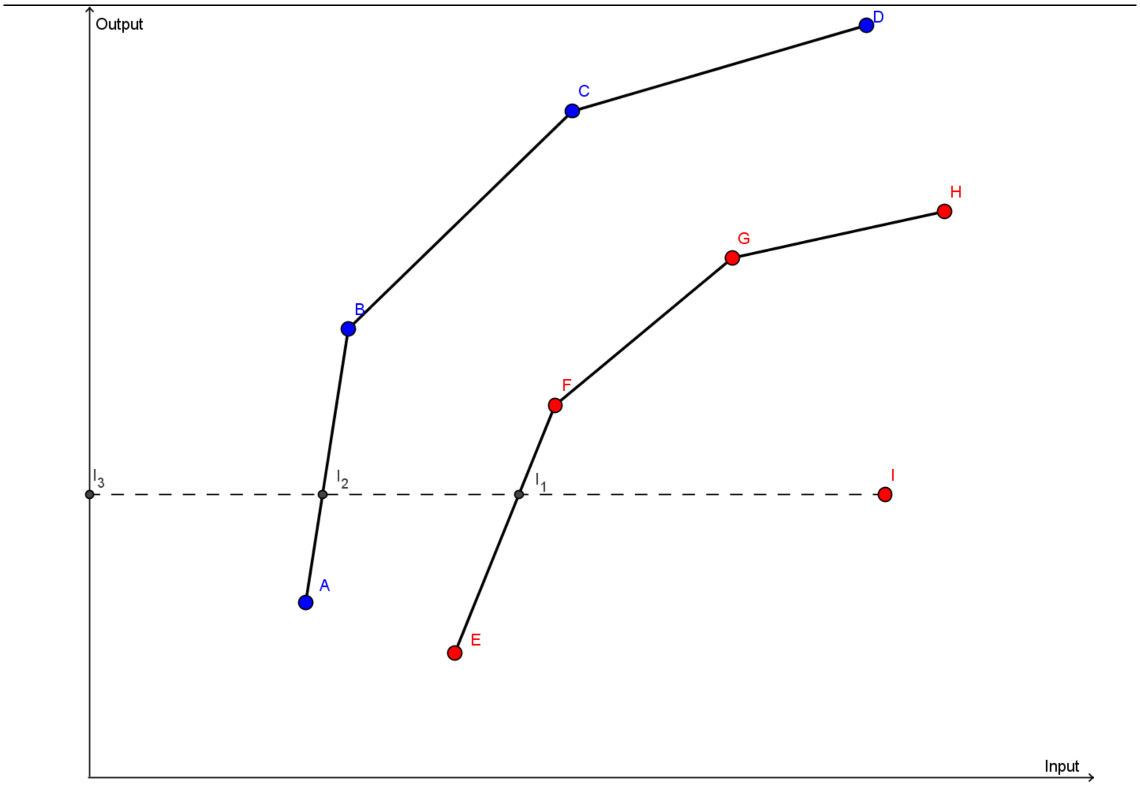
In the DEA literature, Charnes *et al.* (1985) have put the role played by the environmental factors forward for the first time. In their measuring of the Air Forces' performances, Charnes *et al*. (1985) consider the weather conditions as a relevant variable for the successful of the flights, but the variable is beyond the control of the manager.

Figure 1.3 presents the problem in a two dimensional example, in which we assume that there are nine DMUs: A, B, C, D, E, F, G, H and I; producing one output (y axis) with one input (x axis). We assume that the DMUs A, B, C and D (the blues) face a more favorable environment compared to the DMUs E, F, G, H, and I (the reds). Ignoring the environmental factors, the index of Technical efficiency (TE) for the DMU I is given by the ratio of input target to actual input in figure 1.3:

$$TE_I = \frac{\overline{I_3 I_2}}{\overline{I_3 I}} \tag{1.2}$$

According to Ruggiero (1996), the equation (1.2) overestimates the inefficiency because the efficient projection for the DMU I (point I_2) is not feasible. Indeed, there are no DMUs operating with the same environmental factors of I (e.g., red dots) on the frontier which passes through I_2. Moreover, ignoring the environmental factors, the DMUs E, F, G and H would be evaluated as technical inefficient, although they are operating on their frontier.

Figure 1.3 - Technical Efficiency with environmental factors



1.3.1 The Banker and Morey's model

The first DEA model able to deal with the environmental factors is proposed by Banker and Morey (1986), in a fast food chain efficiency evaluation. In the Banker and Morey's study, the environmental factors are treated as non-discretional factors of production[21].

Following Banker, Morey (1986), the efficiency index of the k-th DMU can be obtained with the following linear program[22]:

[21] The environmental factors in Banker and Morey (1986) are: 1. the age of the store; 2. the advertising expenditure; 3. whether the store was located in an urban or rural area; and 4. whether it had a drive in window.
[22] Hereafter the DEA formalizations are based on the dual program in (1).

$$
\begin{gathered}
\min_{\theta,\boldsymbol{\lambda},\boldsymbol{z_k^D},\boldsymbol{z_k^{ND}},\boldsymbol{s_k}} \theta-\varepsilon\left(\boldsymbol{e_1}\boldsymbol{z_k^D}+\boldsymbol{e_2}\boldsymbol{s_k}\right)\\
\theta\boldsymbol{x_k^D}=X^D\boldsymbol{\lambda}+\boldsymbol{z_k^D}\\
\boldsymbol{x_k^{ND}}=X^{ND}\boldsymbol{\lambda}+\boldsymbol{z_k^{ND}}\\
\boldsymbol{y_k}=Y\boldsymbol{\lambda}-\boldsymbol{s_k}\\
\boldsymbol{e_3}\boldsymbol{\lambda}=1\\
\boldsymbol{\lambda},\boldsymbol{z_k^D},\boldsymbol{z_k^{ND}},\boldsymbol{s_k}\geq 0
\end{gathered}
\tag{1.3}
$$

where with n DMUs, m_D discretional inputs, m_{ND} non-discretional inputs, and s outputs:

- θ is the scalar indicating the feasible radial (i.e., proportional) reduction of the discretional input vector (the Technical efficiency index) for the k-th DMU;
- ε is the non-Archimedean scalar[23];
- $\boldsymbol{e_1},\boldsymbol{e_2},\boldsymbol{e_3}$ are vectors of ones, respectively of dimensions $(1\times m_D)$, $(1\times s)$, and $(1\times n)$;
- $\boldsymbol{z_k^D}$ is the discretional residual input slacks vector $(m_D\times 1)$ for the k-th DMU;
- $\boldsymbol{s_k}$ is the residual output slacks vector $(s\times 1)$ for the k-th DMU;
- $\boldsymbol{x_k^D}$ is the discretional input vector $(m_D\times 1)$, which has the discretional inputs used by the k-th DMU on the row;
- X^D is the discretional input matrix $(m_D\times n)$, which has the discretional inputs on the row and all the n DMUs to be evaluated on the column;
- $\boldsymbol{\lambda}$ is the intensity vector $(n\times 1)$;
- $\boldsymbol{x_0^{ND}}$ is the non-discretional input vector $(m_{ND}\times 1)$, which has the non-discretional inputs (environmental variables) used by the k-th DMU on the row;
- X^{ND} is the non-discretional input matrix $(m_{ND}\times n)$,which has the non-discretional inputs (environmental variables) on the row and all the n DMUs to be evaluated on the column;
- $\boldsymbol{z_0^{ND}}$ is the non-discretional residual input slacks vector $(m_{ND}\times 1)$ for the k-th DMU;
- $\boldsymbol{y_0}$ is the output vector $(s\times 1)$, which has the outputs produced by the k-th DMU on the row;
- Y is the output matrix $(s\times n)$, which has the outputs on the row and all the n DMUs to be evaluated on the column.

Unlike the standard DEA models (Charnes *et al.* 1978; Banker *et al.* 1984), in the program

[23] The non-Archimedean scalar is the infinitesimal smaller than any positive real number. The important property of ε is that the product of ε by any real number is still smaller than any positive real number (Ali, Seiford, 1993a; b). This means that ε is not a real number because the real numbers have the Archimedean property: given any real number $r>0$ there exist another real number $r/2>0$ such that $r>r/2>0$ (Cooper *et al.* 2007 pag. 74). In the program (1) it is important that $\theta>\varepsilon\left(\boldsymbol{e_1}\boldsymbol{z_0^D}+\boldsymbol{e_2}\boldsymbol{s_0}\right)$. The latter inequality ensures that regardless the value of θ, the minimization involves first θ and later $\boldsymbol{e_1}\boldsymbol{z_0^D}+\boldsymbol{e_2}\boldsymbol{s_0}$.

(1.3) the non-discretional variables are outside the objective function. Indeed they are not multiplied by the coefficient θ and they do not enter with their relative slacks ($\boldsymbol{z}_{\boldsymbol{0}}^{\boldsymbol{ND}}$). Therefore, the model does not estimate efficiency (inefficiency) on the non-discretional variables. The reason is that since they are non-discretional, the manager cannot work to fill the related gaps. Nevertheless, even though the constraint with the non-discretional variables (the second constraint in (1.3)) have no θ, it plays an important role: it ensures that the frontier for the k-th DMU has the non-discretional variables equal or less favorable than the k-th DMU. In this way, the efficiency evaluation involves only the discretional variables (so that the manager can fill the gaps), but the DMU is compared with a frontier which operates in equal or less favorable environment.

The program (1.3) is a Variable Return to Scale (VRS) model (it has the convexity constraint: $\boldsymbol{e_3\lambda} = 1$), and it can be converted in Constant Return to Scale (CRS) model by removing the forth constraint[24].

1.3.2 After the Banker and Morey's model

In order to improve the Banker and Morey's (1986) model, the literature has proposed a huge quantity of different methods, which mainly differ in the treatment of the environmental factors. On the one hand, there are one-stage models, treating the environmental variables as non-discretional production factors[25]. By this way, the estimated efficiency is conditional on the level of the environmental factors. On the other hand, there are models having two or more stages, which ignore the environmental factors in the first stage, and adjust the results for the environmental effect in the following stages[26].

One of the main drawbacks of the two (or more)-stage models is that this procedure is valid only under the restrictive separability assumption, i.e., that the frontier of the attainable

[24] Hereafter we present DEA models in VRS version, but all of them can be converted in CRS by removing the convexity constraints.
[25] In the one-stage approach the environmental factor is treated either as inputs, as outputs, or as fixed factor, depending whether the effect on the production is respectively either positive, negative, or unknown.
[26] In the two (or more)-stage approach, the first stage includes only discretionary inputs/outputs, and in the following stages, the non-discretionary variables are regressed on the efficiency scores obtained in the first stage. Usually the adjustment is done by using either parametric tools (as Ray, 1991), or non-parametric tools (as Muñiz, 2002).

set is not changing when changing the environmental factors. This is a too strong assumption in the case of education, as the Economic Social and Cultural Status is a clear relevant factor of production. Indeed, a relevant number of studies (among others Agasisti, 2011; 2013; Cordero-Ferrera *et al*. 2011; Perelman and Santín, 2011; Kirjavainen, 2012; Mancebón *et al*. 2012; Thieme *et al*. 2013; Crespo-Cebada *et al*. 2014; Podinovski *et al*. 2014; Aparicio *et al.* 2017) includes the socio-economic status (family, income, employment) in the inputs. Based on this empirical evidence, this chapter focuses on one-stage models.

Among the one-stage proposals, the DEA models have followed either a deterministic or a probabilistic approach. In the deterministic approach, models have been proposed that allow to relax the assumption of convexity of the environmental factors, and to address problems related to endogeneity (Ruggiero, 1996; 1998; 2004). In the probabilistic case, the proposed models have instead tried to address the more general problem related to the robustness of DEA estimates (Cazals *et al.* 2002; Bădin *et al*. 2012)[27]. Several comparisons among the proposed models have been done, by using either empirical (Cordero-Ferrera *et al.* 2008; Huguenin, 2015) or simulated data (Ruggiero, 1998; Syrjänen, 2004; Muñiz *et al*., 2006; Cordero-Ferrera *et al*. 2009; Harrison *et al.*2012). So far, there is no agreement on which is the best model to deal with environmental factors.

In the present analysis, since the ESCS is considered as a factor of production in education, one-stage models can be used to avoid the issue of the separability assumption[28]. Given that the probabilistic models are limited to the use of the basic DEA versions (Radial or Directional Distance Function, as in Bădin *et al*. 2014; Daraio and Simar, 2014; 2016), that are not able to take into account all sources of inefficiency in the estimated indices (more details in section 1.3.4), a deterministic model is used here, in order to estimate a more comprehensive measure of efficiency[29].

[27] Both the approaches have been used in a huge number of efficiency evaluations of the education sector in the last years (see De Witte and López-Torres, 2015, for a literature review).
[28] Focusing on the student-level evaluations, the ESCS has been used as input in Cordero-Ferrera e*t al.* (2011) and Crespo-Cebada *et al*. (2014).
[29] Among the desirable properties of an efficiency measure, Russell (1988) includes: the measure must equal one if, and only if, the observation is Pareto-Koopmans efficient (Koopmans, 1951). Among the others, it has reported in Portela and Thanassoulis (2007, p. 484): ‘‘The calculation of technical (in)efficiency through the

1.3.3 The Ruggiero's model

Ruggiero (1996) proposed a model to overcome one of the main problems of the Banker, Morey's (1986) procedure. The point of Ruggiero (1996) is that the second constraint in (1.3) does not ensures that the reference set (i.e., the set of DMUs on the frontier) has the non-discretional variables equal or less favorable than the k-th DMU.

According to Ruggiero (1996), the second constraint in (1.3) forces the linear combination of the non-discretional inputs used by the DMUs on the frontier ($X^{ND}\boldsymbol{\lambda}$) to be at most as the non-discretional inputs used by the k-th DMU ($\boldsymbol{x_k^{ND}}$). However, this constraint is not enough to avoid that the reference set for the k-th DMU includes DMUs operating in better environment (using more non-discretional inputs)[30].

To overcome this shortcoming, Ruggiero (1996) proposes to estimate the Technical efficiency index of the k-th DMU with the following linear program:

$$
\begin{gathered}
\min_{\theta,\lambda,\boldsymbol{z_k^D},\boldsymbol{s_k}} \theta - \varepsilon\left(\boldsymbol{e_1 z_k^D} + \boldsymbol{e_2 s_k}\right) \\
\theta \boldsymbol{x_k^D} = X^D \boldsymbol{\lambda} + \boldsymbol{z_k^D} \\
\boldsymbol{y_k} = Y\boldsymbol{\lambda} - \boldsymbol{s_k} \\
if\ \boldsymbol{x_j^{ND}} > \boldsymbol{x_k^{ND}} \rightarrow \lambda_j = 0;\ j = 1, \dots, n \\
\boldsymbol{e_3 \lambda} = 1 \\
\boldsymbol{\lambda}, \boldsymbol{z_k^D}, \boldsymbol{s_k} \geq 0
\end{gathered}
\tag{1.4}
$$

The third constraint in (1.4) removes from the reference set the DMUs using more non-discretional inputs than the k-th DMU. Indeed, it zeroed the lambda related to the DMUs operating in better environment[31].

---

hyperbolic or directional models [...] do not account [...] for all the sources of inefficiency, namely those associated with slacks. This is an important problem in a context where overall efficiency is being measured''

[30] In Ruggiero (1996 p. 559) there is a numerical example.

[31] Ruggiero (1998) states that the model (1.4) has a problem: increasing the number of non-discretional variables increases the efficient by default DMUs, as it increases the lambda to be zeroed. Therefore, he proposes a three stages method in Ruggiero (1998). First stage is a standard DEA ignoring the non-discretional variables. Second stage is estimating an overall index of environmental harshness, by regressing the index of efficiency of the first stage on the non-discretional variables. Third stage is using the obtained overall index of environmental

1.3.4 The Pareto-Koopmans efficiency and Slack Based Measure

The k-th DMU is fully efficient if, in the optimal solution of the program (1.4), there are the following conditions:

$$\theta^* = 1 \tag{1.5}$$

$$\boldsymbol{z_k^{D*}} = 0, \boldsymbol{s_k^*} = 0 \tag{1.6}$$

where θ^* is the estimated index of efficiency. A value of $\theta^* < 1$ means that all the discretional inputs, can be simultaneously reduced (at constant output) without altering the input/output vectors mix (i.e., the proportions among the elements in the vectors). $(1 - \theta^*)$ represent the maximal reduction proportionate feasible of the inputs. Nevertheless, given θ^* a value of $\boldsymbol{z_k^{D*}} > 0$ and/or $\boldsymbol{s_k^*} > 0$ means that it is still feasible for the k-th DMU do further improvements (reduction of some inputs and/or increase of some outputs). The latter improvements change the proportions within the inputs-outputs vectors. The inefficiency related to these changes is called mix inefficiency (Cooper *et al.* 2007), while the index θ^* is called index of Technical Efficiency (Farrel 1957). Since θ^* evaluates the radial (proportional) efficiency, it does not reflect the input excess and the output shortfalls that may be represented by:

$$\boldsymbol{z_k^{D*}} > 0, \boldsymbol{s_k^*} > 0 \tag{1.7}$$

So that the k-th DMU is defined weak efficient in the case the optimal solution of the program (1.4) gives:

$$\theta^* = 1 \tag{1.8}$$

$$\boldsymbol{z_k^{D*}} > 0, \boldsymbol{s_k^*} > 0 \tag{1.9}$$

Weak efficiency means that the index of TE is one, but the k-th DMU can still improve comparing with the DMUs on the frontier by changing the proportion within the elements in inputs and/or outputs vectors. To make up for this deficiency Tone (2001) proposed the Slack

harshness as the only non-discretional input in the program (1.4). This procedure can be avoided where the non-discretional variable is just one as in our case.

Based Measure (SBM) model. There are three main advantages of SBM compared with radial models:

a) it is non-oriented, in the sense that it does not require to choose between the output oriented or the input oriented approach, because it estimates an index of efficiency based on all the feasible improvements both on output and input vectors;

b) it is non-radial, in the sense that it does not constrain the input and output vectors to improve proportionally (as the radial models do), but it estimates the maximum feasible improvement for each element in both vectors. With this characteristic, the SBM index of overall efficiency is able to embody all feasible improvements, namely the Pareto-Koopmans inefficiency that includes both the radial (the feasible proportional improvement or technical inefficiency as in Farrell, 1957) and the non-radial inefficiency (inefficiency due to the non-optimal proportion of the elements in the input-output vectors: the mix inefficiency);

c) it allows for a decomposition of the (aggregate) inefficiency indices into the variable-specific efficiency scores among the elements in the input-output vectors. These detailed measures of inefficiency are important, especially because they allow providing more detailed and targeted policy advices.

The SBM model estimates an index of efficiency based on the ratio of the relative average feasible reduction of the inputs to the relative average feasible increase of the outputs. This allows to include in a unique scalar (like θ^*) both the Technical and mix inefficiency.

The non-linear version of the Tone (2001) model is:

$$\begin{gathered}
\min_{\lambda, z_k^D, s_k} \tau = \frac{1 - \frac{1}{m_D}\left(\sum_{i=1}^{m_D} z_{ik}^D / x_{ik}^D\right)}{1 + \frac{1}{s}\left(\sum_{h=1}^{s} s_{hk} / y_{hk}\right)} \\
\boldsymbol{x_k^D} = X^D \boldsymbol{\lambda} + \boldsymbol{z_k^D} \\
\boldsymbol{y_k} = Y\boldsymbol{\lambda} - \boldsymbol{s_k} \\
\boldsymbol{e_3}\boldsymbol{\lambda} = 1 \\
\boldsymbol{\lambda}, \boldsymbol{z_k^D}, \boldsymbol{s_k} \geq 0
\end{gathered} \tag{1.10}$$

where τ is the index of efficiency for the kth DMU, and the term $(1-\tau)$ reflect both the Technical and Mix inefficiency. For this reason, the following inequality is always true:

$$\theta^* \geq \tau^* \tag{1.11}$$

Following Tone (2001) the program (1.10) can be linearised by using the linear transformation of Charnes and Cooper (1962), introducing a positive scalar variable t. So that, the unconditional efficiency (τ_U) can be estimated with the model of Tone (2001) as:

$$\begin{gathered}
\min_{t,\boldsymbol{\lambda_U},\boldsymbol{z^D_{kU}},\boldsymbol{s_{kU}}} \tau_U = t - \frac{1}{m_D}\left(\sum_{i=1}^{m_D} z^D_{ikU}\Big/x^D_{ikU}\right) \\
t + \frac{1}{s}\left(\sum_{h=1}^{s} s_{hkU}\Big/y_{hkU}\right) = 1 \\
t\boldsymbol{x^D_k} = X^D\boldsymbol{\lambda_U} + \boldsymbol{z^D_{kU}} \\
t\boldsymbol{y_k} = Y\boldsymbol{\lambda_U} - \boldsymbol{s_{kU}} \\
\boldsymbol{e_3}\boldsymbol{\lambda_U} = t \\
t, \boldsymbol{\lambda_U}, \boldsymbol{z^D_{kU}}, \boldsymbol{s_{kU}} \geq 0
\end{gathered} \tag{1.12}$$

where:

- t is the variable of the linear transformation (Charnes and Cooper, 1962);
- z^D_{ikU} is the unconditional i-th input slack times t;
- z^D_{ikU}/t measures the amount of i-th input in excess (ignoring environmental factors);
- s_{hkU} is the unconditional h-th output slack times t;
- s_{hkU}/t measures the lack in the h-th output (ignoring environmental factors);
- $\boldsymbol{\lambda_U}$ is of the intensity vector, times t.

1.3.5 The Ruggiero's model in the Tone's framework

The standard SBM model presented in Tone (2001) does not allow controlling for environmental factors. This is the reason why in this section we propose to include Ruggiero (1996)'s procedure in the SBM model of Tone (2001)[32]. This leads to a new model: the Conditional SBM. The Conditional SBM efficiency (τ_C) can be estimated as follows:

[32] The inclusion of the Banker, Morey (1986)'s procedure in the SBM model is in Patrizii, Resce (2013).

$$
\begin{gathered}
\min_{t,\boldsymbol{\lambda_C},\boldsymbol{z^D_{kC}},\boldsymbol{s_{kC}}} \quad \tau_C = t - \frac{1}{m_D}\left(\sum_{i=1}^{m_D} z^D_{ikC} \Big/ x^D_{ikC}\right) \\
t + \frac{1}{s}\left(\sum_{h=1}^{s} s_{hkC} \Big/ y_{hkC}\right) = 1 \\
t\boldsymbol{x^D_k} = X^D \boldsymbol{\lambda_C} + \boldsymbol{z^D_{kC}} \\
t\boldsymbol{y_k} = Y\boldsymbol{\lambda_C} - \boldsymbol{s_{kC}} \\
if\ \boldsymbol{x^{ND}_j} > \boldsymbol{x^{ND}_k} \rightarrow \lambda_{jC} = 0;\ j = 1, \dots, n \\
\boldsymbol{e_3\lambda_C} = t \\
t, \boldsymbol{\lambda_C}, \boldsymbol{z^D_{kC}}, \boldsymbol{s_{kC}} \geq 0
\end{gathered}
\tag{1.13}
$$

where:

- t is the variable of the linear transformation (Charnes and Cooper, 1962);
- z^D_{ikC} is the conditional i-th input slack times t;
- z^D_{ikC}/t measures the amount of i-th input in excess (controlling for environmental factors);
- s_{hkC} is the conditional h-th output slack times t;
- s_{hkC}/t measures the lack in the h-th output (controlling for environmental factors);
- $\boldsymbol{\lambda_C}$ is of the intensity vector, times t.

Model (13) is the first SBM able to remove from the frontier those DMUs operating in a better environment than the environment in which the k-th DMU operates. By this way, the model (1.13) allows to estimate the Conditional Pareto-Koopmans efficiency[33].

3.6 Conditional and Unconditional SBM in our case study

The aim of this analysis is to detect the effect of the ESCS index on the overall efficiency at student level, interpreted as one non-discretionary factor of production[34]. The Conditional

[33] A previous non-radial conditional efficiency evaluation is in Baležentis and De Witte (2015), whose model is Multi-Directional based. Since it is input oriented, the model of Baležentis and De Witte (2015) does not estimate the overall Pareto-Koopmans efficiency because it ignores the residual output slacks.

[34] The Ruggiero (1996) model has led to many applications in the educational sector (among others Ouellette and Vierstraete, 2010; Parteka and Wolszczak-Derlacz, 2013; Essid *et al*. 2014).

SBM leads to detect the effect of ESCS on the overall efficiency index and at the same time to estimate its effect on the production of each output[35].

In more detail, for each student k, of the 611,319 (n) pupils in the sample one has:

- one input x_k (total learning time, measured by minutes per week from OECD PISA database 2009, 2012);
- three (z) outputs (math score, language score, and science score, Plausible values 1 from OECD PISA database 2009, 2012[36]) in the vector $\boldsymbol{y_k}$ of dimension (3×1);
- one environmental variable $ESCS_k$ (the index of economic, social and cultural status from OECD PISA database 2009 and 2012).

Conditional and unconditional SBM indexes of efficiency at student level are estimated. The unconditional estimates are performed using the following standard SBM (Tone, 2001)[37]:

[35] Although our database is a robust evaluation coming from one singular source (PISA, OECD), before the evaluation it has been applied a cleaning procedure suggested in Barone and Mocetti (2011) in order to control for random errors ignored by our deterministic model. The cleaning is done by computing the ratio between the input and each output, and then by trimming all the observations having values less than the first percentile and greater than the last percentile.

[36] Starting from the Third International Mathematics and Science Survey conducted by the IEA in 1995, student proficiency estimates are returned through plausible values. The plausible values are a representation of the range of abilities that a student might reasonably have. Instead of directly estimating a student's ability, a probability distribution for student is estimated. That is, instead of obtaining a point estimate, a range of possible values for student, with an associated probability for each of these values is estimated. Plausible values are random draws from this (estimated) distribution for student. PISA allocates five plausible values to each student on each performance scale (OECD, 2009). Following pervious efficiency evaluations on PISA (De Witte and López-Torres, 2015) we use the first plausible values.

[37] The following two programs have been linearized as in Tone (2001), so all the variables are multiplied for t_U in program (1.14), and for $\mathrm{t_C}$ in program (1.15). Since we assume Variable Return to Scale in the education sector, we add the constraints $\sum_{j=1}^{n} \lambda_{Uj} = t_U$ to the program (1.14), and $\sum_{j=1}^{n} \lambda_{Cj} = t_C$ to the program (1.15) (Banker *et al*. 1984).

$$
\begin{gathered}
\min_{t_U,\lambda_{Uj},s_U^-,\boldsymbol{s}_U^+} \tau_U = t_U - \frac{s_U^-}{x_k} \\
t_U + \frac{1}{z}\left(\sum_{r=1}^{z} \frac{\mathrm{s}_{Ur}^+}{y_{rk}}\right) = 1 \\
t_U x_k = \sum_{j=1}^{n} x_j \lambda_{Uj} + s_U^- \\
t_U \boldsymbol{y_k} = \sum_{j=1}^{n} \boldsymbol{y_j} \lambda_{Uj} - \boldsymbol{s_U^+} \\
\sum_{j=1}^{n} \lambda_{Uj} = t_U \\
t_U, \lambda_{Uj}, s_U^-, \boldsymbol{s_U^+} \geq 0
\end{gathered}
\tag{1.14}
$$

where:

- t_U is the variable of the linear transformation (Charnes and Cooper, 1962);
- s_U^- is the unconditional input slack times t_U;
- s_U^-/t_U measures the learning time in excess at student level ignoring ESCS;
- s_{Ur}^+ is the unconditional r-th output slack times t_U;
- s_{Ur}^+/t_U measures the lack in the r-th attainment score at student level ignoring ESCS;
- λ_{Uj} is a scalar variable of the intensity vector, times t_U.

By solving the linear program (1.14) we obtain τ_U, which is the relative efficiency of the k-th student unconditional on the level of ESCS, where $(1-\tau_U)$ is the estimated inefficiency. As the standard SBM models, this inefficiency is the relative average distance to the unconditional frontier, in each single variable considered in the analysis (learning time, test score math, test score reading, and test score science).

The conditional SBM to control for ESCS is instead obtained by the following linear program[38]:

[38] There is no open source or commercial software that implements Conditional SBM model. We have therefore developed an optimization code in R, that will be sent on request of the interested scholars.

$$
\begin{gathered}
\min_{t_C,\lambda_{Cj},s_C^-,\boldsymbol{S}_C^+} \tau_C = t_C - \frac{s_C^-}{x_k} \\
t_C + \frac{1}{z}\left(\sum_{r=1}^{z} \frac{s_{Cr}^+}{y_{rk}}\right) = 1 \\
t_C x_k = \sum_{j=1}^{n} x_j \lambda_{Cj} + s_C^- \\
t_C \boldsymbol{y_k} = \sum_{j=1}^{n} \boldsymbol{y_j} \lambda_{Cj} - \boldsymbol{S}_C^+ \\
if ESCS_j > ESCS_k \rightarrow \lambda_{jC} = 0;\ j = 1, \dots, n \\
\sum_{j=1}^{n} \lambda_{Cj} = t_C \\
t_C, \lambda_{Cj}, s_C^-, \boldsymbol{S}_C^+ \geq 0
\end{gathered} \tag{1.15}
$$

where:

- t_C is the variable of the linear transformation (Charnes and Cooper, 1962);
- s_C^- is the conditional input slack times t_C;
- s_C^- / t_C measures the learning time in excess at student level controlling for ESCS;
- s_{Cr}^+ is the conditional r-th output slack times t_C;
- s_{Cr}^+ / t_C measures the lack in the r-th attainment score at student level controlling for ESCS;
- λ_{Cj} is a scalar variable of the intensity vector, times t_C.

The optimal solution of linear program (1.15) gives an estimate of τ_C, which is the relative efficiency of the k-th student conditional to the level of ESCS, where $(1 - \tau_C)$ is the average distance to the conditional frontier, in each single variable considered in the analysis.

Since model (15) is a SBM able to remove from the frontier those students operating in a better environment than the environment in which the k-th student operates, the assumed technology is conditional on the level of ESCS. Indeed, following the algorithm suggested by Ruggiero (1996), the third constraint in (1.15) sets to zero the λ_{Cj} related to the students which have ESCS better than the ESCS of the evaluated student (k).

Following the definitions provided by Ruggiero (2000), Lozano-Vivas *et al.* (2001; 2002), Giménez *et al.* (2007), Badin *et al.* (2012), and Johnson, Ruggiero (2014), the effect of ESCS on efficiency are estimated by using the frontier shifting between the unconditional and conditional evaluations to the level of ESCS. To this purpose, the SBM frontier shifting proposed in Tone (2004) is adapted as follows:

$$Frontier\ Shift = \varphi = \frac{\tau_C}{\tau_U} \tag{1.16}$$

The coefficient φ measures the shift of the frontier due to the environmental factor. Thus, it can be interpreted as an index of environmental harshness that indicates the possible negative impact that the ESCS has on the overall performances of the student. A value of $\varphi = 1$ indicates the absence of any effect of ESCS on efficiency, since the frontier has not changed position controlling for it. A value of $\varphi > 1$ indicates a comparative advantage in the performance for the students with better ESCS, since the frontier ignoring environmental factor is higher than the frontier controlling for it. In other words, $\varphi > 1$ implies that some students that may result inefficient with respect to the unconditional frontier (i.e., without controlling for ESCS) are instead more efficient once the disadvantage of being in a less than optimal environment is controlled for. More generally, the higher is φ, the higher is the impact of ESCS on the performance of the student.

Since our analysis is micro-based, it allows to estimate two effects of the ESCS on the performances. The first is the effect of the ESCS on the level of efficiency; the second is the effect of the ESCS on the distribution of the performances. In order to get the first effect, student level indices are aggregated both at the country and income group level, following the procedures proposed in the literature on aggregate efficiency (Färe and Zelenyuk, 2003; 2007; Färe and Grosskopf, 2004; Färe and Karagiannis, 2014)[39]. More specifically, the efficiency scores and the indices of environmental harshness are aggregated by a weighted average, using the input shares (individual total learning time) as weights. In order to get the effect of ESCS on the distribution, instead, the choice has been made to disentangle *Between* and *Within* countries inequality in the performances using the Theil Index (TI) - Theil (1967) -, which is a perfectly decomposable inequality index:

[39] Following the literature related to the aggregate efficiency indices (Färe and Zelenyuk, 2003; 2007; Färe and Grosskopf, 2004; Färe and Karagiannis, 2014), the aggregation consistency requires: i) output-oriented efficiency indices to be aggregate using output shares as weights and ii) input-oriented efficiency indices to be aggregate using input shares as weights. The model presented in this chapter is non-oriented, but since it has the input slacks in the objective function, when aggregate results are presented, the efficiency scores and the indices of environmental harshness are aggregated by using the input shares as weights.

$$TI = \sum_i f_i \left(\frac{\tau_i}{\mu}\right) \log\left(\frac{\tau_i}{\mu}\right) \tag{1.17}$$

where f_i is the population share of student i, τ_i is the efficiency index of the student i, and μ is the average efficiency.

The index (1.17) can be decomposed into a *Between* and *Within* group component as follows:

$$TI = \underbrace{\left[\sum_j g_j \left(\frac{\mu_j}{\mu}\right) \log\left(\frac{\mu_j}{\mu}\right)\right]}_{Between\ Inequality} + \underbrace{\sum_j TI_j g_j \left(\frac{\mu_j}{\mu}\right)}_{Within\ Inequality} \tag{1.18}$$

where *j* refers to the sub-group, g_j is the population share of group *j* and TI_j is the inequality in group j. The *Between* component of inequality is captured by the first term in (1.18), i.e., the level of inequality if everyone within each group *j* had efficiency level μ_j. The second term gives the *Within* component of inequality (Cowell, 2000; Elbers *et al.* 2005).

1.4 Results

The model proposed in this chapter gives estimations of single efficiency indices at student level, covering 611,319 pupils in 60 different countries. This amount of information provides a relevant microeconomic basis of the macro analysis and allows detailed policy suggestions. For convenience section 1.4.1 discusses the impact of ESCS at country level, while section 1.4.2 aggregates the outcomes by income group level, and disentangles the inefficiency at variable-specific level. Finally, section 1.4.3 reports evidences on global inequalities.

1.4.1 The effect of the ESCS at the country level

The first step of the analysis is an efficiency evaluation that ignores the environmental factors (i.e., unconditional on ESCS). It is worth recalling that this is the starting point to isolate the effect of ESCS, as this effect is measured by the shifting between the unconditional and the conditional frontier as in equation (1.16). The model used in this stage is the linear program (1.14), which is the unconditional SBM of Tone (2001). As reported in section 1.2, the total learning time is used as input, while the students' attainments on the three subjects considered in PISA are the outputs of the analysis.

The student performance is measured by the ability to achieve the maximum of attainments with the minimum of learning time. In table 1.2 we show the country level minimum, average, maximum, and standard deviation of the unconditional indices of the overall efficiency.

Table 1.2 – Unconditional SBM Scores (2009-2012)

Countries	2009					2012				
	Obs.	Min.	Aver.	Max.	S. Dev.	Obs.	Min.	Aver.	Max.	S. Dev.
ARE	7823	0.14	0.26	0.95	0.09	5598	0.14	0.27	0.95	0.11
ARG	1409	0.14	0.25	0.93	0.14	1651	0.14	0.30	0.97	0.15
AUS	11725	0.14	0.38	1.00	0.11	6915	0.14	0.37	0.89	0.10
AUT	5373	0.14	0.48	0.99	0.16	2622	0.14	0.49	0.98	0.16
BEL	6414	0.16	0.43	1.00	0.12	4081	0.15	0.42	0.96	0.11
BGR	3933	0.15	0.41	0.90	0.12	3002	0.14	0.43	0.91	0.12
BRA	18020	0.14	0.33	1.00	0.12	8111	0.14	0.36	1.00	0.14
CAN	19092	0.14	0.28	1.00	0.12	12385	0.14	0.29	1.00	0.12
CHE	10247	0.15	0.43	1.00	0.11	6484	0.14	0.43	1.00	0.12
CHL	3761	0.14	0.28	0.96	0.10	2862	0.14	0.26	1.00	0.11
COL	6486	0.14	0.32	0.97	0.13	4063	0.14	0.31	0.96	0.14
CRI	3070	0.14	0.33	1.00	0.09	2528	0.17	0.35	0.90	0.10
CZE	5297	0.16	0.41	0.96	0.13	3169	0.18	0.44	1.00	0.13
DEU	3895	0.15	0.42	0.97	0.11	2313	0.14	0.42	0.94	0.11
DNK	4684	0.14	0.35	0.96	0.10	4156	0.14	0.35	0.95	0.11
ESP	20656	0.14	0.39	0.97	0.10	13923	0.15	0.42	0.97	0.11
EST	4622	0.15	0.41	0.86	0.10	3062	0.17	0.43	0.89	0.10
FIN	5601	0.15	0.52	1.00	0.12	5108	0.15	0.51	1.00	0.12
FRA	3129	0.15	0.39	1.00	0.13	2108	0.16	0.41	0.97	0.13
GBR	10195	0.14	0.35	0.92	0.09	7414	0.14	0.35	0.96	0.10
GRC	4744	0.15	0.39	0.92	0.09	1068	0.24	0.41	0.61	0.06
HKG	2669	0.15	0.32	0.92	0.09	2518	0.14	0.36	0.88	0.11
HRV	4515	0.16	0.49	1.00	0.15	3099	0.15	0.47	1.00	0.15
HUN	3922	0.14	0.49	0.99	0.13	2701	0.16	0.47	1.00	0.12
IDN	3876	0.14	0.31	1.00	0.17	2690	0.14	0.34	1.00	0.17
IRL	2938	0.16	0.48	1.00	0.12	2986	0.18	0.50	1.00	0.13
ISL	3124	0.14	0.41	0.97	0.11	1909	0.15	0.40	0.88	0.11
ISR	3850	0.14	0.37	0.97	0.13	2318	0.14	0.39	0.96	0.13
ITA	25980	0.14	0.37	1.00	0.12	18139	0.14	0.39	0.97	0.11
JOR	5988	0.14	0.26	0.90	0.06	3667	0.14	0.27	1.00	0.08
JPN	5705	0.18	0.44	0.97	0.11	3872	0.17	0.45	1.00	0.13
KAZ	5126	0.14	0.31	0.83	0.08	3042	0.14	0.42	0.99	0.17
KOR	4974	0.18	0.44	0.94	0.09	3133	0.16	0.44	0.96	0.11
LIE	308	0.17	0.43	1.00	0.12	187	0.15	0.48	0.92	0.12
LTU	4082	0.14	0.41	0.96	0.11	2843	0.15	0.35	0.60	0.06
LUX	4115	0.14	0.43	0.96	0.13	2926	0.16	0.44	0.97	0.12
LVA	4357	0.15	0.37	0.95	0.09	2350	0.15	0.41	0.85	0.10
MAC	5199	0.16	0.31	0.66	0.05	2808	0.16	0.36	0.80	0.09
MEX	31919	0.14	0.31	1.00	0.10	18373	0.14	0.30	0.97	0.11
MNE	4077	0.17	0.45	0.93	0.11	2853	0.15	0.51	1.00	0.11
MYS	2943	0.14	0.32	0.85	0.11	1894	0.14	0.35	0.98	0.15

Table 1.2 Continued

Countries	2009					2012				
	Obs.	Min.	Aver.	Max.	S. Dev.	Obs.	Min.	Aver.	Max.	S. Dev.
NLD	3054	0.17	0.49	1.00	0.13	2333	0.14	0.51	1.00	0.17
NOR	4620	0.19	0.46	0.73	0.08	2663	0.14	0.45	1.00	0.12
NZL	4239	0.14	0.36	0.88	0.09	2521	0.14	0.36	0.95	0.09
PER	3106	0.14	0.26	0.95	0.12	1927	0.14	0.28	0.95	0.11
POL	4852	0.17	0.40	0.74	0.07	2997	0.17	0.44	0.76	0.08
PRT	3813	0.14	0.35	0.88	0.11	2341	0.14	0.32	0.95	0.11
QAT	6198	0.14	0.26	1.00	0.10	3268	0.14	0.27	0.63	0.07
ROU	3145	0.17	0.45	1.00	0.12	2759	0.16	0.43	0.94	0.14
RUS	4684	0.14	0.33	0.96	0.10	3037	0.15	0.38	0.98	0.13
SGP	4257	0.14	0.30	0.97	0.12	3670	0.15	0.34	1.00	0.07
SRB	4449	0.15	0.42	0.98	0.15	2723	0.15	0.49	1.00	0.15
SVK	4048	0.17	0.42	1.00	0.17	2286	0.16	0.46	1.00	0.18
SVN	5498	0.14	0.46	0.97	0.10	2968	0.23	0.48	0.94	0.10
SWE	4041	0.14	0.46	0.98	0.14	2788	0.16	0.44	0.95	0.12
THA	5578	0.15	0.33	0.97	0.14	4031	0.15	0.35	1.00	0.14
TUN	4873	0.15	0.27	0.59	0.04	1742	0.14	0.28	0.91	0.11
TUR	4416	0.15	0.41	0.97	0.16	1671	0.20	0.43	0.99	0.15
URY	4834	0.14	0.31	0.97	0.12	2130	0.16	0.43	1.00	0.17
USA	4360	0.14	0.31	1.00	0.12	2625	0.14	0.31	1.00	0.13

Source: Author's elaborations on OECD PISA database (2009, 2012).
Note: The averages are weighted by input shares.

Looking at table 1.2, there is evidence of a widespread variability in the student performances among countries, as well as of some differences between the performances in 2009 and in 2012 (see also the correlation matrix in table A1.1 in the Appendices). Considering the average performances of 2009 and 2012, many European countries are located in the upper side of the rank (the Scandinavian and the Northern-Eastern countries in particular), together with two Asian countries (North Korea and Japan). Instead, the bottom side of the rank includes many Middle Eastern countries (Qatar, Arab Emirates, and Jordan) and both North and South American countries (Chile, Peru, Argentina, Canada, Mexico, and USA). It is worth noting that many Eastern European countries (among others Kazakhstan, Serbia, Montenegro, Russia, Slovakia, and Poland), and South-American countries (Uruguay and Argentina) show a wide improvement in the period. On the contrary, a relevant reduction in the average performances of the students in the same period is observed in Lithuania and Portugal.

At this stage, however, nothing is said about the impact of the ESCS. To this purpose, the conditional efficiency must be estimated by using the Conditional SBM described in (1.15). Conceptually, the unconditional inefficiency is based on the distance between the evaluated student and the frontier ignoring the ESCS index, while the conditional inefficiency is based on the distance between the evaluated student and the frontier controlling for the ESCS. It is worth recalling that the frontier controlling for ESCS involves only those students who share an equal or less favourable environment compared with the environment in which the evaluated student operates. Results are reported in table 1.3 where numbers represent the country level minimum, average, maximum, and standard deviation of the ratios of the conditional to the unconditional efficiency. These ratios are indices of the Economic, Social and Cultural harshness at student level presented in the equation (1.16).

Table 1.3 – Indices of Economic, Social and Cultural harshness (2009-2012)

Countries	2009					2012				
	Obs.	Min.	Aver.	Max.	S. Dev.	Obs.	Min.	Aver.	Max.	S. Dev.
ARE	7823	1.00	1.00	1.40	0.01	5598	1.00	1.00	1.49	0.01
ARG	1409	1.00	1.01	1.18	0.01	1651	1.00	1.01	1.35	0.01
AUS	11725	1.00	1.01	1.56	0.01	6915	1.00	1.01	1.43	0.02
AUT	5373	1.00	1.01	1.33	0.01	2622	1.00	1.01	1.17	0.01
BEL	6414	1.00	1.01	1.54	0.02	4081	1.00	1.01	1.50	0.02
BGR	3933	1.00	1.01	1.39	0.01	3002	1.00	1.01	1.73	0.03
BRA	18020	1.00	1.02	2.83	0.04	8111	1.00	1.02	3.03	0.05
CAN	19092	1.00	1.00	1.64	0.01	12385	1.00	1.01	1.48	0.01
CHE	10247	1.00	1.01	1.79	0.02	6484	1.00	1.01	1.34	0.01
CHL	3761	1.00	1.01	1.55	0.02	2862	1.00	1.01	1.46	0.01
COL	6486	1.00	1.02	2.40	0.04	4063	1.00	1.02	1.80	0.04
CRI	3070	1.00	1.02	1.75	0.04	2528	1.00	1.02	1.69	0.04
CZE	5297	1.00	1.01	1.63	0.02	3169	1.00	1.01	1.19	0.01
DEU	3895	1.00	1.01	1.36	0.02	2313	1.00	1.01	1.83	0.02
DNK	4684	1.00	1.01	1.19	0.01	4156	1.00	1.00	1.14	0.01
ESP	20656	1.00	1.01	1.49	0.02	13923	1.00	1.01	2.12	0.02
EST	4622	1.00	1.01	1.27	0.01	3062	1.00	1.01	1.37	0.01
FIN	5601	1.00	1.01	1.30	0.01	5108	1.00	1.01	1.64	0.02
FRA	3129	1.00	1.01	1.38	0.02	2108	1.00	1.01	1.25	0.02
GBR	10195	1.00	1.01	1.74	0.01	7414	1.00	1.01	1.87	0.02
GRC	4744	1.00	1.01	1.35	0.01	1068	1.00	1.01	1.17	0.01
HKG	2669	1.00	1.05	3.18	0.10	2518	1.00	1.04	2.48	0.07
HRV	4515	1.00	1.01	1.17	0.01	3099	1.00	1.01	1.18	0.01
HUN	3922	1.00	1.01	1.45	0.01	2701	1.00	1.01	1.68	0.02
IDN	3876	1.00	1.02	2.26	0.04	2690	1.00	1.04	6.69	0.12
IRL	2938	1.00	1.01	1.25	0.01	2986	1.00	1.01	1.20	0.01
ISL	3124	1.00	1.00	1.11	0.01	1909	1.00	1.00	1.11	0.01
ITA	25980	1.00	1.01	1.75	0.02	18139	1.00	1.01	1.30	0.02
JOR	5988	1.00	1.01	1.73	0.03	3667	1.00	1.01	2.56	0.05
JPN	5705	1.00	1.01	1.56	0.02	3872	1.00	1.01	1.34	0.02
KAZ	5126	1.00	1.01	5.90	0.07	3042	1.00	1.00	1.30	0.01
KOR	4974	1.00	1.01	1.37	0.02	3133	1.00	1.01	1.43	0.02
LIE	308	1.00	1.01	1.29	0.02	187	1.00	1.01	1.05	0.01
LTU	4082	1.00	1.01	2.03	0.02	2843	1.00	1.01	1.58	0.02
LUX	4115	1.00	1.01	1.30	0.01	2926	1.00	1.01	1.76	0.02
LVA	4357	1.00	1.01	1.30	0.01	2350	1.00	1.01	1.16	0.01
MAC	5199	1.00	1.02	3.11	0.05	2808	1.00	1.03	1.95	0.05
MEX	31919	1.00	1.02	3.06	0.05	18373	1.00	1.02	2.46	0.04
MNE	4077	1.00	1.01	1.10	0.01	2853	1.00	1.01	1.13	0.01
MYS	2943	1.00	1.01	1.26	0.01	1894	1.00	1.01	1.18	0.01

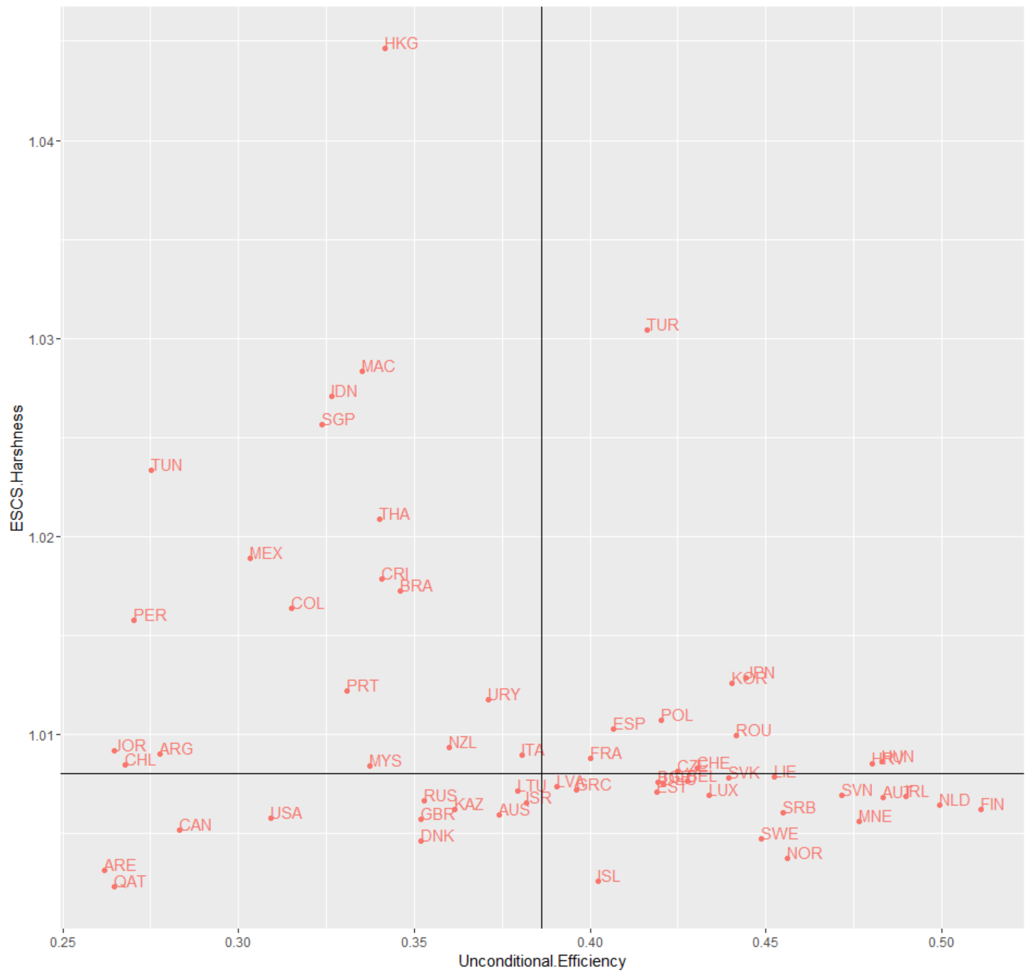
Table 1.3 Continued

Countries	2009					2012				
	Obs.	Min.	Aver.	Max.	S. Dev.	Obs.	Min.	Aver.	Max.	S. Dev.
NLD	3054	1.00	1.01	1.42	0.02	2333	1.00	1.01	1.18	0.01
NOR	4620	1.00	1.00	1.14	0.01	2663	1.00	1.00	1.55	0.01
NZL	4239	1.00	1.01	2.25	0.03	2521	1.00	1.01	1.48	0.02
PER	3106	1.00	1.02	1.70	0.04	1927	1.00	1.01	1.40	0.03
POL	4852	1.00	1.01	1.20	0.01	2997	1.00	1.01	1.38	0.02
PRT	3813	1.00	1.01	1.22	0.02	2341	1.00	1.01	1.32	0.02
QAT	6198	1.00	1.00	1.17	0.01	3268	1.00	1.00	1.09	0.00
ROU	3145	1.00	1.01	1.69	0.02	2759	1.00	1.01	3.59	0.08
RUS	4684	1.00	1.01	1.13	0.01	3037	1.00	1.01	1.20	0.01
SGP	4257	1.00	1.03	1.53	0.04	3670	1.00	1.03	2.61	0.06
SRB	4449	1.00	1.00	1.73	0.02	2723	1.00	1.01	1.16	0.01
SVK	4048	1.00	1.01	1.39	0.01	2286	1.00	1.01	1.15	0.01
SVN	5498	1.00	1.01	1.23	0.01	2968	1.00	1.01	1.21	0.01
SWE	4041	1.00	1.00	1.13	0.01	2788	1.00	1.00	1.28	0.01
THA	5578	1.00	1.02	1.70	0.03	4031	1.00	1.02	2.15	0.06
TUN	4873	1.00	1.02	2.57	0.06	1742	1.00	1.02	3.70	0.10
TUR	4416	1.00	1.02	1.76	0.04	1671	1.00	1.04	2.95	0.07
URY	4834	1.00	1.01	1.80	0.02	2130	1.00	1.01	1.32	0.02
USA	4360	1.00	1.01	1.47	0.01	2625	1.00	1.01	1.20	0.01

Source: Author’s elaborations on OECD PISA database (2009, 2012).
Note: The averages are weighted by input shares.

The first relevant evidence is that the ESCS makes the difference in the education performances. Indeed, as shown in table 1.3, the indexes of environmental harshness are relevant and pervasive, showing a strong variability within countries, between countries and across years (see the correlation matrix in table A1.1 in the Appendices). In particular, one can observe that one expects higher indexes in those countries where the ESCS are more heterogeneous, as this means that the correction provided by the conditional estimates are more marked. Indeed, looking at the average of the period, the highest indexes of ESCS harshness have been found in Hong Kong, Turkey, Macao, Indonesia, and Singapore. On the opposite side, one can find Qatar, Island, Arab Emirates, Norway, Denmark, and Sweden have indices close to one, which means that there is no difference between student performances ignoring and controlling for ESCS. In order to give a graphical idea of the results obtained, figure 1.4 reports a quadrant representation of the unconditional efficiency (x axis) and of the ESCS harshness (y axis) at country level.

Figure 1.4 – Quadrant representation of Unconditional Efficiency and ESCS Harshness at Country level



Source: Author's elaboration on OECD PISA database (2009, 2012). Notes: Country-level 2009-2012 averages weighted by input shares; The lines are on the median values.

Considering the average values of 2009 and 2012, four different groups of educational systems can be identified. In the upper right quadrant, there are countries showing good performances in terms of unconditional efficiency, but also high impact of the ESCS on efficiency (Turkey, Poland, Romania, Hungary, Croatia, Japan and Korea). In line with Agasisti and Longobardi (2014), our estimates show that, in these countries, there are high percentages of “resilient students” (i.e., students from a disadvantaged socio-economic background who achieve relatively high levels of performance in terms of education). Therefore, the already good performances of these systems could be further improved by improving the student level of economic, social and cultural status, i.e., reducing the differences in the starting point of the students within the countries regardless of the specific public provisions targeted to the educational sector.

On the lower right quadrant in figure 1.4, instead, there are countries showing the best performances and low ESCS harshness. Northern-European and Scandinavian countries fall into this class. As expected, the lower impact of the ESCS index is mainly explained by the relative greater homogeneity of social and cultural conditions in countries like Sweden, Denmark, Norway, Finland, Luxembourg, Iceland, and other similar systems (Esping-Andersen and Wagner, 2012).

On the lower left quadrant, there are countries with low unconditional efficiency and a low ESCS impact on the performances, including some Middle-East countries (Arab Emirates and Qatar) and the Anglo-Saxon systems (USA, Canada and UK). To some extent, this may imply that the measured inefficiency is independent from ESCS, meaning that other sources of inefficiency (e.g., institutional factors, migration, etc.) may be important in explaining the underperformances at student level (Chetty *et al.* 2016; Raitano and Vona, 2016; Chetty and Hendren, 2015; Andersson *et al.* 2010; Entorf and Minoiu, 2005).

Finally, the upper left quadrant includes countries with low efficiency and a high ESCS harshness, which seems a characteristic of many South-East Asian countries (Hong Kong, Macao, Indonesia, Singapore, and Thailand), and of South American countries (Brazil, Colombia, and Argentina among others). Again, where the heterogeneity of the social and cultural conditions is strong, and where at least part of the measured inefficiency may indeed be due to the ESCS index. It is in these countries that, in order to get a general improvement of the education performances, it becomes particularly important to improve the student level of ESCS.

1.4.2. The effect of ESCS by income groups

In this section, we investigate whether relevant differences in average inefficiencies that have been found among countries, may have some definite patterns across the same countries when classified by income groups. To this purpose, the previous results are aggregated by income groups according to the World Bank's classification, and reported in table 1.4, which includes the values of both unconditional (U) and conditional (C) efficiency for high income (HI), upper-medium income (UMI) and lower-medium income (LMI) countries.

Table 1.4 – Average Efficiencies for Income group

Index		2009			2012		
		HI	UMI	LMI	HI	UMI	LMI
Efficiency	U.	0.37	0.32	0.31	0.38	0.34	0.34
	C.	0.37	0.33	0.32	0.38	0.35	0.35
Learning T. Slack	U.	0.53	0.51	0.50	0.52	0.49	0.45
	C.	0.58	0.61	0.62	0.57	0.59	0.59
Math Slack	U.	0.27	0.53	0.64	0.26	0.49	0.62
	C.	0.12	0.20	0.22	0.12	0.19	0.20
Language Slack	U.	0.28	0.47	0.52	0.26	0.45	0.53
	C.	0.14	0.16	0.13	0.12	0.16	0.12
Science Slack	U.	0.27	0.52	0.61	0.26	0.48	0.61
	C.	0.13	0.20	0.20	0.12	0.19	0.19

Source: Author's elaborations on OECD PISA database (2009, 2012).
Notes: High Income (HI), Upper Medium Income (UMI) and Lower Medium Income (LMI); The average Efficiencies are weighted on the input shares; The Slacks are the ratios of total slack on the total relative variable; U=Unconditional, C=Conditional.

The first relevant evidence in table 1.4 is that there is a general improvement in the performances between 2009 and 2012 for all income groups. A tendency that matches with the findings by OECD (2015). At the same time, the improvement is more marked in LMI and UMI countries, which may be at least partially an effect of a catching-up process of those countries that are lower in the efficiency scale, even though HI countries have best performances in both periods according to both U and C models. HI countries also show the lowest impact of the ESCS on the performances both in 2009 and in 2012, while efficiency – as expected – is higher in UMI and LMI countries when controlling for the ECSC.

Since the SBM model is non-radial, our overall efficiency index can be decomposed into the variable-specific efficiency scores, using the ratios of slacks on the original variables (see section 1.3). It is worth recalling that this an important feature of the model used in the analysis, since it allows to estimate both the conditional and unconditional performance on each variable (learning time, math, reading, and science scores).

The slacks presented in table 1.4 are the relative feasible improvements in each input and outputs. Two opposite trends in outputs and input slacks can be identified. On the outputs side, the unconditional slacks are higher than the corresponding conditional measures for all income groups both in 2009 and 2012. Furthermore, the difference between the unconditional and conditional slacks (the ESCS effect) increases when income decreases both in 2009 and 2012, suggesting that economic, social and cultural background may be more relevant in poorer countries. An opposite path is identified on the input side (learning time), where the unconditional slacks are lower than conditional slacks for all income groups both in 2009 and 2012. Also in this case, the difference between the unconditional and the conditional input slacks increases when income decreases.

The last phenomenon may appear paradoxical because, since the Production Possibility Set of the unconditional Technology is equal or bigger than the Production Possibility Set of the conditional Technology, the expectation is that the conditional efficiency is higher than the unconditional efficiency in all the variables. However, while this is true for the overall efficiency, when the overall index is decomposed into the variable-specific efficiency scores, in the non-radial models nothing guarantees that the proportions among the variables are maintained, and consequently the conditional inefficiency (slack) can even be higher than the unconditional inefficiency (slack) in some variables.

In our specific case of the PISA 2009-2012 database, from the input side the students living in HI countries have, in average, more learning time than the students living in UMI countries, and the students living in UMI countries have more learning time than the students living in LMI countries[40]. From the output side the students living in the HI countries have far more attainments than the students living in UMI countries, and the students living in UMI countries have more attainments than the students living in LMI countries[41].

In the unconditional estimates, the HI students outperform the UMI, and the UMI are more efficient than the LMI students (third row in table 1.4). It follows that, on the unconditional frontier there are, in average, more HI students, and when the LMI and UMI students are compared with this frontier, they have pervasive slacks on the output side, but they have relatively less slacks on the input side (fifth, seventh, ninth, and eleventh row in table 1.4), because the reference HI students are using in average more input.

In the conditional estimates many HI students with higher ESCS are often excluded from the frontier by the fourth constraint in program (1.15). Thus, on average, there are less HI students on the conditional frontier than HI students on the unconditional frontier. It follows that when the LMI and UMI students are compared with the last frontier, the conditional slacks are less pervasive on the oputput vector, but they are bigger on the input side (sixth, eigth, tenth, and twelfth row in table 1.4). This is because the students on the conditional frontier (more UMI and LMI) are using less input than the students on the unconditional frontier (more HI). In other terms, this effect is due to the fact that ESCS has positive correlation both with the input and the outputs (see figure 1.2).

These trends cannot be examined by using the traditional radial measures of efficiency, because the radial models can only estimate an index of overall efficiency, and they ignore what happens to the specific-variables considered. Moreover these evidences make clear that ESCS are extremely relevant for policy decisions on education systems. Neglecting the impact of this effect may not only lead to identify wrong results on the efficiency rankings of countries, but may also drive policymakers to wrong decisions and policy advices that

[40] The average learning time 2009-2012 is: 665.26 in the HI countries, 632.20 in the UMI countries, and 596.37 in the LMI countries.
[41] The average math score 2009-2012 is: 502.52 in the HI countries, 416.72 in the UMI countries, and 379.29 in the LMI countries. The average language score 2009-2012 is: 520.78 in the HI countries, 447.18 in the UMI countries, and 422.19 in the LMI countries. The average science score 2009-2012 is: 520.41 in the HI countries, 434.91 in the UMI countries, and 397.123 in the LMI countries.

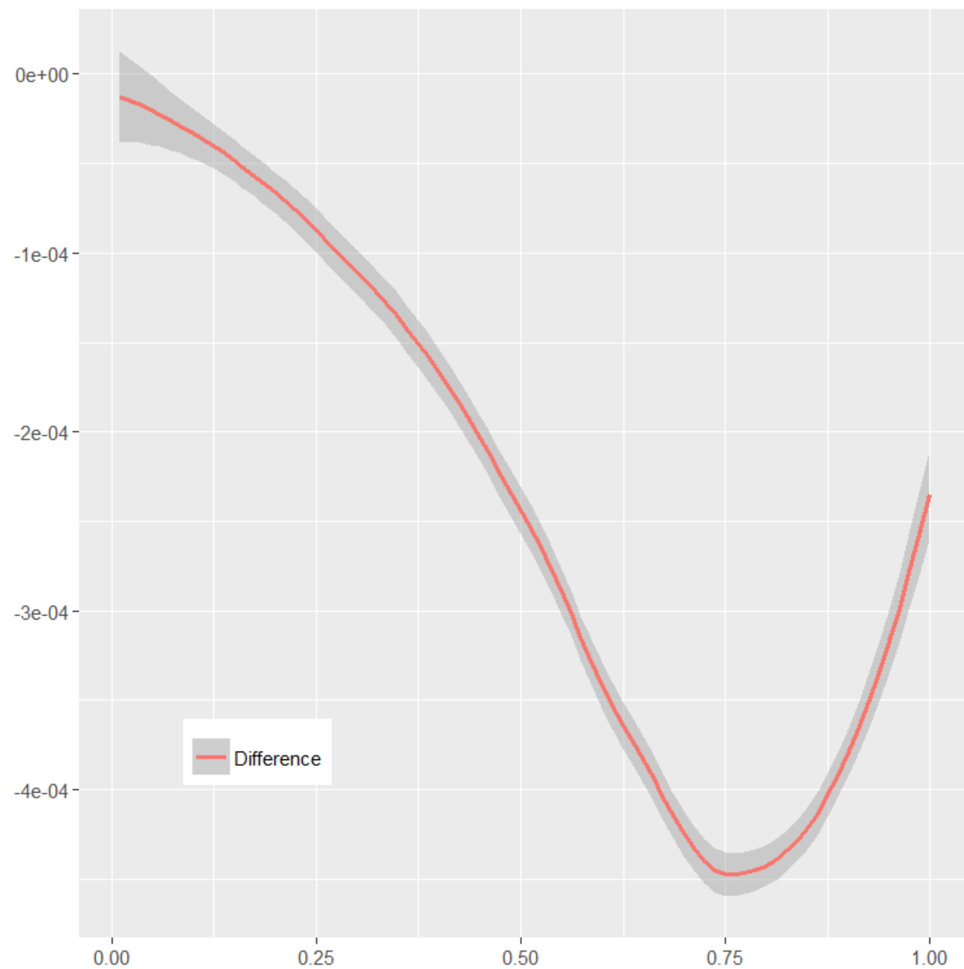
may significantly differ from the outcomes obtained when controlling for ECSC. Technically because ignoring ESCS, the risk is to compare systems with different productive processes.

These results may be translated in terms of feasible improvements. Focussing on the input side, there is a significant part of inefficiency, expecially in UMI and LMI countries, that cannot be seen when the ESCS effect is not taken into account in the analysis. By looking in the output vector, greater feasible improvements should be possible in UMI and LMI – especially in maths and science – if some of the disadvantageous ESCS conditions were removed. This makes a huge difference with the HI countries, where these feasible improvements are still possible but of less relevant.

1.4.3. The inequalities in education performances

This section deals with inequalities of the estimated student performances. The country perspective is therefore replaced by an analysis where efficiency at the student level is considered. In order to capture whether the ESCS has an impact on the inequality of the distribution of students' performances, figure 1.5 reports the difference between the Lorenz curve of the unconditional efficiency indices (LU) and the Lorenz curve of the conditional efficiency indices (LC).

Figure 1.5 – Difference between Lorenz Curves on Conditional and Unconditional indices of efficiency



Source: Author's elaboration on OECD PISA database (2009, 2012). Notes: Grey borders are the 95 percent confidence interval; The shape does not change by using the concentration curves, and by changing the cumulates (Unconditional and Conditional) by which the series are sorted.

It is of some relevance to note that LU always dominates LC, which means that students' performances may appear more equally distributed when not controlling for ESCS. The explicit consideration of ESCS, instead, reveals that inequality is greater than that estimated by the conventional methods, by this way suggesting once more that controlling for ESCS is fundamental for the policy analysis. This apparently counterintuitive result may be explained by the fact that when controlling for ESCS there are more students that becomes close to the maximum efficiency relative to their background, possibly generating a greater dispersion with respect to students that are left behind. In terms of Lorenz curve, this means that LC may cumulate a greater number of high scores, by this way recording a higher concentration when students are ranked by their efficiency score level. Thus, what appears counterintuitive *prima facie*, is in line with the expected outcome of controlling for ESCS. When the unconditional frontier is shifted, more students are more efficient and obtain a higher score, which contributes to increase the distance among students that are inefficient because of a low ESCS and those that are instead inefficient for other reasons. This aggregate result, however, may not necessarily be the outcome in each single country, as it will be shown below (table 1.6), even though it appears as a general tendency of the analysis.

Total observed inequality can then be decomposed in order to estimate the variability *Between* and *Within* countries according to equation (1.18). To this purpose, table 1.5 reports the Theil index for students' performances, with three additive components: the *Between* macro regions (corresponding to the sub-regional groups in the United Nations geoscheme[42]); the *Between* countries (estimated within the macro regions); and the *Within* countries.

Table 1.5 – Theil Index

Year	Total		Betw. Macro Reg.		Betw. Countries		Within Countries	
	U	C	U	C	U	C	U	C
2009	0.0556	0.0559	0.0092	0.0089	0.0055	0.0055	0.0409	0.0415
2012	0.0555	0.0560	0.0087	0.0085	0.0057	0.0057	0.0411	0.0418

Source: Author's elaborations on OECD PISA database (2009, 2012).
Notes: The Macro Regions are the sub-regional groups in the United Nations geo-scheme; The Between Countries is estimated considering the Macro Regions; U = Unconditional; C = Conditional.

The first relevant evidence is that almost the four-fifths of the global inequality in education performances is due to inequality *Within* countries, which means that ESCS is a relevant variable to control for the heterogeneity of the initial conditions in any specific country. Indeed, the decreasing path of inequality between macro regions suggests that there is a convergence in the average performances of macro regions, both with the conditional

[42] The considered sub-regional groups are: Australia and New Zealand; Central America; Central Asia; Eastern Asia; Eastern Europe; Northern Africa; Northern America; Northern Europe; South America; South-Eastern Asia; Southern Europe; Western Asia; and Western Europe.

and the unconditional approach. It is worth recalling that the average improvement of performances has involved LMI and UMI countries more than HI countries, a feature that has been interpreted as caused by some catching-up process of best performances. Combining this result with inequality of performances may suggest that this catching-up may occur at the price of amplifying inequalities within macro regions and countries. Remarkably, the general tendency in the inequalities of education performances is in line with the trend of the world distribution of income (Liberati, 2015; Arestis *et al.* 2011). This evidence extends to the efficiency, the findings reported in OECD (2013) about the link between inequality in literacy and numeracy skills, and inequality in the distribution of income.

Furthermore, as reported in table 1.6 where the *Within* index is calculated at country level, there is some evidence that the highest contribution to global *Within* inequality comes from many North and South American countries (Argentina, Peru, Colombia, Canada, Uruguay, and USA among others) and from many South East Asian countries (Indonesia, Thailand, and Malaysia).

Table 1.6 – Country level Within Theil indices

Countries	2009		2012	
	U	C	U	C
ARE	0.0513	0.0513	0.0609	0.0610
ARG	0.0958	0.0955	0.0848	0.0849
AUS	0.0394	0.0399	0.0317	0.0325
AUT	0.0475	0.0479	0.0457	0.0461
BEL	0.0336	0.0341	0.0307	0.0313
BGR	0.0434	0.0433	0.0386	0.0384
BRA	0.0556	0.0563	0.0601	0.0609
CAN	0.0657	0.0662	0.0680	0.0686
CHE	0.0327	0.0337	0.0349	0.0355
CHL	0.0503	0.0507	0.0614	0.0618
COL	0.0639	0.0641	0.0712	0.0718
CRI	0.0303	0.0314	0.0309	0.0315
CZE	0.0415	0.0424	0.0385	0.0389
DEU	0.0339	0.0346	0.0324	0.0330
DNK	0.0364	0.0366	0.0424	0.0425
ESP	0.0302	0.0309	0.0296	0.0304
EST	0.0268	0.0273	0.0247	0.0253
FIN	0.0255	0.0262	0.0279	0.0285
FRA	0.0429	0.0435	0.0431	0.0434
GBR	0.0295	0.0299	0.0343	0.0349
GRC	0.0278	0.0282	0.0104	0.0107
HKG	0.0355	0.0417	0.0398	0.0447
HRV	0.0399	0.0400	0.0395	0.0397
HUN	0.0299	0.0301	0.0292	0.0296
IDN	0.0969	0.0979	0.0874	0.0889
IRL	0.0299	0.0304	0.0287	0.0293
ISL	0.0320	0.0322	0.0355	0.0357
ISR	0.0508	0.0513	0.0481	0.0487
ITA	0.0451	0.0457	0.0347	0.0355
JOR	0.0214	0.0215	0.0328	0.0344
JPN	0.0297	0.0308	0.0335	0.0346
KAZ	0.0285	0.0289	0.0639	0.0641
KOR	0.0182	0.0195	0.0286	0.0294
LIE	0.0371	0.0379	0.0287	0.0286
LTU	0.0330	0.0332	0.0172	0.0176
LUX	0.0434	0.0436	0.0366	0.0374
LVA	0.0283	0.0286	0.0258	0.0261
MAC	0.0143	0.0169	0.0286	0.0313
MEX	0.0444	0.0455	0.0490	0.0499
MNE	0.0281	0.0282	0.0245	0.0246
MYS	0.0491	0.0491	0.0701	0.0700

Table 1.6 Continued

Countries	2009		2012	
	U	C	U	C
NLD	0.0310	0.0313	0.0484	0.0486
NOR	0.0148	0.0150	0.0348	0.0352
NZL	0.0277	0.0290	0.0307	0.0320
PER	0.0764	0.0765	0.0600	0.0601
POL	0.0171	0.0179	0.0165	0.0176
PRT	0.0416	0.0418	0.0461	0.0467
QAT	0.0588	0.0588	0.0302	0.0302
ROU	0.0336	0.0335	0.0416	0.0422
RUS	0.0390	0.0394	0.0466	0.0469
SGP	0.0573	0.0599	0.0212	0.0244
SRB	0.0507	0.0508	0.0409	0.0412
SVK	0.0668	0.0671	0.0600	0.0601
SVN	0.0238	0.0242	0.0181	0.0184
SWE	0.0428	0.0431	0.0362	0.0367
THA	0.0639	0.0638	0.0585	0.0599
TUN	0.0135	0.0149	0.0598	0.0626
TUR	0.0565	0.0570	0.0475	0.0485
URY	0.0579	0.0582	0.0603	0.0604
USA	0.0569	0.0571	0.0613	0.0614

Source: Author’s elaborations on OECD PISA database (2009, 2012).
Note: U = Unconditional; C = Conditional

A lower contribution, instead, comes from some European and Asian countries (Macao and North Korea). These results, with the exception of Malaysia, Kazakhstan, Qatar, Singapore, Tunisia, and Jordan, are rather stable across years and indices. Combining the information about the inequality of students’ performances at country level with the corresponding information on inefficiency – as shown in table A1.1 of the Appendices – finally reveals that, on average, those countries with more inequality are also the more inefficient. Thus, in line with Raitano and Vona (2016) and OECD (2013), the perceived trade-off between equity and efficiency in education (Hanushek and Wößmann, 2006), is not confirmed by our analysis.

1.5. Conclusions

This chapter investigates the impact of Economic, Social, and Cultural Status on the education performances at student level, in all countries where the PISA data are available. The analysis is conducted at student level, allowing to combine micro and macro effects. In order to link the literature on efficiency and inequality, a methodology employed in efficiency studies has been used, with the aim of conditioning the results to the level of the ESCS index, widely investigated in the inequality of opportunity literature.

From a methodological perspective, the innovative feature of the chapter is to combine the consolidated conditional procedure, proposed by Ruggiero (1996), with a non-radial model: the Slack Based Measure model proposed by Tone (2001). The analysis is conducted on the PISA surveys for 2009 and 2012, using learning time as input, and the student achievement in the three subjects of PISA survey (math, reading, and science) as outputs.

A strong and widespread effect of the ESCS on the student performances is found. This effect has a pervasive heterogeneity among variables, students, and countries. Some of those heterogeneity, in particular the heterogeneity among the slacks in mathematics, language, and science, cannot be found by using the traditional (radial) DEA models. In many systems with pervasive inefficiencies (South American and South East Asian countries), a relevant part of the lacks is due to the presence of bad environments, as measured by a low ESCS. On the contrary, in many Anglo-Saxon and Middle East systems, the pervasive inefficiency is independent from the ESCS. These different roles of the ESCS in the presence of inefficiency in different countries clearly reveal the importance to control for environmental factors when making decisions on the education systems. Furthermore, in line with some previous studies, there is evidence that some of the problems of the education sector may not be due to the education systems themselves, but to the socio-economic gaps.

When an average improvement of students' performances has been found, this improvement is usually higher in LMI and UMI countries than in HI Countries. This catching-up phenomenon among countries may be possibly attributed to a general improvement of the technology and the possibility to get information in simpler ways at lower costs, but also to the fact that students and teachers have begun to familiarize with the test. However, there are also a strong evidences that inequalities within countries have increased in the same years, suggesting that those improvements may not equally spread their benefits. This last conclusion may prove particularly important for the more general issue of inequality of opportunities, where free education should be combined with the removal of all barriers to social mobility that are imputable to the socio-economic background of students.

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Appendices

Table A1.1 – Rank Correlations (95 % bootstrap upper and lower bounds)

	Un. 2009	Un. 2012	Harsh. 2009	Harsh. 2012	Theil Un. 2009	Theil Un. 2012	Theil Con. 2009	Theil Con. 2012
Un. 2009	1							
LB	0.820							
Un. 2012	0.904	1						
UB	0.951							
LB	-0.541	-0.529						
Harsh. 2009	-0.298	-0.262	1					
UB	-0.001	0.025						
LB	-0.464	-0.424	0.740					
Harsh. 2012	-0.225	-0.193	0.872	1				
UB	0.048	0.039	0.968					
LB	-0.627	-0.599	-0.217	-0.112				
Theil Un. 2009	-0.397	-0.362	0.100	0.154	1			
UB	-0.117	-0.111	0.391	0.404				
LB	-0.663	-0.615	-0.147	-0.198	0.472			
Theil Un. 2012	-0.462	-0.402	0.117	0.091	0.675	1		
UB	-0.208	-0.151	0.349	0.350	0.834			
LB	-0.646	-0.593	-0.179	-0.114	0.991	0.457		
Theil Con. 2009	-0.407	-0.372	0.123	0.179	0.998	0.672	1	
UB	-0.116	-0.087	0.410	0.436	0.999	0.844		
LB	-0.673	-0.625	-0.106	-0.151	0.411	0.986	0.402	
Theil Con. 2012	-0.481	-0.419	0.152	0.129	0.644	0.996	0.644	1
UB	-0.229	-0.170	0.386	0.375	0.841	0.999	0.829	

Source: Author's elaborations on OECD PISA database (2009, 2012).
Note: The indices are at country level, Bootstrap with 1000 replicates using R package by Hervé (2015); Un. = Unconditional, Harsh. = Harshness, Con. = Conditional; LB = Lower Bound, UP = Upper Buond.

2. Exploring health outcomes by Stochastic Multi-Objective Acceptability Analysis. A regional analysis of the Italian case[43]

Abstract

This chapter introduces the Stochastic Multi-Objective Acceptability Analysis (SMAA) in order to investigate the evolution of the health care performances in the Italian regions over the period 1990-2013. We propose to explore the overall outcome of health sector by a Composite Index of mortality based on the combination of standardized mortality rates for seventeen different diseases. From a methodological standpoint, we propose to overcome the arbitrariness of the weighting process, by using the SMAA, which is a methodology that allows to rank regions considering the whole set of possible vectors of weights. Moreover, we explore the spatial segregation in health using the multidimensional generalization of the Gini index, and introducing the multidimensional generalization of the Analysis of Gini (ANOGI). The unprecedented use of SMAA in evaluating the health sector allows us to explore regional multidimensional paths beyond the order of importance given to the single dimensions. Our analysis shows that in the 24 years considered there has been no convergence path in terms of health care performances in Italy, neither between nor within regions. High level of stratification is in some areas of the South, and some provinces in the Centre-North converge beyond the regional borders.

JEL Codes: H75, I14, C44.

Keywords: Stochastic Multi-Objective Acceptability Analysis; Composite Indicators; Health; Spatial Inequality; ANOGI

[43] This chapter has been produced within a project in collaboration with Raffaele Lagravinese (Department of Economics and Finance, University of Bari "A. Moro" and CEFIP, Roma Tre University) and Paolo Liberati (Department of Economics and CEFIP, Roma Tre University). The short version of the essay is in Lagravinese, R., Liberati, P., Resce, G. (2017). Exploring Health Outcomes by Stochastic Multi-Objective Acceptability Analysis: An application to Italian Regions. GEN Working Paper B 2017 – 3. Currently, the paper is under revision in European Journal of Operational Research.

2.1 Introduction

One of the most problematic issues in evaluating the health care sector is that its outcome is multidimensional and consequently should not be assessed by one single metric[44]. The multidimensionality of health is not easily addressed in the evaluation literature for two main reasons. First, agreement on what indicators should be considered to evaluate the performance of the health sector is not trivial. Second, even assuming a solution for the first issue, the problem remains of how to weigh different indicators in one single index.

This chapter addresses these two issues by proposing a new methodology for comparing the regional performance of the Italian health sector. With regard to the first point, a solution of multidimensionality is proposed by using mortality rates caused by different diseases. Mortality rates are among the most important comparable sources of information on health. Registering death is compulsory in almost all countries, and the data collected are often used to monitor diseases and health status, plan health services, and compare health care systems (OECD, 2016). Furthermore, mortality rates are often used as a robust outcome of the health care system and have been extensively used to get information about the efficiency and the effectiveness of managerial organization (among others: Or, 2001; Häkkinen, Joumard, 2007; Porcelli, 2014; Medin *et al.* 2015; Cavalieri, Ferrante, 2016).

In this respect, the Italian case is worthy of attention, as it shows a large heterogeneity of mortality rates among regions which are partly explained by the unresolved social-economic dualism between the Northern and Southern regions. In addition, Italy has experienced a significant decentralization of the health sector since more than fifteen years ago, whose progress may be fruitfully investigated through the evolution of mortality rates in different areas of the country. To this purpose, a Composite Index (CI) of health outcome is advanced in this chapter, built as a combination of 17 standardized mortality rates collected in Italian regions by ISTAT (2017) and covering the most widespread diseases.

[44] Among others, Klomp, de Haan (2010) suggest that multidimensionality is intrinsic in the definition of health provided in the Constitution of the World Health Organization (World Health Organization, 1946).

However, the need for multidimensionality, as well as our choice of mortality rates, leaves the issue of how to weigh different indicators unresolved. From an operational perspective, the concerns about treating multidimensional outcomes have paved the way to the development of Composite Indicators (see Nardo *et al.* 2008; Costanza *et al.* 2016). While a CI summarizes different dimensions into a single metric (OECD, 2017), the problem remains of how to assign a weight to those dimensions. The focal point in the literature is that in order to aggregate many dimensions into one single index, a choice must be made about the relative importance of each dimension, as different weights may give rise to significant differences in the final synthetic evaluation (Cherchye *et al.* 2008; Foster *et al.* 2009; Permanyer, 2011; Costanza *et al.* 2016; Patrizii *et al.* 2017; Greco *et al.* 2017).

In line with the Tiebout (1956) seminal work, we argue that the importance attached to single outcomes of public services may change according to individual preferences. In the health care sector, preferences are directly related to needs. For instance, a young family might be more interested in the 'mortality rate for complications of pregnancy' rather than in the 'mortality rate for tuberculosis', while an old man might be more interested in the 'mortality rate for disease circulatory system'. Given a differentiation in needs and in the health care specialization among different regions, it could be reasonable to expect that some regions would be 'more preferred' by some categories of individuals, and 'less preferred' by others. In this context, the choice of weights by which the single outcomes are aggregated in a CI to evaluate the overall performance of the health sector, may affect the representativeness of the final synthetic proxy. In other words, any single vector of weights allows to build a CI that, at the best, represents a satisfactory proxy of outcome for a fraction of the population exclusively.

To overcome this criticism, our proposal is to aggregate the 17 mortality rates considering the whole space of feasible weights vectors. From a methodological standpoint, we use the idea of Greco *et al.* (2017), where the Stochastic Multi-Objective Acceptability Analysis (SMAA) approach (Lahdelma *et al.* 1998; Lahdelma, Salminen, 2001) is used to take into account a large sample of randomly extracted vectors of weights to rank regions. According to this methodology, each region is assigned a probability of being in a given position in the national rank in terms of the composite index. With this innovative approach, we propose to summarize the multidimensional health outcome without any assumption about the individual preferences and thus without any *a priori* judgement on specific vectors of weights.

Our results show a pervasive and persistent territorial segmentation in the Italian health care sector, regardless of the set of weights that is used to aggregate mortality rates. Furthermore, evidence of significant spatial segregation both between and within regions emerge from our estimates. Both the multidimensional Gini index, originally proposed in Greco *et al.* (2017), and the multidimensional generalization of Analysis of Gini (ANOGI) - Yitzhaki (1994) -, introduced for the first time in this study, confirm and reinforce these findings.

The rest of the chapter is organized as follows. Section 2.2 describes the Italian National Health Service. Section 2.3 introduces the dataset, the SMAA methodology, the multidimensional Gini Index, and the multidimensional ANOGI. Section 2.4 discusses results, and section 2.5 concludes.

2.2 The institutional framework

The Italian National Health Service (NHS), introduced in 1978, is a universal health care system providing comprehensive health insurance coverage and uniform health benefits to the whole population. Since its introduction, and like other European countries (see Costa Font and Greer 2013), the Italian NHS has undergone important reforms to decentralize health management and policy responsibilities to the sub-layers of government (Turati 2013). Italy is divided into 20 regions: 15 are ordinary statute regions (OSRs) and 5 are special statute regions (SSRs)[45]. After one of the most important federal reforms (Legislative Decree 56/2000), each region is responsible for the organization of the health system, following the guidelines defined by the central government.

[45] The difference between OSRs and SSRs is mostly linked to the way they are financed.

A first step towards the organization of a fiscal decentralized system was the introduction of two regional taxes in 1998: the regional tax on productive activities (RTPA) and the regional personal income tax (RPIT). The revenue from these two taxes covers a significant share of the cost of the national health system. However, given the heterogeneity of the Italian regions in economic, social and demographic terms, these two regional taxes are not sufficient to finance the health system. Since both RTPA and RPIT are positively related to per capita GDP and their revenues greatly vary among Italian regions (Lagravinese *et al.* 2017), this requires an equalization fund (funded by a system of VAT revenue-sharing and by the tax on petrol) to compensate for different regional fiscal capacities (Cavalieri, Ferrante, 2016).

A second step towards the decentralization of the health system was the definition of the Essential Levels of Health Service (LEA, *Livelli Essenziali di Assistenza*), and the Constitutional reform of 2001. The reorganisation assigned the responsibility for the provision of health to regions, at the same time keeping the power to regulate and to finance health functions at the central level (Cappellaro *et al.* 2009; Ferrario, Zanardi, 2011). LEA is not a problematic issue per se; it is a list of health care services that the central government requires to be guaranteed in all regions[46]. However, the separation of financing responsibilities from expenditure responsibilities in the provision of LEA (and before LEA in the provision of uniform levels of service), has provided a non-negligible incentive to the uncontrolled growth of Italian health expenditure. This has historically contributed in creating bailing out expectations in regional behaviour (Liberati, 2003), in a context of often inadequate regional health governance and accountability (Carinci *et al.* 2012; Lagravinese, Paradiso, 2014).

The focus on the regional health sectors, however, should not disregard the fact that Italy is historically a dual country in many dimensions (among others, Del Monte, De Luzenberger, 1989; Spadavecchia, 2007; Torrisi *et al.* 2015). In the Southern regions, on average, socioeconomic conditions, social capital and administrative behaviour are of poorer

[46] The LEA list was recently updated by a ministerial decree in 2017.

quality than in the Northern regions (Charron *et al.* 2014; Greco *et al.* 2017). Significant differences also exist in GDP per capita (on average 31,045 euros in the Centre-North and 17,436 euros in the South), unemployment rates (9.1% in the Centre-North and 19.7% in the South), and deprivation index (15.3 point in the Centre-North and 40.8 point in the South)[47]. In 2013, per capita public expenditure on health amounts to 1,816 euros (see table 2.1), but their level varies widely, due to both different socio-economic conditions and different management strategy in regional health systems. While the North and the Centre are clearly above the average national value (1,839 and 1,877 euros, respectively), the South is below the same average (1,727 euros) despite the high level of spending in Molise (2,210 euros). In the Northern regions, Aosta Valley registers the highest per capita expenditure (2,145 euros), followed by Trentino[48] (2,085 euros), and Friuli (2,040 euros)[49]. Per capita expenditure is lower in Veneto (1,710 euros), Campania (1,668) and Sicily (1,719 euros).

[47] Source ISTAT: Rilevazione sulle forze di lavoro; Indagine sul reddito e condizioni di vita (Eu-Silc).
[48] The value of Trentino is the average of the two autonomous provinces of Bolzano and Trento.
[49] All these tree regions are SSRs.

Table 2.1 – Public Health Expenditure and Mortality rates in Italy

Region	Health Expenditure per capita (current price)			Mortality rate (Standardized) Men			Mortality rate (Standardized) Women		
	1990	2001	2013	1990	2001	2013	1990	2001	2013
Piedmont	699	1271	1828	162.18	129.92	100.17	100.81	79.14	65.18
Aosta V.	751	1491	2145	171.80	141.47	98.43	90.07	83.29	61.58
Lombardy	713	1273	1818	172.68	130.32	94.74	98.98	75.58	60.81
Trentino	740	1474	2085	157.64	124.27	90.14	88.80	68.36	57.12
Veneto	762	1279	1710	161.45	122.58	95.31	91.61	70.86	60.27
Friuli	762	1355	2040	171.00	129.76	100.17	94.49	75.26	64.17
Liguria	901	1508	2003	163.51	128.44	102.15	96.71	78.37	65.42
Emilia-R.	859	1337	1860	148.85	118.03	92.25	91.37	72.41	62.15
Tuscany	780	1341	1805	147.06	118.52	94.02	91.29	72.40	61.67
Umbria	754	1306	1840	144.25	118.59	93.8	91.87	71.90	59.12
Marche	845	1319	1760	140.00	112.37	92.25	87.73	67.77	58.73
Lazio	785	1434	1962	153.83	127.59	98.08	98.47	80.17	65.02
Abruzzi	703	1385	1736	144.28	118.52	97.99	94.74	69.58	63.23
Molise	691	1377	2210	128.25	118.64	97.09	90.94	72.98	61.59
Campania	687	1301	1668	163.32	139.34	114.13	116.47	90.32	74.90
Apulia	670	1232	1764	145.96	119.18	95.76	99.09	77.64	63.70
Basilicata	584	1158	1829	144.71	122.96	98.97	98.26	75.87	62.28
Calabria	607	1263	1709	141.73	117.48	99.41	98.71	81.22	65.39
Sicily	692	1163	1719	155.60	124.58	103.83	113.28	87.28	70.52
Sardinia	686	1304	2043	143.72	127.76	98.16	95.47	76.53	60.04
Italy	734	1303	1816	156.29	125.18	98.22	98.32	77.17	64.01
North	757	1310	1839	163.24	126.37	95.97	95.99	74.83	62.04
Centre	789	1379	1877	148.44	121.43	95.75	93.67	74.89	62.62
South	667	1279	1727	150.54	126.17	103.48	104.45	81.7	68.01

Source: ISTAT (2017)

The trend of mortality rates also reflects the dualism of the country. The mortality rates in 2013 for all regions fell in comparison with 1990 and 2001. However, while in 1990 and 2001 the mortality rate was on average higher in the Northern regions, the trend reversed in 2013, with significantly higher rates in the South (of about 5 points with respect to the national average), and peaks in Campania and Sicily. Further, a significant gender gap can be identified in mortality rates in all regions[50]. Among men, the mortality rate is, on average, 34% higher than among women in 2013.

[50] Gender gap is also observed in other European countries (see OECD, 2016).

2.3 Methodology

23.1. The multidimensionality of health outcome

With the aforementioned decentralization process, the Italian regions have the organizational responsibility of the healthcare system with the ultimate aim of reducing the various causes of death and increasing the life expectancy of their resident population. The National Institute of Statistics collects several aspects of the multidimensionality of health outcome at the regional and provincial level into the 'Health for All' dataset (ISTAT, 2017). In particular, this database contains the standardized regional mortality rates for seventeen different diseases[51], along the intervals 1990-2003 and 2006-2013; and the same data at provincial level for 2003 and 2006-2013.

The advantage of using standardized mortality rates consists of isolating the influence of a different number of individuals in sub-groups of populations (Julious *et al.* 2001). In our dataset (ISTAT, 2017) the sub-groups are defined in terms of age and sex. The descriptive statistics for the regional standardized mortality rates are reported in table 2.2. It is worth mentioning that the Italian trend of standardized mortality rates from 1990 to 2013 is on average decreasing for all the causes of death, at relatively higher levels in cancer and circulatory system diseases.

[51] The 17 mortality rates are: infectious disease; AIDS; tuberculosis; cancer; disease endocrine gland; diabetes mellitus; blood disorders; mental disorders; nervous system disease; disease circulatory system; disease respiratory system; disease digestive system; disease genitourinary system; complications of pregnancy; skin condition; disease muscular system; unclearly defined symptoms.

Table 2.2 - Standardized Mortality Rates

Cause of mortality	Coverage	Min	Max	Mean	Std. Dev.
AIDS	1990-2003, 2006-2013	0.000	1.775	0.260	0.306
Complications of pregnancy	1990-2003, 2006-2013	0.000	0.270	0.012	0.025
Diabetes mellitus	1990-2003, 2006-2013	1.215	6.985	3.028	1.034
Mental disorders	1990-2003, 2006-2013	0.145	4.020	1.603	0.551
Disease digestive system	1990-2003, 2006-2013	2.535	9.365	4.699	1.361
Disease respiratory system	1990-2003, 2006-2013	4.800	14.920	7.247	1.449
Disease endocrine gland	1990-2003, 2006-2013	1.410	7.265	3.580	1.032
Infectious disease	1990-2003, 2006-2013	0.130	2.325	0.891	0.448
Skin condition	1990-2003, 2006-2013	0.000	0.500	0.127	0.058
Blood disorders	1990-2003, 2006-2013	0.135	2.355	0.634	0.375
Disease circulatory system	1990-2003, 2006-2013	24.335	69.875	42.287	9.958
Disease muscular system	1990-2003, 2006-2013	0.050	0.995	0.385	0.123
Nervous system disease	1990-2003, 2006-2013	1.085	4.405	2.667	0.608
Unclearly defined symptoms	1990-2003, 2006-2013	0.485	6.040	1.604	0.888
Tuberculosis	1990-2003, 2006-2013	0.030	0.170	0.100	0.043
Cancer	1990-2003, 2006-2013	20.560	40.725	29.422	4.067
Disease genitourinary system	1990-2003, 2006-2013	0.680	2.385	1.509	0.293

Source: ISTAT (2017)

2.3.2 The Composite Index

From a methodological perspective, Multiple Criteria Decision Analysis (MCDA, Greco *et al.* 2005; Ishizaka, Nemery, 2013) can combine multidimensional information into one index. In the MCDA problem, a set of alternatives A (regions) is evaluated on a set of criteria G's (the seventeen standardized mortality rates):

$$A = \{a_1, \dots, a_m\} \tag{2.1}$$

$$G = \{g_1, \dots, g_n\} \tag{2.2}$$

The individual function that aggregates standardized mortality rates can be assumed as the weighted average of the seventeen mortality rates multiplied by the weights associated to each of the seventeen diseases. Given the individual preferences, for each region a_k in A, we can estimate the following individual CI of mortality depending on a set of weights w:

$$CI(a_k, w) = \sum_{i=1}^{n} w_i g_i(a_k) \tag{2.3}$$

Where w_i reflects the importance that the citizen gives to the disease i, and $g_i(a_k)$ is the mortality rate in the region a_k for the disease i. The main problem is that the order of importance may change among people and even among different policy-makers, which implies that one single vector of w that is representative for the whole population does not exist.

The simplest way would be to assume that each citizen gives the same importance to each disease, i.e., $w_1 = w_2 = w_3 = \cdots = w_i$. This method, while representing one of the most popular ways to build composite indices (see, among others, Floridi *et al.* 2011), is rather unsatisfactory and in our case implicitly assumes the existence of an unrealistic 'representative agent' consuming health care. Assuming that preferences are different, weights should also be different. This poses the problem of which is the best set of weights in the absence of *a priori* information and without recourse to a set of weights reflecting a merit good approach on the part of the policy-maker. This issue is particularly relevant in the evaluation of the performance of public services, as by changing the set of weights the ranking of regions in the health outcome may change.

2.3.3 Stochastic Multi-Objective Acceptability Analysis

In the MCDA literature, this question was addressed with the SMAA. Introduced by the seminal work of Lahdelma *et al.* (1998), SMAA is a method able to take into account the uncertainty with respect to the weights assigned to the considered criteria. After the original SMAA, that estimates acceptability index for each alternative measuring volume of weights that give each alternative the best ranking position, several modifications to the basic model have been proposed in the literature. Lahdelma, Salminen (2001) introduce SMAA-2 that extend SMAA by considering all ranks. Lahdelma *et al.* (2003) develop SMAA-O, which is a method dealing with problems with ordinal criteria information. Lahdelma and Salminen (2006) propose the combination of SMAA-2 and Data Envelopment Anaysis (Charnes *et al.* 1978). Tervonen and Lahdelma (2007) present methods for computations through Monte Carlo simulation. Corrente *et al.* (2014) combine SMAA with PROMETHEE methods, in order to explore the parameters compatible with preference information of the decision maker. Angilella *et al.* (2015, 2016) combine the Choquet integral with SMAA, and obtain robust recommendations and robust ordinal regression.

In order to embody unknown preferences on the weights assigned to each dimension, SMAA considers the probability distributions $f_W(w)$ in the set of the feasible weights W defined as:

$$W = \{(w_1, \dots, w_n) \in R_+^n, \qquad w_1 + \dots + w_n = 1\} \tag{2.4}$$

The set of feasible weights is a $(n-1)$ dimensional simplex. Total lack of knowledge about weights is represented by a uniform weight distribution in the set of feasible weights W. In detail, to rank regions according to the composite index of mortality, the rank is defined as an integer from 1 to m (the number of regions). Starting from the probability distributions $f_\chi(\xi)$ on χ, where χ is the evaluation space (in our case the space of the values assumed by the mortality rates $g_i$in G), Lahdelma, Salminen (2001) introduce a ranking function relative to the region a_k:

$$rank(k, \xi, w) = 1 + \sum_{h \neq k} \rho[CI(\xi_h, w) > CI(\xi_k, w)] \tag{2.5}$$

where $\rho(true) = 1$, and $\rho(false) = 0$. In words, the rank of region a_k, given a vector of weights w, is one plus how many times the weighted average of mortality rates of a_k ($CI(\xi_k, w)$) is dominated by the weighted average of mortality rates of the other regions ($CI(\xi_h, w)$). Thus, the value assumed by the variable $rank(k, \xi, w)$ in equation (2.5) is one plus the number of regions that performs worse than region a_k in terms of mortality rates. It follows that the higher the value of $rank(k, \xi, w)$ the better the performance of the region a_k.

Accordingly, for each region a_k and for each value that can be taken by mortality rates $\xi \in \chi$, SMAA computes the set of weights for which region a_k assumes rank r:

$$W_k^r(\xi) = \{w \in W: rank(k, \xi, w) = r\} \tag{2.6}$$

From equation (2.6), one can then compute the rank acceptability index, which is a relative measure of (2.6). In symbols:

$$b_k^r = \int_{\xi \in \chi} f_\chi(\xi) \int_{w \in W_k^r(\xi)} f_W(w)\, dw d\xi \tag{2.7}$$

Equation (2.7) gives the probability that the region a_k has the r-th position in the ranking. In other words, b_k^r is the ratio of the number of the vector of weights by which region a_k gets rank r to the total amount of feasible weights (i.e., the number of cases in which region a_k achieves the rank r on the total number of cases considered). From a computational perspective, the multidimensional integrals are estimated by using Monte Carlo simulations. To this purpose, our estimates are the result of 100,000 random extractions of vectors w from a uniform distribution in W[52].

2.3.4 The multidimensional generalization of the Gini index

The previously defined rank acceptability index b_k^r can be used to define a multidimensional generalization of the Gini index, as suggested by Greco *et al.* (2017). This result is obtained by first defining the upward cumulative rank acceptability index of rank l, i.e., the probability that the region a_k has a rank l or higher (Angilella *et al.* 2016). In symbols:

$$b_k^{\geq l} = \sum_{s=l}^{m} b_k^s \tag{2.8}$$

Given (2.8), one can calculate a Gini index in the traditional way, a measure that we can refer as to the Gini index of the upward cumulative rank acceptability index of rank l (Greco *et al.* 2017):

$$G^{\geq l} = \frac{\sum_{h=1}^{m} \sum_{k=1}^{m} \left| b_h^{\geq l} - b_k^{\geq l} \right|}{2ml} \tag{2.9}$$

[52] Tervonen and Ladhelma (2007) shows that 10,000 extractions are enough to get an error limit of 0.01 with a confidence interval of 95%.

Equation (2.9) measures how the probabilities of attaining rank l or higher are concentrated among the considered regions. For each l, the higher $G^{\geq l}$, the more concentrated the probability to be above this rank in terms of the composite index of mortality. More specifically, $G^{\geq l}$ measures the dispersion of the probability that each region may have in occupying rank l or higher. If this probability were the same for all regions, $G^{\geq l}$ would be zero. A high level of $G^{\geq l}$, instead, would signal that this probability is heavily concentrated in few regions, as it would be the case if there were great differences in the health outcome.

Using the same rationale, the downward cumulative rank acceptability index of position l for region a_k is:

$$b_k^{\leq l} = \sum_{s=1}^{l} b_k^s \tag{2.10}$$

Analogously to (2.9), the Gini index of the probability to attain rank l or lower can be defined as:

$$G^{\leq l} = \frac{\sum_{h=1}^{m}\sum_{k=1}^{m}\left|b_h^{\leq l} - b_k^{\leq l}\right|}{2m(m-l+1)} \tag{2.11}$$

The interpretation is the same as before. For each l the higher $G^{\leq l}$ is the more concentrated is the probability to be below the l–th rank in terms of the composite index of mortality. According to Greco *et al.* (2017), $G^{\geq l}$ and $G^{\leq l}$ are generalizations of the Gini index because they take into account all the possible vectors of weights rather than being based on one specific vector, as is the case in most of the multidimensional concentration indices proposed in literature (see Savaglio, 2006; Weymark, 2006).

2.3.5 The multidimensional generalization of ANOGI

As a further step of our analysis, we decided to analyse health inequality not only between regions but also within them. As is well known, however, the Gini index is not perfectly decomposable in between- and within-inequality (Pyatt, 1976). To overcome this problem, we extend the ANOGI, as developed by Yitzhaki (1994) and applied by Liberati (2015) to the analysis of the world income distribution, to the decomposition of (2.9) and (2.11). More in detail, the following decomposition will be used for the case of the Gini index of the upward cumulative rank acceptability index:

$$G^{\geq l} = \sum_i \underbrace{s_i G_i^{\geq l} p_i}_{Standard\ WI} + \underbrace{\sum_i s_i G_i^{\geq l} \sum_{j \neq i} p_j\, O_{ji}^{\geq l}}_{Impact\ of\ overlapping\ on\ WI} + \underbrace{G_{Bp}^{\geq l}}_{Standard\ BI} + \underbrace{\left(G_B^{\geq l} - G_{Bp}^{\geq l}\right)}_{Impact\ of\ overlapping} \quad (2.12)$$

Before interpreting equation (2.12) it is worth discussing the meaning of the term $O_{ji}^{\geq l}$. In principle, this term can be interpreted as an overlapping term (i.e., as a measure of how the distribution of probabilities in region i overlaps with the distribution of probabilities in another region j). If no provinces in region j lies in the range of the distribution of probabilities in region i, region i would be a perfect stratum and $O_{ji}^{\geq l} = 0$. Thus, if all regions were perfect stratums, the second term on the right-hand side of (2.12) would collapse to zero. This unlikely assumption would mean that all regions would show a within distribution of probabilities that is not within the range of any other region. The general case, instead, is to observe overlapping among probabilities of some provinces in one region and those of other provinces in other regions, which means that one can expect $O_{ji}^{\geq l} > 0$. Furthermore, $O_{ji}^{\geq l} \leq 2$, and the maximum value is achieved when all probabilities associated to region j that are located in the range of i are concentrated at the mean of the distribution i. This implies that the probabilities of region j would separate the probabilities of region i that are below the average from those that are above the average. Finally, it is worth noting that the higher $O_{ji}^{\geq l}$, the lower will be $O_{ij}^{\geq l}$, which is obtained by changing the region used as a baseline. This is intuitive, as the more the probabilities of region j are included in the range of the distribution of probabilities in region i, the less the probabilities of region i are expected to be included in the range of region j.

In symbols, the overlapping coefficient is defined as:

$$O_{ji}^{\geq l} = \frac{\operatorname{cov}\left(b_i^{\geq l}, F_j(b^{\geq l})\right)}{\operatorname{cov}\left(b_i^{\geq l}, F_i(b^{\geq l})\right)} \quad (2.13)$$

where the numerator is the covariance between the upward cumulative rank acceptability indices of rank l of region i, and their ranking in the distribution of the upward cumulative rank acceptability indices in region j; while the denominator is the covariance between the same upward cumulative rank acceptability indices and their ranking within the region i.

This definition helps to understand the meaning of equation (2.12). The first term on the right-hand side is the standard within-region inequality (WI) in the absence of overlapping, obtained as the sum of the inequalities among provinces of each region, where s_i is the probability of region i to be in rank l or higher and p_i is the share of population of region i. The second term, instead, would be the impact of overlapping on within inequality, driven by the contribution of the overlapping index of each region with all other regions weighted by their population shares.

In the context of the measurement of health outcomes in the Italian regions, overlapping is particularly important, as it gives information on the quality of ranking regions according to mortality rates. It reveals whether the variable chosen to rank regions is meaningful to describe the performance of the health sector.

The last two terms of equation (2.12), instead, deal with the between-region inequality (BI). The term $G_{Bp}^{\geq l} = \frac{2cov(\bar{b}_i, \bar{F}_i(b))}{\bar{b}}$ is based on the between inequality as originally defined by Pyatt (1976), where the covariance is between the mean probability of each region $\bar{b}_i$ and its rank in the distribution of the mean probabilities of all regions $\bar{F}_i(b)$. This definition would imply that $G_{Bp}^{\geq l} = 0$ when all the mean probabilities are equal.

While according to Yitzhaki, Lerman (1991), one can alternatively define $G_B^{\geq l} = \frac{2cov(\bar{b}_i, \bar{F}(b))}{\bar{b}}$, which is based on the covariance between the mean probability of each region $\bar{b}_i$ and the average rank of all regional probabilities in the national distribution of probabilities

$\bar{F}(b)$[53]. In this case, $G_B^{\geq l} = 0$ implies that the average rank of all regions in the national distribution would be equal.

If regions were perfectly stratified, $G_{Bp}^{\geq l} = G_B^{\geq l}$. This implies that in the absence of the overlapping of probabilities, between-inequality would be uniquely defined by $G_{Bp}^{\geq l}$. With overlapping, $G_B^{\geq l} - G_{Bp}^{\geq l} < 0$, which can be used as an indicator of the reduction in between inequality caused by the overlapping of probabilities.

It is clear from above that with perfect stratification the decomposition (2.12) would collapse to $G^{\geq l} = \sum_i \underbrace{s_i G_i^{\geq l} p_i}_{Standard\ WI} + \underbrace{G_{Bp}^{\geq l}}_{Standard\ BI}$, i.e., to a decomposition of the Gini index in within- and between-inequality without any residual component.

With the same rationale, one can decompose the downward cumulative Gini coefficient as follows:

$$G^{\leq l} = \sum_i \underbrace{s_i G_i^{\leq l} p_i}_{Standard\ WI} + \underbrace{\sum_i s_i G_i^{\leq l} \sum_{j \neq i} p_j\, O_{ji}^{\leq l}}_{Impact\ of\ overlapping\ on\ WI} + \underbrace{G_{Bp}^{\leq l}}_{Standard\ BI} + \underbrace{\left(G_B^{\leq l} - G_{Bp}^{\leq l}\right)}_{Impact\ of\ overlapping} \quad (2.14$$

With terms having the same meaning as before, but with respect to the probabilities of having rank l or lower.

2.4 Results

In our analysis, we apply SMAA to the regional standardized mortality rates in the period 1990-2013. In what follows, ranks are thus defined in terms of the composite mortality. As previously discussed, for each region the higher the value of the rank, the higher the multidimensional health outcome. The focus will be on four aspects: a) the calculation of the composite index of mortality rates using constant weights; b) how the rank changes using uniform random weights with SMAA; c) the multidimensional spatial inequality using the

[53] As argued by Yitzhaki and Schechtman (2013; 484), $G_{Bp}^{\geq l}$ is a Gini coefficient, while $G_B^{\geq l}$ is not. By construction $G_B^{\geq l} < G_{Bp}^{\geq l}$.

generalization of Gini Index; d) the analysis of within and between regions inequality, using the generalization of ANOGI.

2.4.1 Ranking regions using equal weights

The simplest composite index of mortality can be obtained by computing the arithmetic mean of the seventeen standardized mortality rates presented in table 2.2. Table 2.3 shows the moving average of these regional ranks[54]. For convenience, we split the time series into 4 periods: beginning of the Nineties (1990-1995); the period before decentralisation (1996-2001); the period after decentralization (2002-2007); and the period of economic crisis (2008-2013).

Table 2.3 - Moving average in rank by the average standardized mortality rates

Region	1990-1995	1996-2001	2002-2007	2008-2013
Piedmont	6.67	6.33	4.50	4.83
Aosta V.	6.83	2.50	3.75	10.33
Lombardy	3.67	5.50	9.50	12.67
Trentino	15.00	16.17	15.75	19.83
Veneto	10.83	13.17	13.75	15.00
Friuli-V. G.	5.17	8.50	8.00	7.50
Liguria	6.00	6.83	6.50	4.17
Emilia-R.	18.33	18.33	16.75	16.50
Tuscany	16.00	16.00	15.50	13.83
Umbria	15.67	16.83	18.50	17.33
Marche	19.83	20.00	20.00	19.17
Lazio	6.83	6.00	5.75	6.83
Abruzzi	14.67	16.50	15.50	12.00
Molise	18.00	14.67	14.75	11.67
Campania	1.00	1.00	1.00	1.00
Apulia	11.00	10.00	8.00	7.33
Basilicata	9.50	9.67	8.75	10.00
Calabria	9.17	8.50	9.75	5.00
Sicily	2.00	2.50	2.25	2.00
Sardinia	13.67	11.00	11.75	13.00

Source: Authors' elaboration on ISTAT (2017)

Five groups of regions could be identified using this method: constant good performers (Trentino-Alto Adige, Emilia-Romagna, Tuscany, Umbria, Marche, and Abruzzi); constant

[54] The ranks attached to each year in the considered period are in table A2.1 in the Appendices.

bad performers (Piedmont, Liguria, Campania, and Sicily); regions that have improved performances over time (Aosta Valley, Lombardy, and Veneto); regions that have worsened (Molise, Apulia, and Calabria); and regions with no clear path (Friuli, Lazio, Basilicata, and Sardinia). As previously discussed, however, the main drawback of this approach is the arbitrariness of the weighting process, which simply gives all mortality rates the same weight. To overcome this assumption, we apply the SMAA approach in order to consider the whole set of possible vectors of weights.

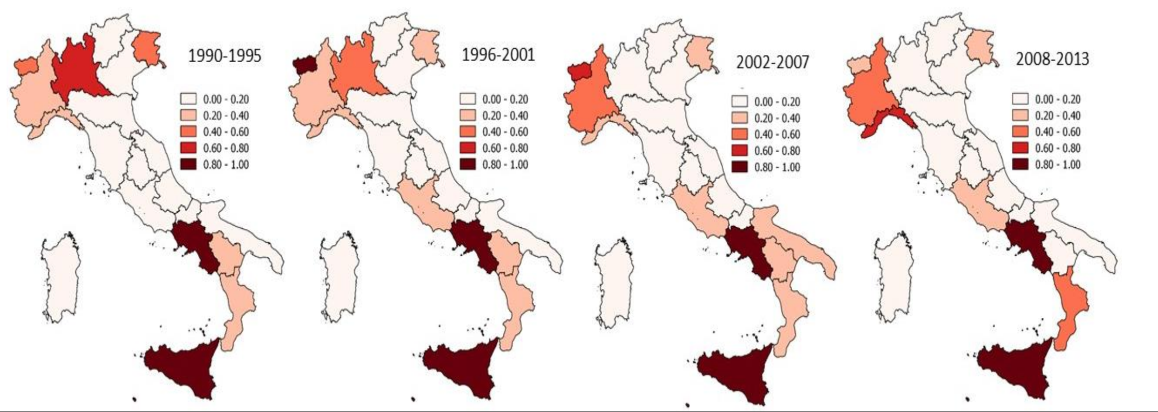
2.4.2 Ranking regions by SMAA

The shortcomings of equal weights could be overcome by applying SMAA. This methodology produces a relevant amount of information, as the full dataset of ISTAT (2017) covers 20 regions in the intervals 1990-2003 and 2006-2013. For each of the 22 years of analysis, SMAA gives the probability of each region to have the r-th position in the ranking of the composite mortality index. To save space, the detailed results are in tables A2.2-A2.23 in the Appendices. They report the rank frequencies, i.e., number of occurrences, out of the 100,000 cases, a region achieves each possible rank from 1 to 20, taking a uniform distribution of the weights assigned to each of the 17 mortality rates. In order to summarize the results, figures 2.1 and 2.2 show the cumulative rank acceptability indices for the upper and the lower side of the ranking, i.e., - respectively - what is the probability that each region is a bad or a good performer, given the whole set of feasible weights.

Figure 2.1 shows the moving average of the downward cumulative rank acceptability index starting from rank 5 (i.e., we show $b_k^{\leq 5} = \sum_{s=1}^{5} b_k^s$). This approximates the probability that the region has the fifth or a lower rank position, considering all the feasible convex linear combinations of standardized mortality rates. As can be seen, there have been few changes in the highest five attainable ranks (i.e., the highest mortality rates). More precisely, there are two regions, Campania and Sicily, which are the worst performers in the whole period, always having above an 80% probability to be in the lowest five ranks. Looking at the data in more detail, tables A2.2-A2.23 show that Campania is almost constantly well above 90%, which means that this region has the highest composite indexes of mortality in more than 90% of cases.

On the opposite side, nine regions (Trentino-Alto Adige, Veneto, Emilia-Romagna, Tuscany, Umbria, Marche, Abruzzi, Molise, and Sardinia) constantly have less than a 20% probability to be in the lowest five ranks in the whole period. Lastly, some cases of reduction (Lombardy, Aosta Valley, Friuli, and Basilicata) as well as of increase (Piedmont, Liguria, Lazio, and Calabria) of this probability occur in the remaining regions.

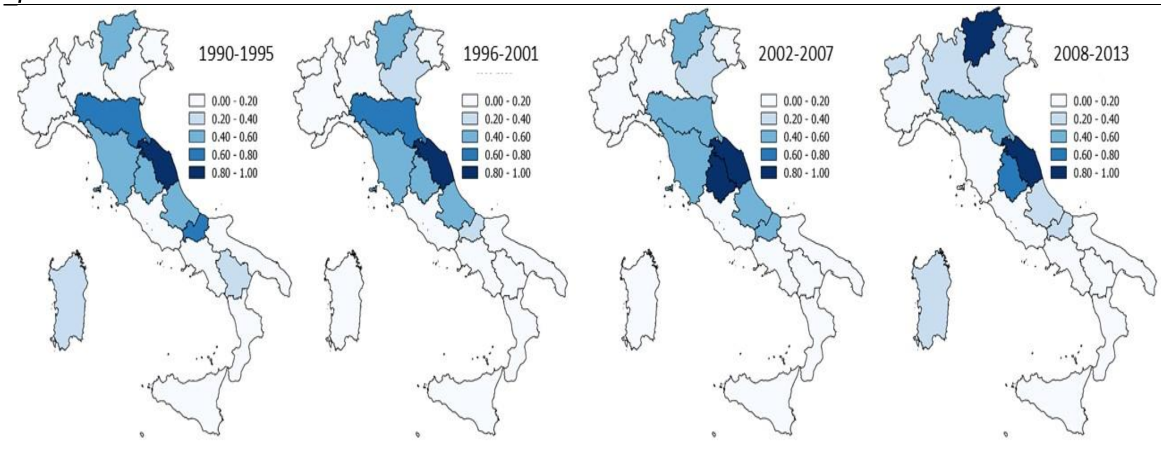
Figure 2.1 - Moving average of downward cumulative rank acceptability index of mortality for the rank 5



Source: Authors' elaboration on ISTAT (2017).
Note: moving average of $b_k^{\leq 5} = \sum_{s=1}^{5} b_k^s$

Figure 2.2, rather, shows the moving average of the upward cumulative rank acceptability index of mortality for rank 16 or higher, i.e., for the best performer with the lowest composite mortality rate (we show $b_k^{\geq 16} = \sum_{s=16}^{20} b_k^s$). In figure 2.2, only Marche has more than an 80% probability to be at or above rank 16 in the whole period. On the opposite side, we can identify eight regions, Friuli, Piedmont, Liguria, Lazio, Campania, Apulia, Calabria, and Sicily, which constantly have less than a 20% probability to be among the best five regions, regardless of the weighting scheme. In the remaining regions, increases in the probability of being among the top five are observed in Lombardy, Veneto, Aosta Valley, Trentino, and Umbria; reductions are in Emilia-Romagna, Tuscany, Abruzzi, and Molise.

Figure 2.2- Moving average of upward cumulative rank acceptability index of mortality for the rank 16



Source: Authors' elaboration on ISTAT (2017).
Note: moving average of $b_k^{\geq 16} = \sum_{s=16}^{20} b_k^s$

More generally, figures 2.2 and 2.3 show that in the period 1990-2013, there is a persistent spatial inequality in the Italian multidimensional health outcome. The Centre-North of the country was mainly a place with a lower composite mortality rate and still, the South was a place with a higher composite mortality rate, regardless of health reforms and decentralization. To strengthen this conclusion, we can note that significant improvements can be observed only in specific regions of the North (Lombardy and Trentino in particular); while pronounced worsening in performances have involved some regions in the South, such as Calabria. According to these results, no convergence seems to emerge in health outcomes across regions over the 24 years of the analysis, with rather stable differences in mortality rates that are not significantly reduced in any period.

2.4.3 The multidimensional spatial inequality among regions

The absence of convergence along the period analysed gives the opportunity to extend the investigation to the multidimensional spatial inequality using the set of multidimensional Gini indices as proposed in Greco *et al.* (2017) and reported in equations (2.9) and (2.11). As argued, for each level of l the higher $G^{\geq l}$ ($G^{\leq l}$) the more concentrated the probability for the regions to be over (under) the l-th rank in terms of the composite index of mortality. Accordingly, the higher $G^{\geq l}$ ($G^{\leq l}$) the greater the inequality in these cumulative probabilities across regions.

Table 2.4 reports $G^{\leq l}$ for the downward cumulative rank acceptability on the 4-th, 5-th, and 6-th ranks, and $G^{\geq l}$ for the upward cumulative rank acceptability on the 15-th, 16-th, and 17-th ranks[55]. As expected, inequality decreases when moving from rank 4 to 6 and from rank 17 to 15, as both these movements imply a greater probability of each region of occupying the specific rank or lower and higher, respectively. The relevant information is in inequality across years. Whatever rank is chosen, inequality is stable over the whole period, and high to any standard (see tables A2.24 and A2.25 in the Appendices). For instance, to grasp the implication of inequality of 0.75 at rank 17 or highest in 2013, one can observe that the same coefficient would be obtained by a hypothetical distribution where 75% of the regions have zero probability of being at rank 17 or higher, and the other regions have an equal probability to be there. This underlines a strong inequality in the opportunity to achieve that rank. Thus, regardless of the specific set of weights used, table 2.4 reveals a strong inequality in both probabilities of being among the worst and among the best performers, which means that there are strong differences of health outcomes among regions.

[55] Detailed results for all ranks are in tables A2.24 and A2.25 in the Appendices.

Table 2.4 - Multidimensional Gini indices

Year	Downward cumulative ($G^{\leq l}$)			Upward cumulative ($G^{\geq l}$)		
	Rank 4	Rank 5	Rank 6	Rank 15	Rank 16	Rank 17
1990	0.75	0.70	0.65	0.65	0.68	0.74
1991	0.74	0.67	0.62	0.60	0.65	0.71
1992	0.76	0.72	0.65	0.66	0.69	0.73
1993	0.75	0.69	0.63	0.62	0.67	0.74
1994	0.75	0.65	0.59	0.66	0.70	0.76
1995	0.74	0.68	0.64	0.65	0.69	0.74
1996	0.77	0.72	0.66	0.62	0.67	0.73
1997	0.77	0.69	0.62	0.66	0.70	0.74
1998	0.74	0.66	0.59	0.66	0.72	0.77
1999	0.73	0.68	0.64	0.66	0.70	0.76
2000	0.76	0.68	0.62	0.66	0.71	0.78
2001	0.77	0.69	0.65	0.66	0.68	0.72
2002	0.76	0.69	0.64	0.66	0.71	0.76
2003	0.75	0.71	0.66	0.64	0.69	0.74
2006	0.73	0.67	0.62	0.67	0.71	0.76
2007	0.78	0.72	0.66	0.64	0.68	0.74
2008	0.76	0.71	0.65	0.60	0.66	0.73
2009	0.79	0.73	0.66	0.67	0.73	0.80
2010	0.74	0.67	0.62	0.63	0.69	0.77
2011	0.74	0.66	0.61	0.66	0.71	0.78
2012	0.76	0.70	0.64	0.61	0.66	0.74
2013	0.77	0.70	0.63	0.63	0.69	0.75

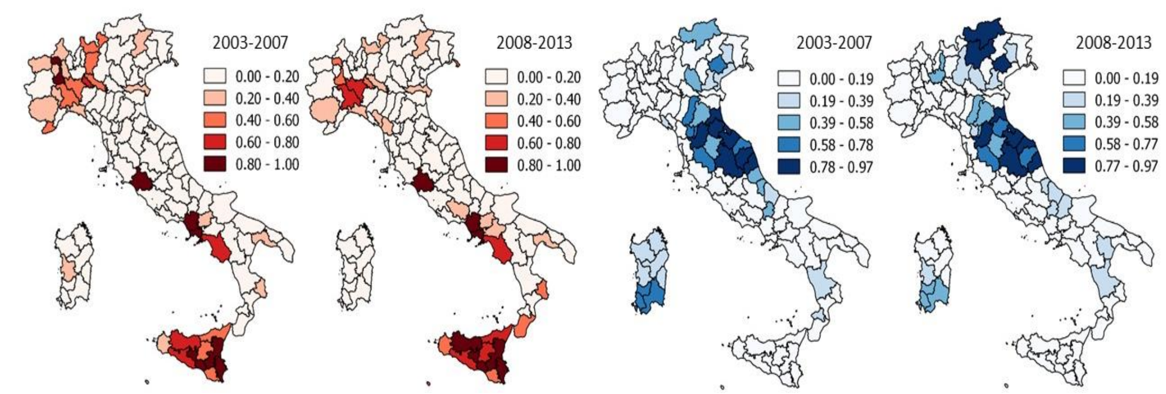
Source: Authors' elaboration on ISTAT (2017)

2.4.4 The multidimensional ANOGI

A sub-set of our panel dataset with regional standardized mortality rates contains provincial data. In particular, provincial standardized mortality rates are available in ISTAT (2017) from 2003 to 2013. This feature of the dataset allows us to decompose the multidimensional inequality studied in the previous paragraph. Specifically, the traditional components of inequality among regions (between) and inequality within regions (at provincial level) may be disentangled and discussed. However, the decomposition of the Gini index does not contain solely these two components, but appears with a residual that may have an interesting interpretation in the present analysis.

To this purpose, we use ANOGI as in equations (2.12) and (2.14). In order to estimate total inequality, as well as both between and within components, we apply SMAA to 103 provinces[56]. Figure 2.3 reports the results by showing the moving average of both the upward and the downward cumulative rank acceptability indices of mortality for the ranks 84 and 20, respectively[57]. For the sake of brevity, we split the panel in two periods: the post reform period (2003-2007), and the period of economic crisis (2008-2013). In figure 2.3 there are four maps: the two maps on the left side show the moving average of the downward cumulative rank acceptability index of mortality for rank 20 (i.e., $b_k^{\leq 20} = \sum_{s=1}^{20} b_k^s$), while the two maps on the right side show the moving average of the upward cumulative rank acceptability index of mortality for rank 84 (i.e., $b_k^{\geq 84} = \sum_{s=84}^{103} b_k^s$). It is worth recalling that a high value of the rank identifies the best performers, while the opposite applies for bad performers.

Figure 2.3 - Moving average of downward and upward cumulative rank acceptability index for the ranks 20 and 84



Source: Authors' elaboration on ISTAT (2017).
Note: Moving averages of $\mathrm{b}_\mathrm{k}^{\leq 20} = \sum_{s=1}^{20} \mathrm{b}_\mathrm{k}^\mathrm{s}$ (on the left), and $\mathrm{b}_\mathrm{k}^{\geq 84} = \sum_{s=84}^{103} \mathrm{b}_\mathrm{k}^\mathrm{s}$ (on the right)

The main result of figure 2.3 is that the general territorial trends observed in figures 2.1 and 2.2 are confirmed by the analysis at provincial level. In particular, figure 2.3 confirms a bad performance in the Southern-West side of the country (Campania and Sicily above all) and a good performance of the Northern-East, and this involves the bulk of provinces in the

[56] In 2017, there are 107 provinces in Italy, but until 2005 there were 103, in order to keep our panel balanced, we do not include in our analysis the provinces introduced in 2005 and 2009. Nonetheless, the main results shown in this section are confirmed when the analysis is conducted on 107 provinces from 2005 and on 110 provinces from 2009.

[57] Detailed annual provincial rank frequencies for all years of analysis can be forwarded on request.

corresponding regions[58]. Moreover, over time an improvement of the performance of some Northern provinces emerges (for example, Trento and Bolzano), and a worsening in some provinces in Sardinia and Calabria. Again, convergence in health outcomes is hardly detectable after using a provincial analysis.

Table 2.5 shows the ANOGI of the downward cumulative rank acceptability index of mortality for rank 20. The level of total inequality, as calculated by the overall Gini, is slightly increasing over time, especially in the period of economic crisis. This indicator signals the concentration of probabilities to be among the worst 20 provinces in terms of health outcomes. Thus, a slight increase in concentration over time may suggest that there is a greater dispersion among the probabilities of being at the top of the rank in terms of mortality.

Table 2.5 - Multidimensional ANOGI of Downward cumulative rank acceptability index for rank 20

Year	Total Inequality	Standard Within	Impact of Overlapping on Within	Between	Impact of Overlapping on Between
2003	0.730	0.029	0.222	0.595	-0.115
2006	0.738	0.029	0.311	0.568	-0.170
2007	0.737	0.028	0.242	0.590	-0.123
2008	0.738	0.032	0.322	0.554	-0.170
2009	0.759	0.029	0.246	0.629	-0.145
2010	0.751	0.032	0.278	0.590	-0.149
2011	0.752	0.020	0.194	0.642	-0.104
2012	0.761	0.026	0.271	0.610	-0.147
2013	0.758	0.026	0.248	0.621	-0.139

Source: Authors' elaboration on ISTAT (2017)

With respect to table 2.5 one can note that the bulk of total inequality is due to an increase of inequality between regions, while the standard within inequality remains low and almost constant. A non-monotonic path is also in the impact of overlapping on within inequality.

[58] The territorial distribution of these performances is quite in line with previous estimates of health care efficiency in Italy (Giordano, Tommasino, 2011; Patrizii, Resce, 2015), although they use different outcome measures (Giordano, Tommasino, 2011 use life expectancy; Patrizii, Resce, 2015 use proxies of health service provided) and a different technique (Data Envelopment Analysis).

This means that, over time, the distribution of the provincial probabilities of being among the worst 20 has been intertwined without any significant change.

To this purpose, table 2.6 and 2.7 report the matrices of $O_{ji}^{\leq 20}$, respectively for 2003 and 2013, obtained by the decomposition of the general overlapping index in table 2.5, with rows indicating the baseline region i and columns reporting each region j. By construction, each element of the main diagonal of this matrix equals one. If no provinces in region j lies in the range of the distribution of probabilities of provinces in i, region i could be defined a perfect stratum and $O_{ji}^{\leq 20} = 0$.

Table 2.6 - Overlapping Matrix of Downward cumulative rank acceptability index for rank 20 by region, 2003

	PI	VA	LO	TR	VE	FR	LI	ER	TU	UM	MA	LA	AB	MO	CA	AP	BA	CL	SI	SA
PI	1.00	1.37	0.63	0.00	0.16	0.68	0.93	0.23	0.09	0.00	0.00	0.60	0.00	0.00	0.67	0.34	0.28	0.39	1.21	0.42
VA	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
LO	1.58	1.86	1.00	0.00	0.48	1.30	1.35	0.56	0.19	0.00	0.00	0.71	0.00	0.00	1.08	1.27	0.84	1.11	1.32	1.25
TR	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
VE	0.23	0.00	0.83	0.92	1.00	0.61	0.23	0.98	0.82	0.92	0.92	0.55	0.92	0.92	0.00	1.64	1.37	1.40	0.00	1.75
FR	1.39	1.77	0.52	0.40	0.60	1.00	1.43	0.71	0.54	0.40	0.40	0.88	0.40	0.40	1.06	0.92	0.60	1.12	0.98	0.95
LI	0.87	1.70	0.73	0.64	0.82	0.80	1.00	0.90	0.74	0.64	0.64	0.64	0.64	0.64	0.34	1.28	0.96	1.23	0.00	1.28
ER	0.39	0.00	0.76	0.83	1.05	1.00	0.57	1.00	0.75	0.83	0.83	0.79	0.83	0.83	0.00	1.71	1.28	1.29	0.00	1.63
TU	0.50	0.00	1.09	1.00	1.29	1.25	0.75	1.33	1.00	1.00	1.00	1.00	1.00	1.00	0.40	2.00	1.50	1.60	0.00	2.00
UM	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
MA	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
LA	1.47	1.74	1.34	0.33	0.61	1.17	1.39	0.70	0.47	0.33	0.33	1.00	0.33	0.33	0.96	1.18	0.82	1.26	1.35	1.14
AB	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
MO	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
CA	0.86	1.06	0.84	0.00	0.00	0.41	0.53	0.00	0.11	0.00	0.00	0.62	0.00	0.00	1.00	0.00	0.00	0.21	1.52	0.00
AP	0.23	0.00	0.54	0.00	0.26	0.19	0.00	0.20	0.00	0.00	0.00	0.21	0.00	0.00	0.00	1.00	0.92	0.57	0.00	0.92
BA	0.25	0.00	0.91	1.00	0.71	0.25	0.25	0.89	0.90	1.00	1.00	0.60	1.00	1.00	0.00	0.80	1.00	1.20	0.00	1.00
CL	0.85	1.75	0.61	0.00	0.48	0.84	0.87	0.55	0.17	0.00	0.00	0.46	0.00	0.00	0.35	1.29	0.80	1.00	0.00	1.31
SI	0.00	0.00	0.57	0.00	0.00	0.39	0.00	0.00	0.00	0.00	0.00	0.45	0.00	0.00	0.42	0.00	0.00	0.00	1.00	0.00
SA	0.13	0.00	0.48	0.00	0.19	0.34	0.00	0.33	0.00	0.00	0.00	0.21	0.00	0.00	0.00	1.23	0.80	0.80	0.00	1.00

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA= Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table 2.7 - Overlapping Matrix of Downward cumulative rank acceptability index for rank 20 by region, 2013

	PI	VA	LO	TR	VE	FR	LI	ER	TU	UM	MA	LA	AB	MO	CA	AP	BA	CL	SI	SA
PI	1.00	1.12	0.79	0.19	0.83	1.25	1.14	0.28	0.40	0.19	0.19	0.53	0.60	0.65	0.68	0.70	0.65	1.64	0.77	0.48
VA	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
LO	0.99	1.37	1.00	0.57	1.06	0.97	1.37	0.90	0.92	0.57	0.57	0.66	1.18	0.97	0.00	1.27	0.97	1.52	0.19	1.26
TR	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
VE	1.04	1.51	0.98	0.57	1.00	0.95	1.52	0.99	0.96	0.57	0.57	0.72	1.32	1.04	0.00	1.36	1.04	1.56	0.17	1.51
FR	0.77	0.85	0.86	0.43	0.88	1.00	1.25	0.62	0.66	0.43	0.43	0.76	0.75	0.64	0.66	0.90	0.64	1.43	0.35	0.85
LI	1.07	1.89	0.69	0.00	0.54	0.95	1.00	0.22	0.39	0.00	0.00	0.20	0.72	0.95	0.00	1.15	0.95	1.52	0.21	0.50
ER	0.09	0.00	0.47	0.70	0.50	0.18	0.43	1.00	0.76	0.70	0.70	0.75	0.59	0.35	0.00	0.42	0.35	0.00	0.00	0.83
TU	1.63	1.83	1.13	0.46	1.12	1.44	1.67	0.89	1.00	0.46	0.46	1.36	1.26	1.15	1.04	1.47	1.15	1.78	1.54	1.43
UM	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
MA	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
LA	1.53	1.90	1.06	0.32	1.04	1.33	1.74	0.74	0.79	0.32	0.32	1.00	1.18	1.11	1.00	1.45	1.11	1.90	0.96	1.26
AB	0.78	1.96	0.63	0.34	0.52	0.09	0.83	0.72	0.67	0.34	0.34	0.61	1.00	1.15	0.00	1.12	1.15	0.39	0.00	1.17
MO	0.63	0.00	0.64	1.00	0.71	0.25	1.00	1.44	1.20	1.00	1.00	1.00	1.25	1.00	0.00	1.40	1.50	0.00	0.00	2.00
CA	0.45	0.00	0.00	0.00	0.00	0.45	0.00	0.00	0.15	0.00	0.00	0.65	0.00	0.00	1.00	0.00	0.00	0.00	1.40	0.00
AP	0.65	1.59	0.62	0.29	0.44	0.47	0.56	0.49	0.46	0.29	0.29	0.40	0.90	0.94	0.00	1.00	0.98	0.32	0.00	1.00
BA	0.63	0.00	0.64	1.00	0.71	0.25	1.00	1.44	1.20	1.00	1.00	1.00	1.25	0.50	0.00	1.00	1.00	0.00	0.00	2.00
CL	0.32	0.00	0.32	0.00	0.34	0.63	0.52	0.00	0.14	0.00	0.00	0.00	0.24	0.00	0.00	0.19	0.00	1.00	0.17	0.00
SI	0.48	0.00	0.19	0.00	0.15	0.60	0.52	0.00	0.04	0.00	0.00	0.49	0.00	0.00	0.70	0.00	0.00	0.42	1.00	0.00
SA	0.22	0.00	0.14	0.00	0.00	0.00	0.38	0.50	0.48	0.00	0.00	0.60	0.81	0.00	0.00	0.65	0.00	0.00	0.00	1.00

Source: Authors' elaboration on ISTAT (2017); Notes: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Some features of table 2.6 are worth explaining. First, rows with missing values represent the cases in which all provinces of the baseline region have the same probability of being among the worst 20. This happens in Aosta Valley because it has just one province, and in Trentino, Umbria, Marche, Abruzzi, and Molise because all of their provinces have zero probability of being among the worst 20 in 2003. This implies that there is no distribution of probabilities to compare with other regions. Second, there are cases in which cells equal zero. As previously observed, these are cases where no member of the region j lies in the distribution of probabilities of the members of region i, which means that region i is a perfect stratum. In this context, being a perfect stratum means that, for the provinces of a given region, the probabilities of being among the worst 20 are extremely different from the probabilities attached to other provinces in other regions. Excluding the regions with missing values, the most frequent cases of perfect stratum are associated to Campania, Apulia, Sicily and Sardinia. This result suggests that a non-negligible number of provinces in the South of Italy represents a `world apart' with respect to the health outcomes. Looking at the elementary data, indeed, confirms that many provinces in these regions have extremely high probabilities of being in the highest ranks in terms of mortality.

Third, the territorial high stratification is also confirmed by looking at sufficiently low values of $O_{ji}^{\leq 20}$, which denotes a high level of stratification. Reading table 2.6 by rows, it emerges that, on average, $O_{ji}^{\leq 20} < 0.4$ again in Campania, Apulia, Sicily and Sardinia. On the opposite side, a relatively low degree of stratification (i.e., $O_{ji}^{\leq 20} > 0.4$) is mainly found in Northern regions (with the exceptions of Basilicata and Lazio in the South and Centre respectively). The combination of these two results suggests that usually there are relatively more provinces of the poorest part of the country in the range of the distribution of the richest part than there are provinces in the richest part in the range of the distribution of the poorest part. In other words, there are relatively more good performer provinces in the bad performer regions than there are bad performer provinces in the good performer regions[59].

[59] To some extent, the distribution of the provincial performances of Italian health services takes the opposite direction of the distribution of income. Indeed, the overlapping matrices of world income distribution in Liberati

Consider, for example, the relationship between Lombardy (L) and Apulia (A). Taking L as a baseline, $O_{AL}^{\leq 20} = 1.27$, while taking A as a baseline $O_{LA}^{\leq 20} = 0.54$. This means that there are relatively more provinces of Apulia overlapping the distribution of provinces in Lombardy than there are provinces of Lombardy overlapping the distribution of Apulia.

Finally, there are cases where $O_{ji}^{\leq 20} \geq 1.5$, as in the case of using Tuscany as a baseline with respect to Basilicata, Calabria, Apulia, and Sardinia. These cases are particularly interesting, as high values of the overlapping term suggest that the bulk of the observations of distribution j that are located in the range of distribution i are concentrated around the mean of the distribution i. In particular, $O_{ji}^{\leq 20} = 2$ in the case of Apulia and Sardinia with Tuscany as a baseline. It means that all probabilities of the provinces of Apulia and Sardinia are included between the lowest and the highest probability of the provinces of Tuscany. More specifically, Apulia and Sardinia split the probabilities of Tuscany in two parts, one above and one below the mean.

Table 2.7 reports the same matrix for the downward cumulative rank in 2013. Only marginal changes are actually visible. Many regions that were a perfect stratum in 2003 still are (Campania, Sardinia, and Sicily). Apulia seems to have left this characteristic, while Calabria has gained it. On average, high levels of stratification mainly appear in the regions of the South, which means that their probabilities of being in the lowest rank are not shared by many other regions. Moreover, it still holds that there are more provinces of the poorest regions overlapping the distribution of provinces in the richest regions than there are provinces of the richest regions overlapping the distribution of the poorest ones. Thus, overall, moving from 2003 to 2013 has only marginally improved the convergence of provinces across the country in terms of health outcomes.

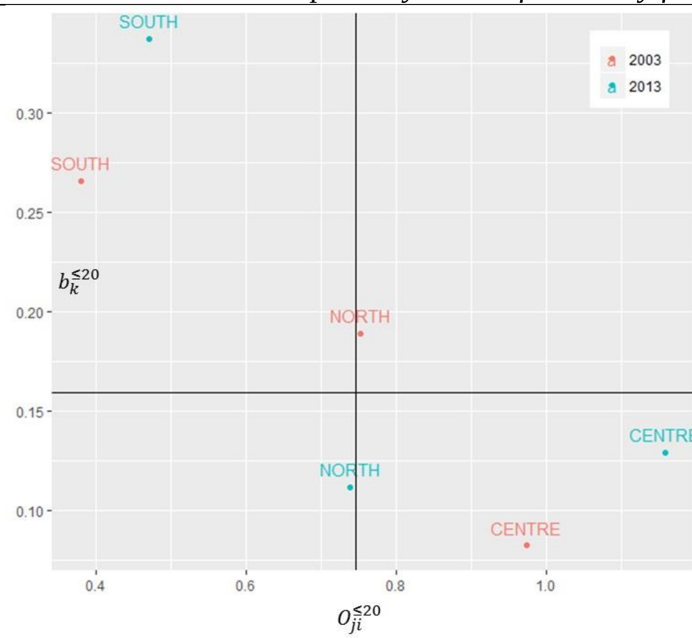
Comparing these results with the information reported in table 2.5 suggests that while the standard within inequality is low, its value becomes greater because the distributions of

(2015), show that usually there are relatively more citizens of the richest areas in the range of distribution of the poorest areas, than there are citizens of the poorest areas in the range of distribution of the richest areas.

probabilities of provinces has some degree of overlapping, even though a significant degree of stratification occurs in the regions of the South.

In order to explore the relation between the stratification and the performances among the three macro-areas of the country (North, Centre, and South), figure 2.4 reports a quadrant representation of the average $O_{ji}^{\leq 20}$ (x axis) and of the average $b_k^{\leq 20}$ (y axis) for the Northern, Central, and Southern regions. In average, the upper left quadrant in figure 2.4 confirm a bad performance with high level of stratification for the Southern regions (both high $b_k^{\leq 20}$ and low $O_{ji}^{\leq 20}$). On the opposite side, the lower right quadrant in figure 2.4 shows that Central regions have good performances and low level of stratification. Finally, the Northern regions show average performances and a median level of stratification. From dynamic perspective, it emerges that both Southern and Central regions have worsened performances and reduced stratification in the 2003-2013 interval. An opposite trend is instead observed in the Northern regions, where both performances and stratification have increased in the same interval.

Figure 2.4 - Quadrant representation of average performance and average stratification by area (downward cumulative rank acceptability index of mortality for the rank 20)



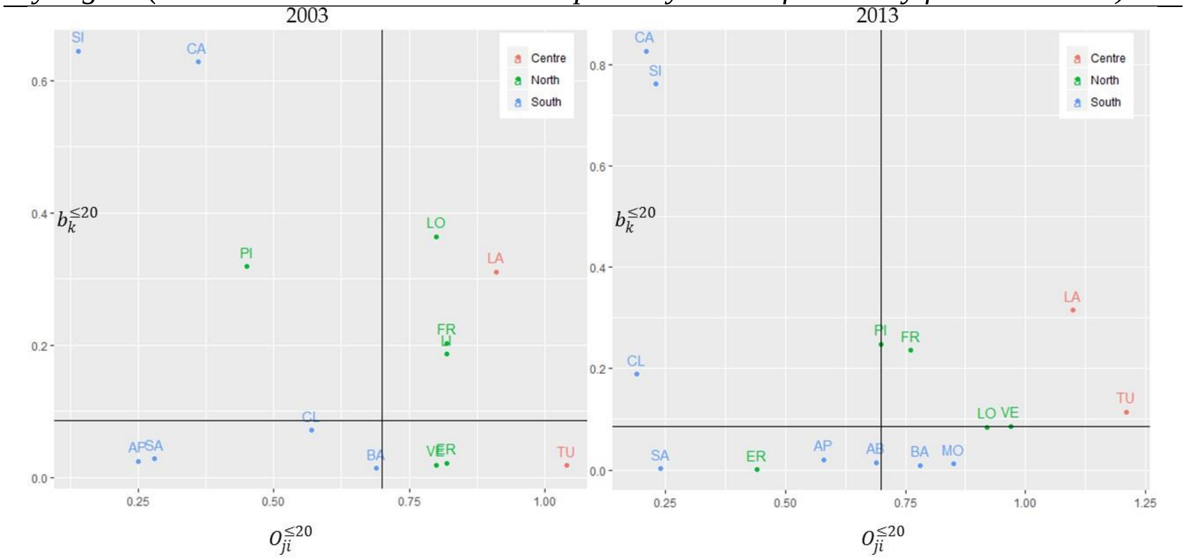
Source: Authors' elaboration on ISTAT (2017).
Notes: Quadrant representation of average performance (downward cumulative rank acceptability index of mortality for the rank 20), and average stratification (Overlapping of downward cumulative rank acceptability index of mortality for the rank 20) by area (North, Centre, and South); $O_{ji}^{\leq 20}$ values are averages of regional estimates, and $b_k^{\leq 20}$ values are averages of provincial estimates; the lines are on the median values.

In figure 2.5, we explore the relation between stratification and performances at regional level. This analysis does not involve regions having missing values in tables 2.6 and 2.7 (i.e., cases in which all provinces have the same probability of being among the worst 20). Figure 2.5 reports a quadrant representation of the average $O_{ji}^{\leq 20}$ (x axis) and of the average $b_k^{\leq 20}$ (y axis).

In the upper left quadrant in figure 2.5, there are regions with low performances and high stratification (high $b_k^{\leq 20}$ and low $O_{ji}^{\leq 20}$). In 2003, two Southern regions (Campania and Sicily) and one Northern region (Piedmont) belong to this quadrant. In 2013, the only Northern region in the quadrant goes out, and another Southern region (Calabria) goes in the group of regions with high stratification and bad performances at provincial level. In the upper right quadrant in figure 2.5, there are regions with low performances and low stratification (high $b_k^{\leq 20}$ and high $O_{ji}^{\leq 20}$). In 2003, three Northern regions (Lombardy, Friuli, and Liguria) and one Central region (Lazio) are in this quadrant. In 2013, there are some changes in this category due, in particular, to a significant increasing in the performance of Lombardy and worsening in the performance of Tuscany. In the lower right quadrant in figure 2.5 there are good performer regions with low degree of stratification (low $b_k^{\leq 20}$ and high $O_{ji}^{\leq 20}$). In 2003, two Northern regions (Veneto and Emilia Romagna) and one Central region (Tuscany) are part of this quadrant. In 2013, all of those regions move in other quadrants because of a slightly decreasing in the performances of Veneto and Tuscany, and an increasing of stratification of Emilia Romagna. Finally, in the lower left quadrant in figure 2.5 there are regions showing good performances and high stratification (low $b_k^{\leq 20}$ and low $O_{ji}^{\leq 20}$). Three Southern regions (Apulia, Sardinia, and Basilicata) are in this quadrant in 2003. In 2013, Emilia Romagna takes the place of Basilicata because Basilicata becomes less stratified compared with 2003.

More broadly, figure 2.5 shows a high dispersion in the mix of performances-stratification. Southern regions (both good and bad performers) are more stratified compared with the others. In particular, the two worst performer regions, Campania and Sicily, seems to be completely disconnected from the rest of the country, and their distance to the others is increasing in the 2003-2013 interval.

Figure 2.5 - Quadrant representation of average performance and average stratification by region (downward cumulative rank acceptability index of mortality for the rank 20)



Source: Authors' elaboration on ISTAT (2017).
Notes: Quadrant representation of average performance (downward cumulative rank acceptability index of mortality for the rank 20), and average stratification (Overlapping of downward cumulative rank acceptability index of mortality for the rank 20) by region; $O_{ji}^{\leq 20}$ values are regional estimates, and $b_k^{\leq 20}$ values are regional averages of provincial estimates; the lines are on the median values.

In the same vein, table 2.8 reports the results for the upward cumulative rank acceptability index for rank 84. The path of the various components of the Gini index is almost the same as in table 2.5. Total inequality is stable and high between 2003 and 2013, which means that there is a great concentration among the probabilities of being at the top ranks. As before, the bulk of total inequality is by inequality between regions, even with a declining weight. Within inequality shows a small increase over time. Thus, while regions have a weak tendency to converge, on average, there is some evidence of a greater inequality among provinces within regions, mainly because some provinces converge with others beyond the regional borders in the Central-North areas (e.g., Bolzano, Florence, Ascoli Piceno, Ravenna, Treviso, Perugia, and Milan).

Table 2.8 - Multidimensional ANOGI of Downward cumulative rank acceptability index for rank 84

Year	Total Inequality	Standard Within	Impact of Overlapping on Within	Between	Impact of Overlapping on Between
2003	0.759	0.029	0.325	0.615	-0.210
2006	0.762	0.029	0.308	0.625	-0.200
2007	0.755	0.029	0.357	0.581	-0.213
2008	0.747	0.033	0.396	0.546	-0.228
2009	0.749	0.030	0.324	0.585	-0.190
2010	0.756	0.029	0.357	0.595	-0.225
2011	0.751	0.034	0.300	0.572	-0.155
2012	0.748	0.034	0.371	0.523	-0.179
2013	0.750	0.033	0.349	0.565	-0.198

Source: Authors' elaboration on ISTAT (2017)

To investigate the role of overlapping, tables 2.9 and 2.10 report the matrix related to the upward cumulative rank for 2003 and 2013, respectively. Rows with missing values represent now the cases in which all provinces of the baseline region have the same probability of being above rank 84. With the exception of Aosta Valley (in which this is because it has just one province), this occurs in 2013 only for Liguria, in which all of the provinces have zero probability of being in the best 20. Still, the picture does not dramatically change, as most regions of the South appear to be relatively stratified, which means – in the specific case – that they usually have a lower probability to be in the top ranks. This picture holds both in 2003 and in 2013, even though the distributions of probability seem to be more intertwined on average. Indeed, according to table 2.9 higher stratification emerges in five regions (by row $O_{ji}^{\geq 84} < 0.4$ on average). In particular, Abruzzi, Basilicata, Marche, Molise, and Trentino show a relatively high stratification because they have relatively high probabilities of being above rank 84; Sicily appears more stratified, on average, because of very low probabilities of belonging to that group. In 2013 (table 2.10), instead, relatively higher stratification is in five regions: Basilicata, Calabria, Marche, Molise and Trentino. In this case, however, stratification occurs because of lower probabilities in Basilicata, Calabria and Molise, while Marche and Trentino do not show significant changes with respect to 2003.

Table 2.9 - Overlapping Matrix of Upward cumulative rank acceptability index for rank 84 by region, 2003

	PI	VA	LO	TR	VE	FR	LI	ER	TU	UM	MA	LA	AB	MO	CA	AP	BA	CL	SI	SA
PI	1.00	1.00	0.91	0.00	0.14	0.75	1.00	0.33	0.30	0.00	0.00	0.80	0.00	0.00	0.60	1.00	0.00	0.00	0.67	0.25
VA	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
LO	0.73	0.61	1.00	0.00	0.76	0.93	0.66	0.40	0.57	0.00	0.00	0.53	0.00	0.00	1.13	1.43	0.00	0.38	1.48	1.52
TR	0.00	0.00	0.00	1.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.40	0.00	0.00
VE	0.03	0.00	0.26	1.85	1.00	0.58	0.46	0.11	0.42	0.93	0.66	0.74	1.76	0.93	0.39	0.38	1.85	1.77	0.54	0.61
FR	0.46	0.33	0.88	2.00	1.05	1.00	1.00	0.33	0.50	1.00	0.00	1.20	0.50	0.00	1.00	1.27	1.00	1.20	1.33	1.42
LI	0.83	0.67	1.21	1.00	1.14	1.00	1.00	0.44	0.60	0.00	0.00	1.33	0.50	0.00	1.20	1.73	1.00	1.20	1.63	1.67
ER	0.81	0.72	1.13	1.92	1.78	1.38	1.20	1.00	1.20	0.96	0.96	1.34	1.92	1.92	1.20	1.39	1.92	1.92	1.49	1.50
TU	0.64	0.57	0.89	1.87	1.55	1.18	1.03	0.82	1.00	0.93	0.80	1.20	1.87	1.60	0.87	1.17	1.87	1.87	1.13	1.18
UM	0.00	0.00	0.00	0.00	0.86	0.50	0.00	1.11	1.00	1.00	1.00	0.00	1.50	2.00	0.00	0.00	1.00	0.80	0.00	0.00
MA	0.00	0.00	0.00	0.00	0.68	0.00	0.00	0.91	0.80	0.82	1.00	0.00	0.78	1.59	0.00	0.00	0.78	0.31	0.00	0.00
LA	0.75	0.60	1.09	0.70	1.03	0.90	0.75	0.40	0.54	0.00	0.00	1.00	0.35	0.00	1.08	1.56	0.70	1.00	1.47	1.50
AB	0.00	0.00	0.00	1.00	0.21	0.25	0.25	0.00	0.00	0.50	0.39	0.20	1.00	0.73	0.00	0.00	1.27	0.80	0.00	0.00
MO	0.00	0.00	0.00	0.00	0.86	0.00	0.00	0.00	0.40	0.00	0.50	0.00	0.50	1.00	0.00	0.00	0.00	0.40	0.00	0.00
CA	0.93	0.83	1.06	0.00	0.47	1.04	0.83	0.46	0.42	0.00	0.00	0.66	0.00	0.00	1.00	1.16	0.00	0.00	1.29	1.46
AP	0.41	0.25	0.64	0.00	0.78	0.68	0.25	0.30	0.47	0.00	0.00	0.20	0.00	0.00	0.94	1.00	0.00	0.39	1.27	1.43
BA	0.00	0.00	0.00	2.00	0.00	0.50	0.50	0.00	0.00	1.00	0.50	0.40	0.50	0.00	0.00	0.00	1.00	0.80	0.00	0.00
CL	0.00	0.00	0.07	1.52	0.11	0.41	0.41	0.00	0.00	0.82	0.30	0.61	1.06	0.60	0.00	0.15	1.30	1.00	0.08	0.00
SI	0.41	0.30	0.59	0.00	0.58	0.66	0.37	0.26	0.39	0.00	0.00	0.30	0.00	0.00	0.79	0.76	0.00	0.29	1.00	1.09
SA	0.55	0.49	0.79	0.00	0.41	0.84	0.49	0.38	0.34	0.00	0.00	0.39	0.00	0.00	0.68	0.87	0.00	0.00	1.17	1.00

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

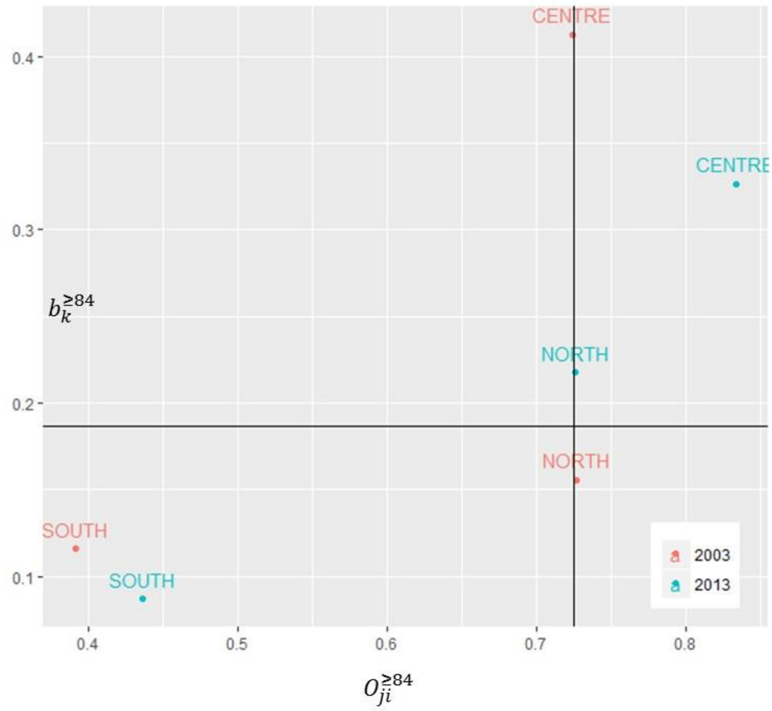
Table 2.10 - Overlapping Matrix of Upward cumulative rank acceptability index for rank 84 by region, 2013

	PI	VA	LO	TR	VE	FR	LI	ER	TU	UM	MA	LA	AB	MO	CA	AP	BA	CL	SI	SA
PI	1.00	0.00	0.21	0.00	0.67	0.71	0.94	0.31	0.61	0.94	0.00	0.94	0.00	0.00	1.32	1.13	0.00	0.28	1.41	0.47
VA	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
LO	0.22	1.62	1.00	0.00	0.48	0.64	0.15	0.47	0.37	0.15	0.22	0.60	1.21	1.62	0.21	0.49	1.12	1.05	0.26	0.83
TR	0.00	0.00	0.00	1.00	0.29	0.00	0.00	0.67	0.40	1.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
VE	0.49	1.74	1.47	0.57	1.00	1.26	0.22	1.13	0.84	0.78	0.94	1.27	1.68	1.74	0.66	0.88	1.74	1.66	0.63	1.20
FR	0.60	1.94	1.34	0.00	0.44	1.00	0.34	0.76	0.45	0.34	0.00	1.01	1.31	1.94	0.75	0.94	1.94	1.83	0.69	0.17
LI	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na	na
ER	0.35	1.88	1.37	0.78	0.88	0.92	0.20	1.00	0.79	0.74	1.24	0.71	1.61	1.88	0.44	0.70	1.18	1.24	0.45	1.51
TU	0.68	1.79	1.58	0.68	1.17	1.31	0.45	1.18	1.00	0.82	1.31	1.29	1.79	1.79	0.75	0.96	1.79	1.73	0.84	1.46
UM	0.50	2.00	1.82	1.00	1.43	1.50	0.00	1.33	1.20	1.00	1.50	1.60	2.00	2.00	0.80	1.20	2.00	2.00	1.00	2.00
MA	0.00	0.00	0.13	0.54	0.36	0.00	0.00	0.52	0.40	0.54	1.00	0.00	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.73
LA	0.61	0.00	0.64	0.00	0.43	0.91	0.28	0.57	0.46	0.28	0.00	1.00	0.43	0.00	0.81	0.55	0.87	1.02	0.79	0.14
AB	0.00	1.63	0.85	0.00	0.23	0.64	0.00	0.31	0.00	0.00	0.41	0.19	1.00	1.63	0.00	0.19	0.94	0.89	0.00	0.81
MO	0.00	2.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
CA	0.68	0.00	0.08	0.00	0.65	0.68	0.91	0.30	0.46	0.91	0.00	0.91	0.00	0.00	1.00	1.00	0.00	0.00	1.16	0.46
AP	0.87	0.00	0.94	0.00	0.71	1.00	0.51	0.88	0.70	0.51	0.00	1.49	0.49	0.00	1.00	1.00	1.97	1.58	1.06	0.25
BA	0.00	0.00	0.36	0.00	0.00	0.00	0.00	0.44	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	1.00	0.80	0.00	0.00
CL	0.09	0.00	0.52	0.00	0.11	0.19	0.00	0.47	0.07	0.00	0.00	0.45	0.93	0.00	0.00	0.30	1.37	1.00	0.08	0.00
SI	0.59	0.00	0.17	0.00	0.56	0.58	0.57	0.25	0.47	0.64	0.00	0.79	0.00	0.00	0.95	0.91	0.00	0.26	1.00	0.35
SA	0.35	1.40	1.14	0.00	0.97	1.05	0.00	0.62	0.66	0.00	0.35	1.12	1.35	1.40	0.56	0.84	1.40	1.40	0.62	1.00

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Figure 2.6 reports a quadrant representation of the average $O_{ji}^{\geq 84}$ (x axis) and of the average $b_k^{\geq 84}$ (y axis) for the Northern, Central, and Southern areas of the country. The evidences in figure 2.4 are confirmed by figure 2.6. In average, the lower left quadrant in figure 2.6 shows that Southern regions have a generally bad performance combined with high level of stratification (both low $b_k^{\geq 84}$ and low $O_{ji}^{\geq 84}$). Central regions are instead on the upper right quadrant in figure 2.6, showing both good performances and low level of stratification. As before, the Northern regions show average performances and a median level of stratification. The dynamic perspective confirms the results in figure 2.4 as well. Indeed, we observe that both Southern and Central regions in 2013 have performances and stratification lower than in 2003. Northern regions have instead relevantly increased their performances in the same interval.

Figure 2.6 - Quadrant representation of average performance and average stratification by area (upward cumulative rank acceptability index of mortality for the rank 84)

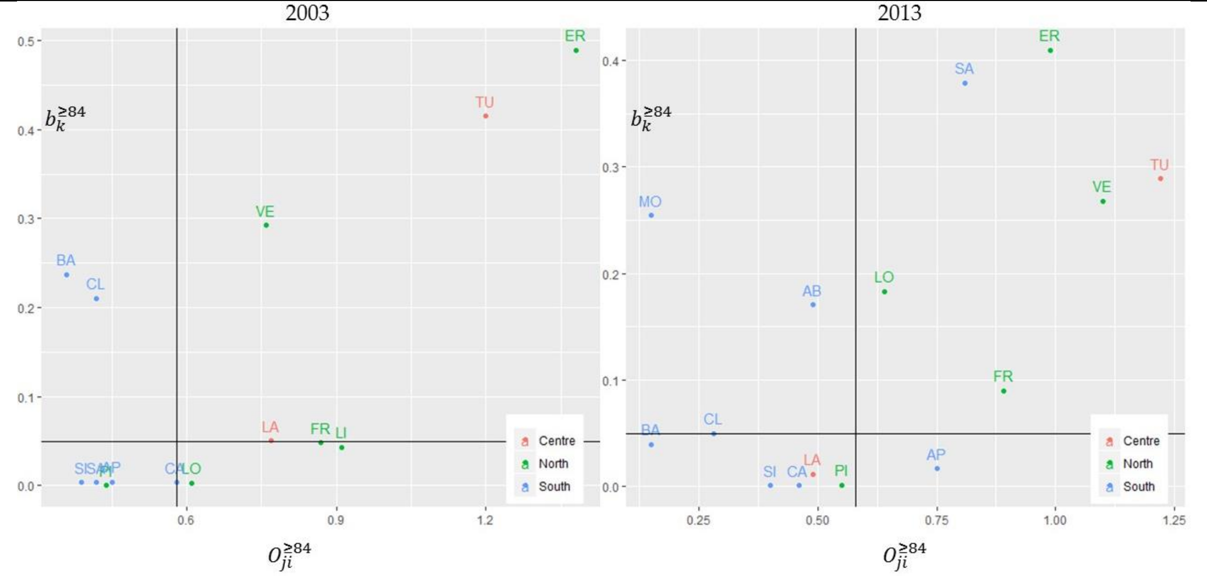


Source: Authors' elaboration on ISTAT (2017).
Notes: Quadrant representation of average performance (upward cumulative rank acceptability index of mortality for the rank 84), and average stratification (Overlapping of upward cumulative rank acceptability index of mortality for the rank 84) by area (North, Centre, and South); $O_{ji}^{\geq 84}$ values are averages of regional estimates, and $b_k^{\geq 84}$ values are averages of provincial estimates; the lines are on the median values.

Figure 2.7 shows the relation between performance ($b_k^{\geq 84}$) and stratification ($O_{ji}^{\geq 84}$) at regional level. The $O_{ji}^{\geq 84}$ is represented on the x axis, and the average $b_k^{\geq 84}$ is presented on the y axis. Regions showing n. a. cells in tables 2.9 and 2.10 are excluded from this analysis. In the upper left quadrant in figure 2.7, there are regions having good performances and high stratification (high $b_k^{\geq 84}$ and low $O_{ji}^{\geq 84}$). In 2003 two Southern regions belong to this group: Basilicata and Calabria. In 2013, Abruzzi and Molise replace Basilicata and Calabria because of decreasing in the performances of the latter. In the upper right quadrant in figure 2.7 there are good performer regions with low level of stratification (high $b_k^{\geq 84}$ and high $O_{ji}^{\geq 84}$). Two Northern regions (Emilia Romagna and Veneto) and one Central region (Tuscany) are on this quadrant in 2003. Friuli, Lombardy, and Sardinia improve their performances and join this group in 2013. On the lower right quadrant in figure 2.7 there are regions with bad performances and low stratification (low $b_k^{\geq 84}$ and high $O_{ji}^{\geq 84}$). Only Lombardy belongs to this category in 2003, and it is replaced by Apulia in 2013. Finally, on the lower left quadrant in figure 2.7 there are regions with bad performances and high stratification. Four Southern regions (Campania, Apulia, Sicily, and Sardinia) and one Northern region (Piedmont) belongs to this group in 2003. In 2013 Lazio and Basilicata replace Sardinia and Apulia in this category.

More in general, figure 2.7 confirms that Southern regions are in average more stratified compared with Northern and Central regions. In addition, there is a strong dispersion in the levels of performance and stratification. Among the best performers, Emilia Romagna and Tuscany show a persistent low level of stratification in the 2003-2013 interval.

Figure 2.7 - Quadrant representation of average performance and average stratification by region (upward cumulative rank acceptability index of mortality for the rank 84)



Source: Authors' elaboration on ISTAT (2017).
Notes: Quadrant representation of average performance (upward cumulative rank acceptability index of mortality for the rank 84), and average stratification (Overlapping of upward cumulative rank acceptability index of mortality for the rank 84) by region; $O_{ji}^{\geq 84}$ values are regional estimates, and $b_k^{\geq 84}$ values are regional averages of provincial estimates; the lines are on the median values.

The results provided in this section show that some regions of the South still appear to be relatively stratified with respect to the national distribution and to the distribution of other regions. Some provinces converge beyond the regional borders in the Central-Northern area of country, as also suggested by the increase in within inequality especially when considering the top ranks. In the 2003-2013 interval, there are evidences of a relevant worsening in the performances of both the Central and Southern provinces, and a consistent increasing of the performances in the Northern provinces.

2.5 Conclusions

This chapter introduces an innovative measure of the regional outcome of the Italian National Health Care Service. We estimate a Composite Index of mortality at regional and provincial level. Our CI of mortality is esteem of weighted average of the standardized mortality rates for seventeen diseases, weighed by a random set of weights from a uniform distribution. We employ, for the first time in literature related to health performance, the Stochastic Multi-Objective Acceptability Analysis approach, which allows summarizing the multidimensional health outcome without any assumption about the health care preferences (needs) of people. Furthermore, we measure the spatial segregation using the multidimensional generalization of the Gini index presented in Greco *et al.* (2017), and we introduce the multidimensional generalization of the Analysis of Gini (ANOGI) to disentangle between and within inequality.

Our results show that there is a pervasive and persistent spatial segregation in the health outcome. In particular, we observe a bad performer area in the Southern-West side of the country (Campania and Sicily above all), and a good performer area in the Northeast. Moreover, it emerges that in the period 1990-2013 there was improvement in some Northern regions, such as Lombardy and Trentino, and a worsening in some Southern regions, Sardinia and Calabria in particular. The inequality of the distribution of probabilities is high by any standard, both for the downward and for the upward cumulative rank acceptability, with the bulk of this inequality given by inequality between regions. This feature, to some extent, contradicts the constitutional provision of providing the right for essential levels of care over the whole country.

From a general perspective, the results show that some regions of the South still appear to be relatively stratified with respect to the rest of the country, and that some provinces converge beyond the regional borders in the Centre-North, as also suggested by the increase in within inequality especially when considering the top ranks. Regional disparities seem to be persistent over time and the decentralisation reforms that have given more organizational and spending power to the regions seems to have altered this pattern. This study provides evidence that the general positive effect of decentralization on health performance in Italy, mainly found in infant mortality rates (Porcelli, 2014; Cavalieri, Ferrante 2016), has not involved all the dimensions of health, it has not involved all the regions, and to some extent, it came at the cost of increasing the gap between North and South of the country.

As further research, this chapter shows that Multi Criteria Decision Making approach can be fruitfully used to study many problems related to health policy. Social scientists interested in phenomena out of market, need tools to manage the multidimensionality in holistic approach. For instance, the way SMAA manages the lack of knowledge about the order of importance can help to understand and manage the complexity of social phenomena, which are the most relevant component in the Market/Government relationships path.

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Appendices

Table A2.1 - Rank in Composite Index of Mortality by the simple arithmetic mean

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2006	2007	2008	2009	2010	2011	2012	2013
Piedmont	6	6	9	7	7	5	9	9	6	4	4	6	5	5	3	5	3	3	5	7	6	5
Aosta V.	8	8	3	5	10	7	2	3	3	3	2	2	2	4	6	3	11	6	3	12	18	12
Lombardy	3	3	6	4	3	3	4	4	4	6	8	7	8	8	12	10	10	11	11	14	14	16
Trentino-A. A.	13	12	13	17	17	18	17	17	15	16	17	15	16	13	15	19	19	20	20	20	20	20
Veneto	9	10	12	11	12	11	13	14	13	12	14	13	13	15	14	13	14	16	14	16	15	15
Friuli-V. G.	4	6	5	3	4	9	5	8	11	8	10	9	6	7	8	11	5	7	6	10	9	8
Liguria	5	5	11	6	5	4	7	7	10	5	7	5	7	6	5	8	4	4	4	3	7	3
Emilia-R.	17	18	19	19	18	19	18	19	19	18	18	18	17	17	16	17	17	15	17	17	16	17
Tuscany	16	16	15	18	16	15	16	16	18	15	15	16	15	14	17	16	13	14	15	15	13	13
Umbria	18	15	16	14	15	16	14	18	14	19	19	17	18	19	19	18	15	18	18	18	17	18
Marche	19	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	19	19	19	19	19
Lazio	7	4	8	8	6	8	8	5	7	7	5	4	4	3	7	9	8	9	8	6	4	6
Abruzzi	14	13	17	16	14	14	15	15	17	17	16	19	14	16	18	14	18	13	10	11	10	10
Molise	20	19	18	15	19	17	19	12	16	14	13	14	19	18	10	12	9	17	13	8	12	11
Campania	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Apulia	10	11	10	12	11	12	11	10	5	13	9	12	10	9	9	4	7	10	9	4	5	9
Basilicata	11	14	4	13	9	6	6	11	8	11	11	11	12	12	4	7	12	12	12	9	8	7
Calabria	12	9	7	9	8	10	10	6	9	10	6	10	11	11	11	6	6	5	7	5	3	4
Sicily	2	2	2	2	2	2	3	2	2	2	3	3	3	2	2	2	2	2	2	2	2	2
Sardinia	15	17	14	10	13	13	12	13	12	9	12	8	9	10	13	15	16	8	16	13	11	14

Source: Authors' elaboration on ISTAT (2017)

Table A2.2 - Rank Frequency 1990

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	1285	21419	0	0	9	12	0	0	0	0	0	0	0	74101	0	0	0	3174	0
2	0	2242	22701	0	0	10177	549	0	0	0	0	0	0	0	13053	13	0	0	51265	0
3	621	8731	34369	0	135	15446	6795	0	0	0	0	25	0	0	4997	2755	7040	2784	16235	67
4	14875	8506	7150	0	2441	17540	25177	0	0	0	0	317	0	0	3178	4523	5121	4851	5972	349
5	22178	6935	4226	2	5368	12166	25383	19	0	0	0	3414	0	0	1655	4982	3780	2811	5908	1173
6	26576	7835	4532	16	5158	9520	19701	69	0	0	0	9809	0	0	1102	3607	3579	3984	3687	825
7	18127	11088	2443	96	7362	6338	10624	305	0	0	0	26713	15	0	1162	5443	3470	3052	2599	1163
8	8491	8671	1926	919	23117	4062	5114	493	19	0	0	22287	104	0	257	7522	6626	4111	4679	1602
9	4926	15851	707	5023	10537	4653	5255	1369	83	0	0	21489	473	0	151	12601	6751	5387	2419	2325
10	2346	8474	295	14035	7482	5411	1094	4502	366	0	0	9159	4316	0	135	24366	7458	5763	1083	3715
11	948	8113	159	12958	6895	6140	268	7711	2558	3	0	4663	7835	0	186	14353	9793	7428	941	9048
12	612	6244	70	12039	8562	4936	28	8442	7911	197	1	1237	13660	80	16	7775	8308	9978	1138	8766
13	269	3483	3	7887	10464	3366	0	8483	12139	1482	35	736	20253	180	4	6711	5375	6978	463	11689
14	31	1509	0	13281	11640	165	0	6771	10555	7026	110	150	15177	580	3	3745	5516	5083	236	18422
15	0	559	0	16326	592	65	0	8102	6519	34449	401	1	9484	1108	0	1317	3080	5219	129	12649
16	0	266	0	9447	244	3	0	6104	15697	30926	3126	0	19808	3102	0	278	2418	3082	68	5431
17	0	187	0	5675	3	3	0	7678	29084	17245	6666	0	8077	6422	0	9	7280	6490	4	5177
18	0	18	0	1848	0	0	0	23652	14508	8670	6888	0	798	5195	0	0	10303	12146	0	15974
19	0	3	0	323	0	0	0	13953	561	2	54446	0	0	14201	0	0	4100	10853	0	1558
20	0	0	0	125	0	0	0	2347	0	0	28327	0	0	69132	0	0	2	0	0	67

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA= Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.3 - Rank Frequency 1991

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	1010	10283	0	0	23	4	0	0	0	0	0	0	0	87202	0	0	0	1478	0
2	0	3215	20480	0	0	3723	259	0	0	0	0	302	0	0	7077	3	0	0	64941	0
3	1	11165	25686	0	924	10999	1882	0	0	0	0	9475	0	0	2561	1503	0	24484	11317	3
4	2895	11040	11394	1	2563	8811	7298	0	0	0	0	31955	0	0	1000	6179	7338	5297	4198	31
5	8918	5849	7379	128	4629	12445	16213	1	0	0	0	21562	13	0	755	8880	4590	5594	2888	156
6	18702	5588	4415	435	5150	9462	19038	6	0	0	0	16863	146	4	626	9300	4199	3322	2039	705
7	23160	6608	4385	1413	6269	8942	19091	27	0	0	0	10584	3959	63	201	5561	3089	3617	2134	897
8	17812	6965	3884	3856	16538	9070	12655	148	1	0	0	4808	5502	246	216	5496	4110	4795	2788	1110
9	15740	10686	3660	10829	14288	5201	8017	918	57	0	0	3152	4001	902	174	9839	3748	5439	1771	1578
10	6773	9850	4395	18012	7369	5576	6592	4339	660	1	0	848	6452	1494	74	12838	4353	5396	3113	1865
11	3052	7704	2877	11091	7651	5537	6452	7061	5396	492	0	285	7302	2452	107	17978	4733	5559	773	3498
12	2006	6536	834	9717	5520	8557	2058	6894	11864	3752	2	135	7625	4430	6	8008	5198	6210	1492	9156
13	733	3900	279	5362	9471	5671	389	7251	12293	14949	42	16	10201	4131	1	5825	6503	2609	490	9884
14	200	2865	44	9262	7486	3461	43	6620	9002	22842	150	7	9945	3485	0	4683	4418	2533	260	12694
15	7	3038	4	9024	6169	2181	9	6265	7004	32229	397	6	6009	3486	0	3340	4242	4096	216	12278
16	1	2030	1	7376	5856	230	0	5104	13098	17203	6229	1	15693	5539	0	556	4318	4524	101	12140
17	0	1245	0	11722	110	81	0	10015	15422	7309	5052	1	21654	4928	0	10	4503	5777	1	12170
18	0	543	0	1424	7	26	0	13717	24610	1095	7773	0	1498	6895	0	1	15838	9906	0	16667
19	0	163	0	312	0	4	0	30618	593	127	19289	0	0	26731	0	0	16198	829	0	5136
20	0	0	0	36	0	0	0	1016	0	1	61066	0	0	35214	0	0	2622	13	0	32

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.4 - Rank Frequency 1992

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	15390	1862	0	0	925	0	0	0	0	0	0	0	0	81300	0	0	0	523	0
2	0	25249	5506	0	0	7069	59	0	0	0	0	13	0	0	9212	0	16133	0	36759	0
3	0	14126	9155	0	1	16059	279	0	0	0	0	264	0	0	1911	240	27053	212	30700	0
4	59	15988	14411	0	367	11548	2735	0	0	0	0	1175	0	0	5096	3014	13895	26975	4719	18
5	4076	25789	7945	0	1669	11861	6136	0	0	0	0	6797	0	0	979	3642	5138	16122	9764	82
6	11404	2608	11065	1	2642	13551	6325	0	0	0	0	16450	0	1	385	18453	7388	5289	4225	213
7	20070	725	10227	217	4311	7367	6628	5	0	0	0	27462	0	98	592	8649	3698	6204	2566	1181
8	28793	110	7808	649	3763	8358	8005	43	2	0	0	21187	0	2631	240	6385	2626	5765	1547	2088
9	16803	15	8512	4249	7324	7721	9900	120	10	0	0	19800	458	4081	132	7028	2898	5471	3352	2126
10	11511	0	10240	4697	7627	4907	16689	1330	415	0	0	5221	3210	3154	83	18998	3154	3949	2617	2198
11	4283	0	4127	8007	12050	4811	26485	935	2590	3	0	1139	3636	5515	68	13445	4175	3872	1183	3676
12	2193	0	4818	12577	24737	2935	5924	1743	3806	130	1	433	7606	5972	2	7951	3510	5246	862	9554
13	549	0	2573	28030	8648	1369	7836	2514	6657	986	8	51	7756	5814	0	9157	2058	5409	704	9881
14	234	0	1666	10578	4608	1364	2459	4015	25819	6872	13	8	11075	6077	0	2361	1699	2949	343	17860
15	25	0	82	6913	10338	116	459	5438	14775	27288	80	0	9722	6532	0	486	3070	2397	72	12207
16	0	0	3	12196	7228	26	72	11619	3409	30837	1354	0	12634	4307	0	181	1802	3637	64	10631
17	0	0	0	9209	4025	12	9	7721	12444	27033	1730	0	12570	7375	0	10	1437	3469	0	12956
18	0	0	0	2591	662	1	0	5259	30038	6140	6405	0	22556	11457	0	0	257	2088	0	12546
19	0	0	0	80	0	0	0	52283	35	711	13760	0	8776	20707	0	0	9	877	0	2762
20	0	0	0	6	0	0	0	6975	0	0	76649	0	1	16279	0	0	0	69	0	21

Source: Authors’ elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.5 - Rank Frequency 1993

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	639	12645	0	0	1427	91	0	0	0	0	0	0	0	80549	0	0	0	4649	0
2	0	1617	10169	0	0	16042	587	0	0	0	0	0	0	0	7350	0	0	0	64230	5
3	0	12120	16464	0	195	26125	4514	0	0	0	0	142	0	0	5755	981	0	29437	4117	150
4	11	15584	19523	0	864	16255	10924	0	0	0	0	732	0	0	2018	1849	17051	4680	9308	1201
5	2438	28547	8145	0	2547	8890	20240	7	0	789	0	5465	0	1792	1673	4622	4044	5125	3641	2035
6	9412	15845	5584	0	4563	6862	24159	47	0	1224	0	10048	0	2164	1225	4839	3175	3817	3836	3200
7	26102	9596	4112	9	3627	4025	12993	279	0	1448	0	17521	0	2268	641	4370	2817	3366	1511	5315
8	22292	6893	3334	90	7982	3177	9439	268	2	2016	0	23447	3	1773	241	4598	2698	4830	2054	4863
9	14158	4297	3325	527	14733	3217	6658	1517	43	2264	0	21707	23	2192	279	4161	3461	7505	2877	7056
10	9416	2251	3096	4551	9325	3132	4576	2484	227	6775	0	10288	233	2415	102	7381	7640	7073	1130	17905
11	9031	1395	2380	6201	5622	2880	2553	4690	1008	16481	0	5561	1069	2857	101	17149	4802	4017	646	11557
12	4619	708	2643	9068	7743	2700	1942	6408	3778	10243	0	3063	1634	6017	64	12877	7263	6834	651	11745
13	1828	458	3187	8803	5777	1910	972	5297	8535	13034	50	1243	4727	8719	2	12741	7775	2180	1148	11614
14	623	45	2602	6769	5223	2083	322	3009	10224	15189	64	661	10417	8859	0	12990	5082	1488	152	14198
15	70	5	2791	8391	6898	1219	30	3428	6350	16447	405	105	21438	12484	0	6393	3665	2621	33	7227
16	0	0	0	5522	24699	33	0	4768	8713	9654	1897	17	23852	7335	0	3402	2140	6424	14	1530
17	0	0	0	31341	201	11	0	5596	19748	2703	3559	0	20978	4868	0	1098	5186	4368	3	340
18	0	0	0	13042	1	12	0	7208	39566	1057	3548	0	10962	12393	0	403	7937	3817	0	54
19	0	0	0	5318	0	0	0	54215	1806	675	3084	0	4664	22389	0	145	5327	2372	0	5
20	0	0	0	368	0	0	0	779	0	1	87393	0	0	1475	0	1	9937	46	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.6 - Rank Frequency 1994

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	2	7393	0	0	1165	273	0	0	0	0	0	0	0	90618	0	0	0	549	0
2	0	248	16809	0	0	8720	992	0	0	0	0	0	0	0	2850	0	0	0	70381	0
3	62	2133	26131	0	365	17827	7129	0	0	0	0	67	0	0	4009	3307	13997	20590	4328	55
4	2442	6686	9086	0	1637	20117	13730	0	0	0	0	1556	1	0	1280	3337	17500	15035	7262	331
5	19827	9563	5179	0	3884	7470	14737	0	0	0	0	14253	7	0	471	12466	3845	3252	3729	1317
6	18304	9210	5033	0	5269	4997	15006	2	0	0	0	23335	1610	1	359	5721	2940	3214	2486	2513
7	20150	6891	5351	4	4840	4549	13384	17	0	0	0	23050	3155	4	244	5649	3934	3184	1552	4042
8	13893	8334	5487	12	11562	5816	10428	51	0	0	0	17167	3887	120	97	5205	4873	5781	2267	5020
9	8110	12313	4596	982	8530	7196	12457	511	49	0	0	11224	3775	523	36	6732	5445	5782	3769	7970
10	5944	9025	4204	2829	9273	5083	5616	808	674	1	0	4847	3792	1284	10	15387	4871	5479	1343	19530
11	5556	14711	3705	3729	6830	4169	3670	1743	2991	71	0	2962	6104	1508	19	15606	4555	5306	501	16264
12	2924	8291	3424	8025	7925	4719	1487	3018	6976	379	0	1180	5598	2277	6	11456	5115	8097	342	18761
13	2128	7124	2391	5912	8399	4811	955	3879	11059	2466	0	326	11127	2469	1	6409	7258	3674	955	18657
14	609	2974	1173	9938	14327	2841	126	6582	7582	12726	3	32	19822	7520	0	4105	3157	2330	388	3765
15	51	1874	38	6234	6853	518	10	3246	10615	51504	4	1	4022	7193	0	2867	1819	2028	142	981
16	0	436	0	9841	10008	2	0	3810	20671	26059	766	0	9599	8008	0	1164	3347	5648	6	635
17	0	168	0	17044	298	0	0	8508	35720	5426	1583	0	15626	4127	0	585	5443	5316	0	156
18	0	17	0	28463	0	0	0	29241	3654	1299	2399	0	11874	10687	0	4	8248	4111	0	3
19	0	0	0	6699	0	0	0	37489	9	69	15280	0	1	35976	0	0	3350	1127	0	0
20	0	0	0	288	0	0	0	1095	0	0	79965	0	0	18303	0	0	303	46	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.7 - Rank Frequency 1995

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	236	8189	0	0	0	2745	0	0	0	0	0	0	0	88800	0	0	0	30	0
2	0	1884	20519	0	0	1082	9189	0	0	0	0	0	0	0	5161	0	0	0	62165	0
3	1444	5655	19625	0	9	5390	23478	0	0	0	0	65	0	0	2765	338	30526	927	9777	1
4	17581	12370	11274	0	170	6803	15901	0	0	0	0	1488	0	0	1466	657	5620	20921	5717	32
5	31373	9874	7619	0	596	10164	16023	2	0	0	0	6380	0	22	1002	1921	5735	5069	3890	330
6	25411	9882	5571	0	2069	11138	14519	2	0	0	0	14324	0	248	273	2236	6410	3969	3206	742
7	13195	11226	6602	5	6907	10737	8855	87	0	0	0	22524	11	855	418	3517	4837	4909	4043	1272
8	5242	10239	8066	95	7433	8685	6716	184	0	0	0	30690	100	1876	50	4574	5599	5741	2632	2078
9	2932	16261	4514	834	13488	9805	1795	1726	4	0	0	17574	590	3316	41	7827	5664	5418	5105	3106
10	1614	12699	3449	2682	11311	10253	503	3359	774	18	0	4975	2465	3308	13	15881	9814	7617	887	8378
11	950	4500	2100	2843	15925	6156	222	3054	4336	96	0	1329	5731	3511	10	20012	3581	12504	652	12488
12	232	2671	1800	4527	8082	5322	38	4979	9098	519	0	411	10258	5121	1	21843	4357	5491	686	14564
13	24	1535	585	5739	6609	6638	16	4444	10861	1569	4	216	14101	6722	0	9189	2764	5058	723	23203
14	2	587	86	6431	8881	5611	0	4078	14967	4490	11	24	21976	6892	0	6915	1961	2241	460	14387
15	0	267	1	6804	9503	1968	0	7440	13921	13778	68	0	13508	12390	0	2766	5365	2271	10	9940
16	0	85	0	8184	8724	172	0	8072	10698	33220	408	0	11602	3870	0	1371	3234	5178	17	5165
17	0	27	0	7510	293	62	0	7179	34638	20977	1224	0	11764	5499	0	777	2349	4828	0	2873
18	0	2	0	31636	0	14	0	21718	664	23858	2057	0	7030	5488	0	130	1902	4459	0	1042
19	0	0	0	21637	0	0	0	32726	39	1475	12070	0	864	27245	0	46	282	3217	0	399
20	0	0	0	1073	0	0	0	950	0	0	84158	0	0	13637	0	0	0	182	0	0

Source: Authors’ elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.8 - Rank Frequency 1996

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	14436	1657	0	0	33	383	0	0	0	0	0	0	0	83396	0	0	0	95	0
2	0	33320	5707	0	0	1752	959	0	0	0	0	0	0	0	8975	0	1	0	49286	0
3	0	26636	15333	0	0	9592	3418	0	0	0	0	32	0	0	1948	282	22760	5	19933	61
4	0	12867	21281	0	10	17549	7285	2	0	0	0	288	0	0	3401	1665	19054	11446	4630	522
5	273	9878	14735	0	280	18836	14522	50	0	0	0	2343	0	2	2025	3284	5077	16577	9786	2332
6	6359	1526	8800	0	1748	12624	14738	60	0	0	0	16949	2	192	87	11687	10583	4392	6330	3923
7	17928	781	6820	4	2464	6339	8314	107	0	0	0	29539	130	1045	40	8538	4678	5084	2335	5854
8	23286	389	5646	127	3048	6100	8467	605	0	0	0	23863	681	3521	80	8767	3840	4601	1377	5602
9	20055	114	4926	428	8106	5403	9888	1407	0	36	0	16127	2325	1919	30	8971	6014	5828	1586	6837
10	15825	29	4406	1605	8487	5524	10266	3177	10	475	0	6717	3376	2149	14	16014	4056	8700	1207	7963
11	7578	17	3531	3694	10524	5099	10259	3477	341	4981	0	2837	4205	3534	1	20920	3608	5646	1144	8604
12	5398	3	2951	5520	10969	3534	3408	5856	2080	14859	0	990	6539	4245	3	8185	4173	5880	789	14618
13	2553	4	2292	8295	12110	3107	2760	5202	5367	17905	0	278	14593	5116	0	4431	2320	4799	694	8174
14	745	0	1632	8801	7220	2902	3488	4094	14152	20545	5	31	12381	7495	0	2781	1241	2766	488	9233
15	0	0	283	8996	6734	1581	1648	4573	16405	28835	21	4	8150	5150	0	2642	1699	1704	297	11278
16	0	0	0	8619	16156	19	145	7069	28413	9136	1044	2	8703	5256	0	1495	5768	1921	20	6234
17	0	0	0	11398	10975	6	39	10483	27240	2507	1275	0	15860	3399	0	338	3087	7422	3	5968
18	0	0	0	29442	1168	0	13	17309	5937	667	2758	0	22553	7743	0	0	1973	8391	0	2046
19	0	0	0	12687	1	0	0	36393	55	54	12741	0	502	31943	0	0	68	4805	0	751
20	0	0	0	384	0	0	0	136	0	0	82156	0	0	17291	0	0	0	33	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.9 - Rank Frequency 1997

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	5075	1524	0	0	35	133	0	0	0	0	0	0	0	93175	0	0	0	58	0
2	0	21542	5516	0	0	725	624	0	0	0	0	5	0	0	3230	10	0	0	68348	0
3	0	35768	13074	0	0	4176	3657	0	0	0	0	1387	0	30	1315	2703	0	27855	10030	5
4	21	16193	24505	0	13	10906	8472	0	0	0	0	4581	0	588	1415	4054	12223	12028	4939	62
5	3188	8516	9816	0	26	16280	13994	0	0	0	0	18419	0	3628	655	5766	9258	5273	4494	687
6	14671	4169	6817	0	291	10285	10797	0	0	0	0	23542	0	8298	79	6573	4661	4447	3858	1512
7	22372	2896	5838	0	2823	6725	10053	15	0	0	0	18384	1	8759	106	10251	4363	3163	2320	1931
8	19504	4023	3693	48	3123	6396	13093	86	1	0	0	19061	180	5992	13	10974	3588	5185	1725	3315
9	17160	1035	3351	205	11301	6840	14298	772	3	0	0	7084	648	4065	7	13820	5463	6873	2051	5024
10	11566	354	6330	1924	9318	5336	8158	1693	207	0	0	4034	2216	5232	2	20239	7097	5006	740	10548
11	6025	209	7475	2837	9820	6773	7036	2064	934	1	0	2042	3957	10125	3	14272	7113	4163	532	14619
12	3832	108	4070	5373	6090	10576	7541	6257	2997	34	0	873	5748	17832	0	6454	6185	4397	323	11310
13	1528	52	4670	5800	12405	6290	1475	4979	8397	698	0	436	7988	11028	0	2769	6216	3973	275	21021
14	133	50	3314	10001	11613	7375	661	3809	9540	3785	4	114	15794	7158	0	1635	6773	1630	259	16352
15	0	5	7	11656	21329	1125	8	4061	10026	16953	51	35	15039	6582	0	343	2985	2545	35	7215
16	0	4	0	10069	8166	120	0	5486	29105	22769	1258	1	9282	5599	0	117	2486	3132	13	2393
17	0	1	0	9234	3448	30	0	11109	27043	25227	859	2	10598	3485	0	18	4160	2704	0	2082
18	0	0	0	19397	234	7	0	21258	11742	21615	3328	0	11426	1581	0	2	5154	2520	0	1736
19	0	0	0	17328	0	0	0	38141	5	8886	8257	0	17057	18	0	0	6167	3953	0	188
20	0	0	0	6128	0	0	0	270	0	32	86243	0	66	0	0	0	6108	1153	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.10 - Rank Frequency 1998

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	8880	486	0	0	16	4	0	0	0	0	0	0	0	90578	0	0	0	36	0
2	0	22090	5935	0	0	543	230	0	0	0	0	0	0	0	6935	40	0	0	64225	2
3	121	24838	20112	0	0	5275	2741	0	0	0	0	559	0	0	912	3047	5544	24453	12229	169
4	2558	9400	16725	0	22	11757	6600	0	0	0	0	2895	0	0	1215	10811	24005	8848	4453	711
5	12309	6674	5640	6	207	11257	13031	0	0	0	0	12068	0	331	300	17833	7200	4670	4120	4354
6	18008	7379	4788	111	1545	8481	8359	0	0	0	0	15444	0	883	37	14777	5789	4607	3498	6294
7	19538	5419	5060	692	1963	5887	8732	1	0	0	0	18013	5	3001	21	11528	5039	4150	2109	8842
8	18574	4863	6104	763	2294	4825	10029	13	0	0	0	15294	27	2992	1	11046	5985	3238	1684	12268
9	12978	4626	6742	1432	4106	5254	10361	65	0	121	0	12263	159	2871	1	12194	5175	3886	1584	16182
10	10180	2861	5264	2325	5393	7549	10711	244	0	385	0	12638	760	4583	0	9222	4400	4451	1469	17565
11	4122	1275	6852	4169	12575	7385	12162	687	3	655	0	6720	2564	4719	0	6295	6826	4571	2651	15769
12	1412	592	6875	11130	5039	10579	9071	4108	55	3064	0	3223	4855	5006	0	2245	11044	6511	926	14265
13	190	542	3965	12108	17974	6605	4504	5751	579	14367	0	579	5344	8768	0	682	6873	7829	691	2649
14	9	399	4740	12922	11642	4506	2066	2334	1894	35365	0	198	8928	5487	0	264	2338	5984	99	825
15	1	111	699	11723	8639	7701	867	3488	6137	39300	35	71	8591	7169	0	15	2810	2336	214	93
16	0	35	13	12571	17719	2149	477	9743	13559	6271	1114	26	12626	15825	0	1	5057	2790	12	12
17	0	9	0	14094	9958	179	55	10605	31359	472	1536	9	17793	6750	0	0	1354	5827	0	0
18	0	7	0	6870	924	52	0	16559	39461	0	3591	0	17666	11826	0	0	536	2508	0	0
19	0	0	0	4238	0	0	0	42065	6884	0	13637	0	19032	11714	0	0	24	2406	0	0
20	0	0	0	4846	0	0	0	4337	69	0	80087	0	1650	8075	0	0	1	935	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.11 - Rank Frequency 1999

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	11267	37	0	0	366	896	0	0	0	0	0	0	0	87324	0	0	0	110	0
2	1615	23969	1091	0	0	3814	4974	0	0	0	0	1	0	0	6282	0	0	0	58229	25
3	30261	15924	4428	0	0	8707	13778	0	0	0	0	1226	0	11	2534	48	427	14009	7671	976
4	22355	14877	12969	0	0	7359	10577	0	0	0	0	6449	0	28	1369	166	10315	5038	5573	2925
5	23541	6292	20381	0	5	6474	13168	0	0	0	0	10555	0	394	1315	484	4968	5160	2811	4452
6	16986	5891	13307	0	309	11221	13903	0	0	0	0	18635	0	908	865	1096	5701	3684	3476	4018
7	3145	6224	9379	2	4700	12593	11462	8	0	0	0	21983	0	5838	298	1411	3983	4152	7573	7249
8	1063	4679	8946	85	4048	9853	14829	19	0	0	0	25605	1	3324	9	2282	4463	4886	4510	11398
9	543	3798	6960	434	13678	5066	6217	407	1	0	0	11940	9	3549	4	3552	5658	9776	3207	25201
10	364	3138	6426	2209	13287	5608	5023	1302	177	0	0	3188	36	5540	0	12293	10306	7524	3518	20061
11	123	1994	6340	6127	9076	6159	3109	2700	2349	0	0	337	365	8492	0	20305	10435	7295	1258	13536
12	4	1188	6658	5695	6835	7392	1473	4648	11634	11	0	64	1876	11112	0	16489	10503	6386	565	7467
13	0	573	2286	6576	8781	9493	539	6673	10930	145	0	13	6810	13431	0	18986	6723	5120	604	2317
14	0	131	788	11126	16027	4675	45	5764	9286	1346	5	3	15735	11953	0	13724	3967	4277	853	295
15	0	35	4	10567	12065	513	7	2513	29016	7537	20	1	13896	9438	0	4810	5830	3649	23	76
16	0	19	0	10491	4662	615	0	8256	30486	10011	570	0	13518	8777	0	3075	5393	4109	14	4
17	0	1	0	10516	5525	87	0	16991	5864	26710	1930	0	15999	7536	0	971	3960	3906	4	0
18	0	0	0	16050	1002	5	0	19240	257	36293	1554	0	12978	5390	0	308	3667	3255	1	0
19	0	0	0	15024	0	0	0	31479	0	17938	6446	0	18766	3466	0	0	3205	3676	0	0
20	0	0	0	5098	0	0	0	0	0	9	89475	0	11	813	0	0	496	4098	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.12 - Rank Frequency 2000

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	9253	0	0	0	0	70	0	0	0	0	0	0	0	90671	0	0	0	6	0
2	1	41279	302	0	0	205	685	0	0	0	0	3	0	0	8344	0	0	0	49181	0
3	399	31088	5912	0	0	3765	7183	0	0	0	0	241	0	0	462	888	0	16699	33343	20
4	11786	10652	9446	0	3	7105	10920	0	0	0	0	11090	0	0	266	5200	6383	23440	3485	224
5	18428	4021	11521	14	14	6366	9378	0	0	0	0	15909	3	1956	220	6612	14232	7629	1604	2093
6	23658	1968	8364	107	135	7298	7816	0	0	0	0	17758	12	6431	24	9329	7450	4237	2310	3103
7	18889	871	9125	411	1688	8808	8561	0	0	0	0	17648	61	5670	13	10679	6307	4146	3082	4041
8	14554	642	6826	954	2519	9427	11158	5	0	0	0	16541	250	5602	0	13992	5263	4515	2273	5479
9	8986	104	6543	2761	5510	7961	10031	123	4	0	0	9714	665	6884	0	18942	5098	6330	1371	8973
10	2186	59	8065	3603	5625	6421	13054	393	280	0	0	6183	2061	4939	0	16652	5853	4025	1113	19488
11	863	40	7894	3517	10581	7481	9278	631	1641	0	0	3325	5449	5614	0	9371	7013	5373	809	21120
12	246	21	8901	8113	7457	9759	7165	1924	6080	1	0	1013	10803	7393	0	4651	7923	4358	472	13720
13	4	1	11142	6364	7768	12887	3125	3609	13890	9	0	359	7181	8804	0	1898	5153	3230	374	14202
14	0	0	5911	8724	10583	9837	1443	7457	20778	64	4	145	15859	5457	0	1660	4716	3013	573	3776
15	0	1	44	7224	18339	2037	103	5188	33360	752	436	64	13317	5895	0	116	5652	5398	4	2070
16	0	0	4	10461	19171	634	27	6084	21541	6400	1814	7	12013	8545	0	10	6547	5071	0	1671
17	0	0	0	17073	9640	9	3	20781	2356	13429	1224	0	18599	7410	0	0	8558	898	0	20
18	0	0	0	12449	967	0	0	37006	70	18613	2073	0	13505	12756	0	0	1232	1329	0	0
19	0	0	0	10457	0	0	0	16447	0	56454	12449	0	140	1575	0	0	2192	286	0	0
20	0	0	0	7768	0	0	0	352	0	4278	82000	0	82	5069	0	0	428	23	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.13 - Rank Frequency 2001

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	7468	814	0	0	0	1030	0	0	0	0	0	0	0	90686	0	0	0	2	0
2	0	43856	3039	0	0	48	3693	0	0	0	0	11	0	0	6198	0	0	0	43155	0
3	132	34307	12918	0	0	484	14623	0	0	0	0	1781	0	0	1731	28	1	9711	24157	127
4	5769	10129	12549	0	0	4016	19722	0	0	0	0	21342	0	0	789	618	1866	14325	6813	2062
5	17699	2586	8094	0	0	9973	9884	0	0	0	0	24300	0	0	435	739	10087	6161	3389	6653
6	29239	1381	8976	0	7	5072	9014	0	0	0	0	22704	0	71	149	2345	8751	4136	2176	5979
7	24663	172	8721	22	72	7391	15023	2	0	0	0	15148	0	1377	9	4252	7092	4397	1942	9717
8	10930	49	6921	195	443	17382	13144	0	0	0	0	9954	0	2484	2	6280	6646	5019	4319	16232
9	5542	41	5328	923	5166	10124	5269	5	0	0	0	3828	1	3032	0	8791	5524	4395	7068	34963
10	4855	10	4727	4317	6164	6410	3778	1608	8	3	0	860	14	3067	1	32399	4540	8198	2400	16641
11	1144	1	7480	4685	13394	9721	3630	2022	482	15	0	65	205	7562	0	17051	17808	5894	2011	6830
12	25	0	11887	7332	5074	14226	860	8117	3101	693	0	5	1680	4430	0	18673	14161	8043	953	740
13	2	0	6021	12410	9535	11128	256	6007	12058	1548	0	2	4204	19339	0	6789	5224	4694	732	51
14	0	0	2389	18860	14221	2431	67	4400	14882	9450	0	0	11197	11072	0	1738	5800	2699	789	5
15	0	0	129	9050	10549	1240	6	5379	22431	25868	3	0	8894	7099	0	184	6147	2930	91	0
16	0	0	7	7618	6711	307	1	8862	29808	19831	103	0	11314	6196	0	78	4762	4401	1	0
17	0	0	0	7990	13787	47	0	9794	15365	25263	267	0	13165	8506	0	33	1260	4521	2	0
18	0	0	0	7198	14477	0	0	25533	1856	15405	1633	0	13317	16646	0	2	322	3611	0	0
19	0	0	0	15359	400	0	0	28271	9	1924	5808	0	35983	8594	0	0	9	3643	0	0
20	0	0	0	4041	0	0	0	0	0	0	92186	0	26	525	0	0	0	3222	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.14 - Rank Frequency 2002

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	12758	15	0	0	5	177	0	0	0	0	0	0	0	87011	0	0	0	34	0
2	2	43545	381	0	0	1776	1148	0	0	0	0	1	0	0	10374	0	0	0	42757	16
3	175	31538	3717	0	0	14286	6468	0	0	0	0	879	0	0	948	709	123	7929	32840	388
4	8374	6398	13737	0	0	14991	10922	0	0	0	0	23438	0	0	1024	1208	2498	11972	3419	2019
5	22156	1762	11640	0	5	11482	12255	0	0	0	0	20285	0	0	521	1578	5947	5810	3233	3326
6	29824	1792	10599	0	35	10596	9863	0	0	0	0	15886	2	4	99	2578	8221	4000	3696	2805
7	24306	736	12564	0	1377	9222	10757	4	0	0	0	17504	26	48	18	4571	7323	3095	3634	4815
8	11189	397	9300	53	2839	7291	25492	22	0	0	0	13195	117	553	5	9871	4939	3964	4206	6567
9	2441	363	6464	1025	13083	6206	7981	412	0	0	0	5789	786	1537	0	12198	4565	8841	1906	26403
10	1482	274	6175	2598	12455	4944	6125	1734	91	0	0	2454	2835	1275	0	19623	10211	4128	2150	21446
11	51	245	4894	4106	12472	7026	4076	3985	1394	2	0	399	6857	2088	0	23931	10614	4133	1040	12687
12	0	97	7282	5831	5098	5578	2715	8641	8158	10	0	137	10426	2636	0	12362	11048	5785	442	13754
13	0	39	7689	6306	12156	4310	1321	5847	15023	188	0	29	22015	2819	0	6102	7101	5150	338	3567
14	0	19	5283	12531	16034	1811	575	5033	15722	499	0	4	18536	8931	0	4194	5003	3935	281	1609
15	0	13	216	12970	8695	266	123	5286	32788	5590	0	0	18530	4142	0	745	7233	2885	22	496
16	0	16	43	12563	5030	200	2	13379	20648	18039	0	0	12085	5613	0	318	7441	4540	2	81
17	0	4	1	11475	6793	10	0	14381	5789	35230	148	0	6329	6653	0	12	7554	5602	0	19
18	0	4	0	16562	3928	0	0	12419	387	39211	3561	0	1440	7908	0	0	179	14399	0	2
19	0	0	0	11535	0	0	0	28278	0	1231	10783	0	16	45261	0	0	0	2896	0	0
20	0	0	0	2445	0	0	0	579	0	0	85508	0	0	10532	0	0	0	936	0	0

Source: Authors’ elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.15 - Rank Frequency 2003

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	108	1227	0	0	47	929	0	0	0	0	0	0	0	97566	0	0	0	123	0
2	701	8333	7342	0	0	1393	6256	0	0	0	0	8124	0	0	1277	8	0	0	66555	11
3	4018	24322	6514	0	0	4907	7233	0	0	0	0	38896	0	0	582	538	0	4460	8201	329
4	21780	26741	4497	0	0	5670	8062	0	0	0	0	20540	0	0	225	2025	16	6083	2638	1723
5	36456	19545	5874	0	1	5796	6706	0	0	0	0	11256	0	0	202	2796	1259	5029	1855	3225
6	20162	9887	11765	7	2	15878	13759	0	0	0	0	7693	0	10	134	4945	4332	7097	1861	2468
7	8870	8410	15698	83	8	19511	12885	1	0	0	0	8024	0	134	8	7631	6505	4343	3792	4097
8	5431	2605	10265	1830	610	14516	23817	22	0	0	0	3465	3	901	1	12297	4820	3712	7674	8031
9	1488	46	6995	11938	1298	8724	8699	333	0	0	0	1407	87	2128	4	24691	3966	7405	2705	18086
10	1078	3	6849	6648	2974	7942	5726	935	44	0	0	557	700	2008	1	26703	5257	7459	1962	23154
11	16	0	5516	13815	10322	8661	3181	3075	2018	0	0	29	2666	2542	0	11257	8238	13359	566	14739
12	0	0	8103	8647	12380	4175	1646	7660	7325	0	0	8	4614	3412	0	3550	15061	8590	628	14201
13	0	0	3996	12247	8912	2385	655	9214	18908	1	0	1	15583	7228	0	1943	9527	2829	539	6032
14	0	0	5200	10668	9419	376	399	9879	26402	5	45	0	13297	12782	0	1589	3367	2728	868	2976
15	0	0	158	13062	10077	18	47	9674	19092	1184	6718	0	13790	6621	0	27	5645	13018	29	840
16	0	0	1	5954	10753	1	0	12320	21500	6587	3692	0	13317	5377	0	0	16826	3594	4	74
17	0	0	0	5926	17827	0	0	10091	4563	14793	3377	0	25894	8644	0	0	5544	3329	0	12
18	0	0	0	3556	12812	0	0	18284	147	14622	14949	0	8923	18011	0	0	4607	4088	0	1
19	0	0	0	2088	2048	0	0	15316	1	50308	15915	0	916	5901	0	0	4692	2814	0	1
20	0	0	0	3531	557	0	0	3196	0	12500	55304	0	210	24301	0	0	338	63	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.16 - Rank Frequency 2006

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	2649	62	0	0	117	1111	0	0	0	0	0	0	0	94381	0	0	0	1680	0
2	766	11410	355	0	0	1865	5684	0	0	0	0	25	0	4	3960	7	3	0	75921	0
3	17160	11308	1104	0	0	4389	15245	0	0	0	0	3168	0	38	825	1382	39701	3	5677	0
4	27233	10535	2130	0	0	6198	9887	0	0	0	0	8405	0	5524	318	4926	7899	13463	3481	1
5	21297	8974	3887	2	0	6506	11639	0	0	0	0	13978	0	11851	278	4908	8294	6372	2010	4
6	16879	8540	4925	20	10	10227	13415	0	0	0	0	15928	3	7591	215	7393	7027	5907	1853	67
7	9287	8262	7455	799	142	9872	11321	3	0	0	0	20450	31	8280	19	9267	4997	6161	3207	447
8	5130	7493	9236	974	950	10925	11325	14	0	0	0	17222	174	7899	4	13852	4561	5540	2971	1730
9	1941	7966	10241	2558	2275	6355	12276	258	0	0	0	9567	1072	7636	0	18785	8768	5341	870	4091
10	236	11626	6675	3087	3465	8721	6230	751	2	0	0	5735	5038	7584	0	21208	5369	5179	502	8592
11	71	5346	6523	4761	6002	19421	1701	1605	12	36	0	2722	7615	10202	0	9700	2952	7029	444	13858
12	0	2716	19885	5599	8235	9647	159	3489	295	165	0	1709	6230	8619	0	5783	2083	8160	470	16756
13	0	1658	8604	9755	15752	5255	7	6801	955	598	0	768	6143	4289	0	2006	2185	5360	531	29333
14	0	627	13804	13362	17207	402	0	12698	4978	2593	0	206	8374	4085	0	669	2787	3351	356	14501
15	0	246	3483	13866	21587	81	0	16959	14656	5189	0	87	4930	4986	0	108	3128	3715	20	6959
16	0	226	1209	12008	10244	18	0	26290	20974	6699	7	18	5083	9131	0	6	235	4563	6	3283
17	0	202	300	8278	6800	1	0	14752	37374	12696	180	10	6896	1979	0	0	11	10223	1	297
18	0	150	122	7267	5372	0	0	10492	15776	36755	1160	2	17451	267	0	0	0	5112	0	74
19	0	64	0	13394	1957	0	0	5888	4977	35269	7014	0	28852	34	0	0	0	2544	0	7
20	0	2	0	4270	2	0	0	0	1	0	91639	0	2108	1	0	0	0	1977	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.17 - Rank Frequency 2007

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	13526	0	0	0	0	6	0	0	0	0	0	0	0	86131	0	0	0	337	0
2	1	22903	293	0	0	1	105	0	0	0	0	0	0	2	13434	51	0	0	63210	0
3	629	36803	4283	0	0	148	1676	0	0	0	0	0	0	30	326	4018	119	22413	29555	0
4	26318	7864	3413	0	0	1117	8470	0	0	0	0	294	2	419	68	24241	11285	14811	1698	0
5	16685	2268	8212	0	0	1943	9033	0	0	0	0	3394	11	1212	32	33705	12789	9355	1361	0
6	12313	6778	7821	0	62	3733	10761	1	0	0	0	6332	65	7555	7	16911	17796	8727	1135	3
7	17191	4835	7867	4	580	6452	13071	24	0	0	0	11025	1955	8698	1	7984	12384	6421	1480	28
8	14542	1793	4692	43	1312	7985	14344	288	1	0	0	21109	4729	7266	1	6573	10056	4631	522	113
9	7631	1188	8248	89	3001	6887	15105	536	8	0	0	24215	8427	9249	0	3611	6973	3746	210	876
10	4031	1090	11995	185	9207	5929	14930	1902	61	0	0	14459	10342	8767	0	1347	9345	4000	198	2212
11	615	865	7462	480	6194	17242	11801	7132	292	3	0	12701	12399	5518	0	971	5472	5487	130	5236
12	44	52	16928	1112	20529	10681	642	5265	4280	3889	0	2754	5687	6690	0	355	4229	3056	61	13746
13	0	14	5549	2073	15880	14039	56	12102	14543	2869	0	1552	5933	7250	0	145	2543	2206	55	13191
14	0	10	5336	3761	16453	8027	0	9558	19871	3859	0	1193	8046	3924	0	86	2962	2134	47	14733
15	0	5	3979	5161	11086	4355	0	11288	25598	6750	5	447	5041	3675	0	2	2675	3811	1	16121
16	0	5	1977	6420	8580	4941	0	13883	21479	13312	60	270	7431	5718	0	0	1277	3234	0	11413
17	0	0	1553	5917	5809	4484	0	16870	12102	20312	222	165	12636	5610	0	0	81	3037	0	11202
18	0	1	388	11190	1262	1765	0	18601	1721	35249	627	81	11999	6076	0	0	14	1718	0	9308
19	0	0	4	48212	45	262	0	2541	44	13757	16484	9	5281	10639	0	0	0	905	0	1817
20	0	0	0	15353	0	9	0	9	0	0	82602	0	16	1702	0	0	0	308	0	1

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.18 - Rank Frequency 2008

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	1041	129	0	0	362	420	0	0	0	0	0	0	0	97360	0	0	0	688	0
2	823	2101	412	0	0	6995	3479	0	0	0	0	0	0	0	1468	0	0	0	84722	0
3	34860	3157	1982	0	0	7550	18721	0	0	0	0	0	0	771	528	1825	0	27494	3112	0
4	21355	3657	2788	0	0	18056	20811	0	0	0	0	229	1	16714	286	4162	129	9651	2123	38
5	23019	4866	4923	0	0	16347	20698	0	4	0	0	1250	4	9860	212	4227	5445	7385	1581	179
6	14485	8083	14594	0	22	8859	15207	0	14	0	0	6432	14	7063	130	7323	9921	5926	1478	449
7	3910	11519	12256	0	1330	8317	9930	0	110	3	0	15751	103	6027	11	12300	7704	4734	4317	1678
8	1345	7378	5697	0	5074	6701	6782	92	679	130	0	21697	447	7264	2	20197	5468	4780	693	5574
9	156	5504	8879	0	8010	6773	3103	409	3031	1026	0	17744	2438	5673	1	16391	6391	5429	396	8646
10	42	6448	5517	0	9957	8958	728	992	9404	4976	0	11292	4506	4905	2	14778	6721	4351	265	6158
11	4	6700	6437	1	10717	3940	111	2241	16495	11080	0	8275	6202	4095	0	8231	4801	3307	190	7173
12	1	5172	5014	22	11379	3636	10	4443	25945	9581	0	5908	5170	3406	0	5049	4915	2827	185	7337
13	0	4731	5026	140	9555	2695	0	11586	24682	11719	0	4740	5039	3260	0	3244	4376	3610	201	5396
14	0	6419	4763	1311	14363	637	0	4454	12854	28814	0	2097	3456	3705	0	1530	5064	3506	35	6992
15	0	7677	7294	7545	13387	146	0	5652	4924	17155	4	1718	5779	4014	0	564	7322	5735	14	11070
16	0	5567	7664	6360	8974	22	0	11237	1415	9948	1627	1251	8031	7502	0	152	7962	4386	0	17902
17	0	4375	5764	9382	6385	5	0	23134	375	4293	1091	825	10092	6620	0	26	11417	3191	0	13025
18	0	3221	852	22446	806	1	0	29798	68	1275	1142	770	17635	5326	0	1	9522	1250	0	5887
19	0	1599	9	47794	41	0	0	5938	0	0	8980	21	27466	2523	0	0	2241	956	0	2432
20	0	785	0	4999	0	0	0	24	0	0	87156	0	3617	1272	0	0	601	1482	0	64

Source: Authors’ elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.19 - Rank Frequency 2009

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	22	751	195	0	0	65	462	0	0	0	0	0	0	0	97146	0	0	0	1359	0
2	2159	1366	616	0	0	821	4632	0	0	0	0	0	0	0	2081	3	0	0	88316	6
3	31743	4397	1403	0	0	1268	20766	0	0	0	0	0	0	0	337	1258	0	35569	3141	118
4	40534	6422	1911	0	0	3527	26698	0	0	0	0	0	25	0	170	2981	3931	10665	1309	1827
5	14855	12521	7044	0	0	9853	28491	0	0	0	0	156	475	1	96	4506	7115	10043	983	3861
6	5770	17208	9000	0	1	17281	10071	1	0	0	0	7620	2311	10	124	8325	7801	5075	1311	8091
7	2909	13678	10533	0	6	14798	4760	15	0	0	0	9568	4036	168	44	11578	8743	4061	1218	13885
8	1383	11864	11268	0	309	9649	2730	303	13	0	0	14378	5807	536	0	11732	6636	4927	1775	16690
9	571	10932	7620	0	2822	7317	986	2170	215	0	0	21953	7313	1720	1	13574	7366	4449	180	10811
10	40	7257	5430	0	4316	7288	375	4863	1398	0	0	19577	7047	4293	0	11055	6912	5026	192	14931
11	11	6655	4944	0	7276	7652	27	6855	4795	1	0	15531	6055	5385	1	13888	6562	3443	79	10840
12	3	4238	7568	7	7945	7421	2	7899	11321	2	0	7610	6463	5241	0	7678	12070	1718	114	12700
13	0	1618	8225	73	9018	9855	0	9793	22075	67	0	2147	10933	6911	0	7572	4109	2411	19	5174
14	0	677	8879	498	11688	2306	0	12373	29817	2595	0	717	5952	6317	0	4092	5140	8132	3	814
15	0	308	8695	962	16815	653	0	14226	20828	4332	7	442	6227	5756	0	1236	17287	1993	1	232
16	0	71	3651	853	18956	176	0	20475	7427	12478	337	247	25492	4225	0	491	3983	1118	0	20
17	0	34	1980	2463	13980	55	0	16678	2104	27076	270	43	8070	24874	0	29	1621	723	0	0
18	0	3	1038	7700	6862	15	0	4323	7	53408	1490	11	3037	21288	0	2	503	313	0	0
19	0	0	0	19880	6	0	0	26	0	41	73389	0	751	5367	0	0	215	325	0	0
20	0	0	0	67564	0	0	0	0	0	0	24507	0	6	7908	0	0	6	9	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.20 - Rank Frequency 2010

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	2443	16	0	0	133	21	0	0	0	0	0	0	0	97088	0	0	0	299	0
2	38	10542	168	0	0	3723	565	0	0	0	0	0	0	0	2414	0	0	0	82550	0
3	8182	27242	1262	0	0	9969	14473	0	0	0	0	1220	93	192	328	653	118	29031	7237	0
4	14571	13167	2854	0	0	9534	28364	0	0	0	0	3857	6258	6086	106	1993	4389	6094	2727	0
5	20849	8450	3713	0	1	10718	19509	0	0	0	0	5862	7123	5697	36	5909	5876	4669	1574	14
6	20373	6314	6247	0	1	11603	14913	0	0	0	0	7825	7226	5204	26	6037	7604	5217	1325	85
7	12306	6731	14638	0	114	6908	8450	205	0	0	0	14120	7470	5103	0	9586	5744	4835	3133	657
8	6710	6641	10262	0	723	4801	6084	621	2	1	0	23235	7315	6073	2	12844	6593	5097	438	2558
9	5654	4583	5929	0	5460	3757	4757	1620	7	11	0	12910	8812	6759	0	21176	7461	6406	186	4512
10	8206	3324	3976	0	7461	3871	2227	4196	170	68	0	10386	10023	7899	0	16131	8622	5590	166	7684
11	2776	6947	3872	0	8664	5717	620	7244	1250	972	0	12498	9404	8315	0	13275	8630	4009	253	5554
12	267	2087	4739	3	9743	17045	17	6571	5896	7301	0	4306	7866	8502	0	8748	8246	2970	60	5633
13	66	1052	16033	16	13687	4480	0	4077	21801	4282	0	1627	5730	8493	0	3010	8302	2314	43	4987
14	1	225	6562	1332	25234	3681	0	4537	21477	4207	8	936	8121	5785	0	515	9240	2567	8	5564
15	1	141	5883	1277	15260	2999	0	7116	30327	5450	165	556	6900	6511	0	105	6992	3729	1	6587
16	0	83	10091	1354	10392	782	0	16804	13653	11313	561	354	4684	8097	0	16	5807	5035	0	10974
17	0	25	2749	1960	3019	204	0	33182	5400	9976	1937	287	2922	7920	0	2	4989	7183	0	18245
18	0	3	840	5760	241	59	0	12544	17	44980	7688	21	53	1878	0	0	888	2135	0	22893
19	0	0	166	29692	0	16	0	1283	0	9531	52177	0	0	1248	0	0	439	1477	0	3971
20	0	0	0	58606	0	0	0	0	0	1908	37464	0	0	238	0	0	60	1642	0	82

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.21 - Rank Frequency 2011

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	1	513	0	0	0	1	48	0	0	0	0	0	0	0	98211	0	0	0	1226	0
2	17	3671	0	0	0	504	1440	0	0	0	0	0	0	0	1603	13	0	0	92752	0
3	704	4965	3	0	0	2868	36733	0	0	0	0	3713	20	279	112	10854	70	38134	1543	2
4	9335	7562	19	0	0	4954	19265	0	0	0	0	11723	91	19298	46	12361	6859	7268	1161	58
5	15507	5480	174	0	0	8957	9923	1	0	0	0	12643	549	8933	17	11320	18620	6589	988	299
6	17656	4308	1013	0	0	10529	7364	0	7	0	0	10783	6940	9771	8	17163	7235	5308	1076	839
7	12105	5334	1903	0	2	7907	6849	0	17	0	0	14734	9974	9071	2	18563	5742	3889	469	3439
8	8856	5511	3665	0	90	5753	8958	13	38	0	0	18821	7940	8240	0	14821	7190	3371	352	6381
9	11312	3158	6708	0	225	5778	8785	74	127	0	0	13858	10228	6685	1	7726	8376	4505	224	12230
10	23319	4360	9034	0	1145	5645	607	187	337	0	0	8089	13278	5945	0	5590	7552	3922	94	10896
11	966	5011	2764	0	11058	23865	27	1158	4468	1926	0	1984	9451	6085	0	1050	7175	3774	61	19177
12	194	13093	3441	0	3959	11194	1	7312	10247	2036	0	1605	7927	5873	0	500	5747	3216	38	23617
13	28	13962	5925	0	3288	6411	0	4862	20204	3424	6	1352	9107	3930	0	37	5040	2368	16	20040
14	0	7191	17742	151	11456	4930	0	3901	22313	6004	162	441	10340	4769	0	2	5360	2364	0	2874
15	0	5368	13106	193	31475	462	0	8354	15660	5504	417	125	6073	4875	0	0	5688	2554	0	146
16	0	3001	8641	260	29304	152	0	20343	15531	4234	1183	74	4095	4020	0	0	6250	2910	0	2
17	0	2700	9419	336	6999	64	0	43916	11028	7328	2727	47	3972	1795	0	0	2500	7169	0	0
18	0	2343	11513	542	982	19	0	9719	23	56891	16627	8	13	257	0	0	289	774	0	0
19	0	2469	4930	1093	17	7	0	160	0	12259	78180	0	0	160	0	0	288	437	0	0
20	0	0	0	97425	0	0	0	0	0	394	698	0	2	14	0	0	19	1448	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.22 - Rank Frequency 2012

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	41	0	14	0	0	38	32	0	0	0	0	0	0	0	95996	0	0	0	3875	4
2	580	7	147	0	0	1255	612	0	0	0	0	83	0	0	3908	0	0	0	93361	47
3	7989	5	314	0	0	1814	10400	0	0	0	0	25425	33	20	44	5422	5	47695	633	201
4	15394	18	546	0	0	2970	12661	0	0	0	0	26102	1019	3260	28	14643	10343	11297	482	1237
5	19513	53	791	0	0	5135	17399	1	2	0	0	12801	2170	6356	11	17836	10302	5124	253	2253
6	12723	160	1759	0	2	8552	20396	5	27	0	0	11825	6264	5144	9	15064	8607	5088	280	4095
7	14751	312	6656	0	5	8084	10322	16	125	0	0	9910	6858	6190	4	19919	5397	4964	391	6096
8	7669	533	6408	0	89	14427	6228	70	557	0	0	10099	9410	4212	0	13399	11055	3827	477	11540
9	10411	1540	10587	0	1464	10267	9935	530	2951	1	0	2259	10316	6883	0	9015	9687	3106	118	10930
10	10426	2514	10400	0	3990	4257	11902	1995	11269	40	0	1058	10969	10005	0	2296	5760	3782	46	9291
11	368	3184	4592	0	8145	15389	113	5457	23639	11384	0	273	7014	5366	0	1062	3407	2321	39	8247
12	130	3898	5764	0	11639	6955	0	11113	29192	7458	0	94	3823	3747	0	618	4244	1609	34	9682
13	5	6049	4908	0	14415	9468	0	15836	17997	7977	0	45	4465	2858	0	723	2852	2182	11	10209
14	0	9064	6905	9	15408	5065	0	18688	7251	10475	78	18	3658	3313	0	3	5189	6014	0	8862
15	0	6241	6339	118	18267	2994	0	16646	4318	19411	928	8	7306	2850	0	0	6797	1548	0	6229
16	0	6053	7111	469	16077	2314	0	17035	2064	15951	3203	0	9913	4371	0	0	7412	656	0	7371
17	0	10280	18419	1030	8732	715	0	11214	584	17072	4003	0	11166	7799	0	0	4748	558	0	3680
18	0	44619	7759	1165	1767	282	0	1394	24	10221	11901	0	4101	13708	0	0	2842	191	0	26
19	0	5470	581	3195	0	19	0	0	0	10	79874	0	1512	7997	0	0	1307	35	0	0
20	0	0	0	94014	0	0	0	0	0	0	13	0	3	5921	0	0	46	3	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.23 - Rank Frequency 2013

Rank	PI	VA	LO	TR	VE	FR	LI	EM	TO	UM	MA	LA	AB	MO	CA	PU	BA	CL	SI	SA
1	0	280	0	0	0	29	131	0	0	0	0	0	0	0	99559	0	0	0	1	0
2	30	1054	1	0	0	1689	10582	0	0	0	0	0	0	0	319	0	0	0	86325	0
3	1070	1564	5	0	0	5782	38881	0	0	0	0	127	63	1	72	97	454	46386	5493	5
4	17204	2243	139	0	1	13280	19385	0	0	0	0	4796	977	10513	31	1710	16941	10113	2574	93
5	26592	2440	601	0	2	10939	7804	0	0	0	0	12066	4028	10339	15	3374	14685	4846	1918	351
6	15852	4508	1234	0	24	9331	5759	1	0	0	0	21553	14463	4319	2	5182	10464	4329	1641	1338
7	12810	3926	4872	0	185	8523	9750	11	1	0	0	16881	6447	4299	1	11444	7260	9032	622	3936
8	11973	3766	5950	0	1033	6311	5732	19	10	0	0	11851	7833	4547	1	15997	14746	4254	554	5423
9	7510	3955	4908	0	2768	6292	1752	104	55	0	0	15630	9786	5917	0	21435	9669	2869	407	6943
10	6891	5128	5614	0	7116	7857	224	478	535	2	0	10955	14119	7867	0	19140	4620	2450	293	6711
11	64	5562	5438	0	8025	23753	0	2146	5027	628	0	3096	9247	9206	0	15981	3272	2081	117	6357
12	4	11888	8081	0	12757	3919	0	4163	30539	2797	1	1792	3518	4086	0	4242	3165	2286	26	6736
13	0	6127	8529	4	19091	1641	0	5897	26874	9170	13	641	3143	2386	0	1102	3205	2006	26	10145
14	0	6535	7548	927	21700	445	0	11008	17787	5934	1073	376	3924	2371	0	214	5280	3183	3	11692
15	0	6137	7892	588	18026	176	0	19209	13001	5635	1955	167	5304	2612	0	65	4343	3477	0	11413
16	0	6555	9330	1393	7266	20	0	28342	5285	8228	3815	44	12914	4077	0	14	1056	1235	0	10426
17	0	8391	10519	1770	1707	10	0	22963	885	20460	9609	19	1795	11579	0	2	427	419	0	9445
18	0	8187	10661	2967	297	3	0	5311	1	38274	22301	5	1293	3419	0	1	300	401	0	6579
19	0	11588	8676	6829	2	0	0	348	0	8543	56881	1	1146	2837	0	0	111	631	0	2407
20	0	166	2	85522	0	0	0	0	0	329	4352	0	0	9625	0	0	2	2	0	0

Source: Authors' elaboration on ISTAT (2017); Note: PI=Piedmont, VA=Aosta Valley, LO=Lombardy, TR=Trentino, VE=Veneto, FR=Friuli, LI=Liguria, ER=Emilia Romagna, TU=Tuscany, UM=Umbria, MA=Marche, LA=Lazio, AB=Abruzzi, MO=Molise, CA=Campania, AP=Apulia, BA=Basilicata, CL=Calabria, SI=Sicily, SA=Sardinia

Table A2.24 - Multidimensional Gini index of the downward cumulative rank acceptability index

Rank	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2006	2007	2008	2009	2010	2011	2012	2013
1	0.97	0.98	0.97	0.97	0.99	0.98	0.98	0.99	0.99	0.98	0.99	0.99	0.99	1.00	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00
2	0.90	0.92	0.88	0.91	0.92	0.91	0.90	0.92	0.92	0.91	0.92	0.91	0.92	0.90	0.93	0.93	0.93	0.93	0.93	0.94	0.94	0.94
3	0.83	0.83	0.83	0.82	0.82	0.83	0.84	0.84	0.83	0.81	0.86	0.86	0.86	0.82	0.82	0.87	0.83	0.85	0.84	0.85	0.85	0.86
4	0.75	0.74	0.76	0.75	0.75	0.74	0.77	0.77	0.74	0.73	0.76	0.77	0.76	0.75	0.73	0.78	0.76	0.79	0.74	0.74	0.76	0.77
5	0.70	0.67	0.72	0.69	0.65	0.68	0.72	0.69	0.66	0.68	0.68	0.69	0.69	0.71	0.67	0.72	0.71	0.73	0.67	0.66	0.70	0.70
6	0.65	0.62	0.65	0.63	0.59	0.64	0.66	0.62	0.59	0.64	0.62	0.65	0.64	0.66	0.62	0.66	0.65	0.66	0.62	0.61	0.64	0.63
7	0.61	0.58	0.59	0.58	0.55	0.60	0.59	0.57	0.54	0.60	0.58	0.61	0.61	0.62	0.58	0.61	0.60	0.60	0.57	0.57	0.60	0.59
8	0.57	0.54	0.55	0.54	0.52	0.57	0.54	0.54	0.51	0.56	0.54	0.57	0.58	0.58	0.55	0.56	0.54	0.55	0.53	0.53	0.56	0.54
9	0.53	0.50	0.52	0.50	0.49	0.53	0.50	0.50	0.48	0.52	0.50	0.53	0.52	0.53	0.51	0.52	0.49	0.50	0.48	0.50	0.51	0.50
10	0.48	0.45	0.48	0.45	0.45	0.48	0.46	0.46	0.46	0.48	0.46	0.48	0.47	0.49	0.47	0.48	0.44	0.46	0.44	0.47	0.47	0.47
11	0.43	0.41	0.43	0.41	0.41	0.43	0.42	0.42	0.42	0.43	0.42	0.44	0.43	0.44	0.43	0.43	0.39	0.42	0.41	0.42	0.40	0.43
12	0.38	0.36	0.38	0.36	0.37	0.37	0.37	0.38	0.39	0.38	0.37	0.39	0.38	0.39	0.38	0.38	0.34	0.37	0.36	0.37	0.35	0.37
13	0.33	0.31	0.34	0.31	0.33	0.32	0.32	0.33	0.34	0.33	0.33	0.34	0.33	0.33	0.34	0.32	0.30	0.33	0.31	0.33	0.31	0.31
14	0.28	0.26	0.28	0.27	0.28	0.28	0.27	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.29	0.27	0.26	0.29	0.27	0.28	0.26	0.27
15	0.23	0.22	0.23	0.22	0.23	0.23	0.22	0.23	0.24	0.23	0.24	0.23	0.24	0.23	0.24	0.23	0.22	0.24	0.23	0.24	0.22	0.23
16	0.18	0.18	0.18	0.18	0.19	0.18	0.18	0.18	0.19	0.19	0.19	0.18	0.19	0.19	0.19	0.18	0.18	0.20	0.19	0.19	0.19	0.19
17	0.14	0.14	0.14	0.14	0.15	0.14	0.14	0.14	0.14	0.14	0.15	0.14	0.14	0.14	0.14	0.14	0.14	0.15	0.15	0.15	0.15	0.14
18	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.09	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
19	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Authors' elaboration on ISTAT (2017)

Table A2.25 - Multidimensional Gini index of the upward cumulative rank acceptability index

Rank	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2006	2007	2008	2009	2010	2011	2012	2013
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
3	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
4	0.15	0.15	0.15	0.14	0.14	0.15	0.15	0.15	0.15	0.14	0.15	0.15	0.15	0.14	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
5	0.19	0.18	0.19	0.19	0.19	0.18	0.19	0.19	0.19	0.18	0.19	0.19	0.19	0.19	0.18	0.19	0.19	0.20	0.18	0.19	0.19	0.19
6	0.23	0.22	0.24	0.23	0.22	0.23	0.24	0.23	0.22	0.23	0.23	0.23	0.23	0.24	0.22	0.24	0.24	0.24	0.22	0.22	0.23	0.23
7	0.28	0.26	0.28	0.27	0.25	0.28	0.28	0.27	0.25	0.28	0.27	0.28	0.28	0.28	0.27	0.28	0.28	0.28	0.27	0.26	0.28	0.27
8	0.33	0.31	0.32	0.31	0.30	0.32	0.32	0.31	0.29	0.32	0.31	0.33	0.33	0.34	0.31	0.33	0.32	0.32	0.31	0.30	0.32	0.32
9	0.38	0.36	0.37	0.36	0.35	0.38	0.36	0.36	0.34	0.38	0.36	0.38	0.38	0.39	0.36	0.38	0.36	0.37	0.35	0.36	0.37	0.36
10	0.43	0.41	0.42	0.41	0.40	0.43	0.41	0.41	0.40	0.43	0.41	0.43	0.43	0.44	0.42	0.42	0.40	0.41	0.39	0.41	0.42	0.41
11	0.48	0.45	0.48	0.45	0.45	0.48	0.46	0.46	0.46	0.48	0.46	0.48	0.47	0.49	0.47	0.48	0.44	0.46	0.44	0.47	0.47	0.47
12	0.52	0.50	0.53	0.50	0.50	0.52	0.51	0.51	0.52	0.52	0.51	0.53	0.52	0.54	0.52	0.53	0.48	0.51	0.50	0.51	0.49	0.52
13	0.56	0.54	0.58	0.54	0.56	0.56	0.55	0.56	0.58	0.57	0.56	0.59	0.57	0.58	0.58	0.57	0.51	0.56	0.55	0.55	0.53	0.55
14	0.61	0.57	0.63	0.58	0.62	0.60	0.59	0.61	0.62	0.61	0.61	0.63	0.62	0.61	0.62	0.60	0.55	0.61	0.58	0.61	0.57	0.58
15	0.65	0.60	0.66	0.62	0.66	0.65	0.62	0.66	0.66	0.66	0.66	0.66	0.66	0.64	0.67	0.64	0.60	0.67	0.63	0.66	0.61	0.63
16	0.68	0.65	0.69	0.67	0.70	0.69	0.67	0.70	0.72	0.70	0.71	0.68	0.71	0.69	0.71	0.68	0.66	0.73	0.69	0.71	0.66	0.69
17	0.74	0.71	0.73	0.74	0.76	0.74	0.73	0.74	0.77	0.76	0.78	0.72	0.76	0.74	0.76	0.74	0.73	0.80	0.77	0.78	0.74	0.75
18	0.80	0.80	0.81	0.79	0.83	0.82	0.81	0.79	0.82	0.80	0.84	0.79	0.82	0.80	0.82	0.81	0.81	0.86	0.86	0.87	0.84	0.82
19	0.91	0.89	0.90	0.88	0.91	0.89	0.90	0.86	0.87	0.85	0.90	0.88	0.91	0.86	0.87	0.90	0.89	0.94	0.92	0.92	0.93	0.88
20	0.96	0.95	0.97	0.98	0.98	0.98	0.98	0.98	0.96	0.98	0.96	0.99	0.98	0.92	0.98	0.98	0.97	0.96	0.95	1.00	0.99	0.98

Source: Authors' elaboration on ISTAT (2017)

3. Composite Index of Well-Being taking into account the societal relative appreciations of the different topics. An application to Better Life Index[60]

Abstract

Multidimensional measures of well-being, such as the OECD Better Life Index (BLI), allow a detailed overview of the social, economic, and ecological performances, but they also increase the difficulty in evaluating the big picture. In order to overcome this limitation, many composite indices of well-being have recently been proposed, but none of them takes into account the crucial role played by societal relative appreciations of the different dimensions. We propose a composite index that accounts for societal relative appreciation for each of the considered dimensions. Building upon the Stochastic Multi-Objective Acceptability Analysis (SMAA) we apply our novel methodology to the BLI using the data on preferences made available in the dedicated website. Our analysis signals pervasive differences in the country-level performances that cannot be compensated through differences in local preferences. Furthermore, we find evidence that the consideration of individual preferences exacerbates multidimensional inequality on a global scale. We interpret this evidence as supporting our contention that better performing countries offers a policy mix better tailored to fit citizens' preferences.

JEL Codes: C44, H11, I31.

Keywords: Well-Being; Better Life Index; Composite Index; Local Preferences; Stochastic Multi-Objective Acceptability Analysis.

[60] This chapter has been produced within a project in collaboration with Salvatore Greco, Alessio Ishizaka, and Gianpiero Torrisi (Portsmouth Business School, University of Portsmouth, UK)

3.1 Introduction

There is a large consensus about the limits of the Gross Domestic Product (GDP) in predicting societal well-being[61]. After the seminal work of Easterlin (1974), which clearly shows that GDP and happiness are not always positively correlated, this point has been extensively discussed in the literature[62]. More specifically, UNDP (1996) identifies five main negative aspects of growth in GDP: 'jobless growth', 'voiceless growth', 'ruthless growth', 'rootless growth', and 'futureless growth'.

Based on these evidences, many alternative measures of well-being have recently been proposed by the main international institutions, as well as by the national statistics offices (Costanza *et al.* 2014; 2016)[63]. Among them, one of the most influential is the Better Life Index (BLI), launched by the OECD in 2011, and measured in 36 countries in 2016. The BLI is based on the idea of Stiglitz *et al.* (2010), that well-being is multidimensional and has different key aspects of life to take into account simultaneously[64] .

Based on the framework of Stiglitz *et al.* (2010), the BLI is composed of eleven topics: Housing, Income, Jobs, Community, Education, Environment, Civic Engagement, Health, Life Satisfaction, Safety, and Work-Life Balance. OECD measures country-level performances in all these topics by means of 24 different metrics[65].

Despite the efforts of several institutions (for instance, UN in 2015 launched the upgrade of the Sustainable Development Goals, which is a set of international objectives to improve global well-being), "the evolution of GDP remains a fixation for governments around the world" (Blanke, 2016)[66]. One of the reasons of the GDP's persistence is that it is a unique measure,

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[61] It is worth mentioning that even the developer of the GDP was skeptical about the use of national income as measure of welfare (Kuznets, 1934).

[62] Among others: UNDP, 1996; Fleurbaey, 2009; Stiglitz *et al.* 2010; Frey, Stutzer, 2010; Bleys, 2012; Fioramonti, 2013; Costanza *et al.* 2014; De Beukelaer, 2014; Coyle, 2014; Karabell, 2014; Costanza *et al.* 2016; Partizii *et al.* 2017.

[63] UNDP launched the Human Development Index in 1990. At national level see, among others: INSEE (2010) in France; ONS (2011) in Great Britain; ISTAT, CNEL (2013) in Italy.

[64] "Material living standards; Health; Education; Personal activities including work; Political voice and governance; Social connections and relationships; Environment; Insecurity of an economic as well as a physical nature" - Stiglitz *et al.* 2010 pp. 14-15

[65] The 24 metrics are: dwellings without basic facilities, housing expenditure, rooms per person, household net adjusted disposable income, household net financial wealth, employment rate, job security, long-term unemployment rate, personal earnings, quality of support network, educational attainment, student skills, years in education, air pollution, water quality, consultation on rule-making, voter turnout, life expectancy, self-reported health, life satisfaction, assault rate, homicide rate, employees working very long hours, and time devoted to leisure and personal care. See section 3.3 for details.

[66] For instance, with regard to the European framework "Cohesion policy 2014-2020", the classification of regions in order to assign their own eligibility status depends on their ranking in terms of GDP per-capita. Among the few

which allows ranking, and easily comparing, different systems. This useful feature of GDP does not belong to the new multidimensional measures of well-being such as BLI. Indeed, the proposed multidimensional metrics, while on the one hand provide a more detailed overview of the social, economic, and ecological performances; on the other hand, they increase the difficulties evaluating the big picture (Costanza *et al.* 2014; Costanza *et al.* 2016). The problem is well known in the academic and the official statistics sector, and in recent times has opened the way for the Composite Indicators (Nardo *et al.* 2008; Costanza *et al.* 2016).

As defined in OECD (2017), a Composite Index (CI) compiles individual indicators into a single index in order to summarize complex multidimensional realities into one dimension. On pros and cons, there are different positions in the literature. In particular, it has been stressed that while such a summary statistic is extremely useful in garnering the attention of policy makers and the media interest, there is a non-negligible arbitrary nature in the weighting process (Sharpe, 2004; Saisana *et al.* 2005; Cherchye *et al.* 2008; Foster *et al.* 2009; Permanyer, 2011; Costanza *et al.* 2016; Greco *et al.* 2017).

The aim of this chapter is to face directly this gap in the BLI framework. Our proposal is a weighting process based on the societal relative appreciations of the different dimensions of well-being. We argue that the relative appreciations of the different topics (i.e. societal preferences) are one of the most important factors in multidimensional well-being for at least two reasons. First, the preferences of people interested are themselves part of the phenomenon (Helliwell, 2003; Helliwell, Barrington-Leigh, 2010), since the BLI is a metric to assess “the level of well-being of individuals with different preferences” (Stiglitz *et al.* 2010, p. 143). Second, people’s preferences are eventually translated into policies by means of some mechanism of preference aggregation, so that they drive policy makers towards providing specific representations of multidimensional well-being. These issues are far more relevant in the design of a Composite Index since different weights may give rise to relevant differences in the final synthetic evaluation, and thus in the ranking of countries. Therefore, the inclusion of societal relative appreciations in the weighting process of CIs, can be a valid procedure for taking into account the priorities of people involved in the evaluation.

exceptions to this trend there is Italy, in which multidimensional well-being (the BES, ISTAT, 2016) entered for the first time in the evaluation of public policies with the Budget Law approved on July 28, 2016.

To this intent we use for the first time the opinions collected in the OECD website dedicated to Better Life Index[67]. In this website, OECD presents the set of eleven performances indicators at country-level, rather than a single composite index. This is an OECD's deliberate choice to share information without any statement about the overall well-being. Users can bring their own relative importance of each topic, and estimate their personal BLI (OECD, 2016). More specifically, OECD's website allows persons to weights the topic according to their own viewpoint. For each person expressing its opinion, the website build its own Better Life Index, with an algorithm that estimates the weighted average of the national performances in each dimension of the BLI, using the subjective scores given by the person as weights. This allows people to see in real time the changes on the ranks due to the differentiation in weights given to the different dimensions of well-being. Participants have been encouraged to create and share their own Better Life Index and the individual's opinion have been collected since the launch in 2011. At the time of this chapter, the OECD has received and collected more than 100,000 opinions from 180 different countries. It is worth remarking that these opinions are not representative, since there is an intrinsic self-selection in people visiting this dedicated website (mainly economic experts). However, although the sample is only small and admittedly suffers from a sample selection bias, it nevertheless provides the unique source of information about priorities among the different dimensions of well-being included in the BLI.

Recently, several Composite Indices of Better Life Index have been proposed (among others Mizobuchi, 2014; Marković *et al.* 2015; Lorenz *et al.* 2016; Patrizii *et al.* 2017; Mizobuchi, 2017; Peiró-Palomino, Picazo-Tadeo, 2017), but none of them takes into account the societal relative appreciations into the aggregation process. In absence of information about the societal preferences, in previous Composite Indices of well-being the non-parametric methods, in particular the Data Envelopment Analysis (DEA) without input, called Benefit of Doubt (BOD), have been extensively employed as technique of aggregation (Shen *et al.* 2013; Patrizii *et al.* 2017). The basic assumption of the BOD evaluations is that the status-quo is a choice of the local Decision Maker (Policy Maker in the case of public sector). On this assumption, the BOD estimates a Composite Index based on the combination of weights that is the more convenient for the evaluated Decision Making Unit (DMU)[68]. The societal preferences are already included in the CI estimated by BOD, only with another implicit assumption: the local Policy Makers' choice reflects the local societal preferences. In other words, the BOD

[67] www.oecdbetterlifeindex.org
[68] see Chapter 1 section 1.3 for technical details.

Composite Indices of well-being, as well as the DEA evaluations in general, include societal preferences only assuming a 'benevolent dictator' at DMU-level. In this chapter, we have the opportunity to remove this assumption by using as weights for the eleven topics of BLI, the societal preferences collected by OECD website.

The opinions collected in the OECD website are more than 100,000 individual vectors of weights, in which the elements are related to the eleven BLI topics. In order to create a CI based on a set of individual preferences, we need to trade-off between feasibility and representativeness. Feasibility requires just one vector of weights for the aggregation (an abstract 'representative agent'). Representativeness requires taking into account all the points of view. According to the Arrow's theorem (Arrow, 1951), there does not exist any perfect aggregation rule to collapse the different opinions into a unique vector of weights. For this reason, we avoid to aggregate preferences into a unique vector. We prefer to follow the idea of Greco *et al.* (2017), which exploited the Stochastic Multi-Objective Acceptability Analysis (SMAA) approach (Lahdelma *et al.* 1998; Lahdelma, Salminen 2001) for taking into account all the feasible ranks of the regions given all the feasible sets of weights. In practice, given a very large amount of vector of weights, SMAA determines the probability for each region to be first, second, third, and so on in the ranking (i.e., the rank acceptability indices).

We propose two alternative ways to take into account societal preferences in the ranking: considering all the weights collected by OECD (hereafter 'Global preferences'); and using country-specific weights (hereafter 'Local preferences'). Moreover, we estimate a third CI using the standard SMAA, i.e., taking the whole set of possible weights from a uniform distribution (hereafter 'Random preferences'). The comparisons among these three CI of well-being produce unprecedented evidences about the relations between people's preferences and policy outcome as measured in the BLI framework. In this study emerges that the correlations among ranking obtained by Local, Global, and Random preferences, are significantly different from zero. In line with Greco *et al.* (2017), this result confirm that SMAA is a consistent support for decision makers interested to take into account the heterogeneity of individual preferences. Moreover, this proves that there is a uniformity among the country-level preferences (as expressed in the OECD website), and a strong inequality in the multidimensional performance of countries. The global inequality estimates confirm the pervasive polarization of the country-level multidimensional performances, which increases when relative appreciations of people are taken into account. This reveals that good performers' countries have also proportions among multidimensional performances more balanced on the priorities of people. It follows that the polarization in the perceived Better Life Index is higher than the inequality in the multidimensional performances.

We organize the rest of the chapter as follows: the second section presents our model; the third section presents the data; the fourth section shows the results. Section 3.5 concludes and presents ideas about possible contributions to the research agenda emerging from our analysis.

3.2 The Methodology

As shown in Greco *et al.* (2017), from a methodological standpoint a reasonable context to discuss composite indices is Multiple Criteria Decision Analysis (MCDA) - Greco *et al.* (2005); Ishizaka and Nemery (2013). In a basic MCDA problem, a set of m alternatives $A = \{a_1, \dots, a_m\}$ is evaluated on a set of n criteria $G = \{g_1, \dots, g_n\}$. In this perspective, the composite index is a specific aggregation of some criteria represented by the single indices. Usually, the aggregation is quite basic, so that, after being normalized to be expressed on the same scale, the set of considered elementary indices are aggregated using a simple arithmetic mean generally unweighted (among others see the Composite Index proposed in Floridi *et al.* 2011; this is the case of the baseline BLI in the dedicate website). Sometimes, different weights are assigned to the elementary indices. Therefore, for each alternative $a_k \in A$, an overall evaluation $u(a_k, w)$ depending on the adopted weights $w_1, \dots, w_n$ can be obtained as follows:

$$u(a_k, w) = \sum_{i=1}^{n} w_i g_i(a_k) \tag{3.1}$$

As it is shown in chapter 1 section 1.3, in DEA (Charnes *et al.* 1978; Banker *et al.* 1984; Cherchye *et al.* 2007), the weights $(w_1, \dots, w_n)$ are the most favourable in each criterion for the evaluated alternative. Of course, the ranking of alternatives from *A* is heavily dependent on the considered weights: $w_1, \dots, w_n$. The MCDA methodology called SMAA (Lahdelma *et al.* 1998, Lahdelma, Salminen 2001)[69] takes explicitly into account this point. More precisely, under the hypothesis of a given distribution in the set of considered weights (without information, a uniform distribution is considered), for each alternative $a_k \in A$, SMAA gives the probability that alternative a_k has the r-th position in the preference ranking (b_k^r) - see chapter 2 section 2.3.3 for details.

[69] For two surveys see Tervonen, Figueira (2008); and Lahdelma, Salminen (2010)

In this chapter, as the weights in the SMAA procedure, we use the citizens' relative appreciations collected by OECD. Our model allows using the weights collected by OECD in two different ways. The first way requires the assumption that the importance of each topic is the same for all countries. This assumption leads to using all the weights collected by OECD to rank each country. The second way allows considering that, different countries have potentially different relative appreciations (e.g., people in France might consider jobs their top priority, but people in Germany might consider health). This approach leads to using country-specific weights to rank countries. In other words, with the latter method each country is evaluated based on the preferences (weights) of its population. In economic theory, this point was partially addressed with the seminal work of Tiebout (1956) regarding the public services. Adapting the Tiebout's framework to multidimensional well-being, we can assume that citizens/voters have their subjective idea about the optimal proportions among the 11 topics included in BLI (people's mix of well-being), and that policy makers act in providing a specific proportion among the single dimensions of well-being (policy makers' mix of well-being). For instance, in the same country, there could be a relevant share of people interested in a specific aspect of well-being, such as health care, and at the same time, there could be policy makers who are devoting more resources to education than to health. In this context, since the objective function of the policy maker is to be (re-)elected, policy makers are supposed to act according to local preferences (for a broad review of political economic models see Persson, Tabellini, 2002; Dranzen, 2004; Alesina, Giuliano, 2009).

With this model in mind, the best way to evaluate the overall national BLI should be using local (national) preferences. However, the provision of some dimensions of the BLI go beyond national borders (the sustainability topics are the most evident case), and indeed many of them are regulated by supranational institutions. This suggests that both the approaches are valid in the evaluation of overall well-being. We therefore decided to estimate two composite indices of BLI, one with global and one with local weights. In addition, we repeated the analysis with the standard SMAA, i.e., taking the whole set of possible weights from a uniform distribution. Finally, we compare the results in order to explore how much the Local and Global preferences matter in the evaluation.

Summarizing, we consider three different sets of weights:

1. Local preferences ($W_L = \{(w_{L1}, \ldots, w_{Ln}) \in OECD\_P_k^n\}$);
2. Global preferences ($W_G = \{(w_{G1}, \ldots, w_{Gn}) \in OECD\_P^n\}$);

3. Random preferences ($W_R = \{(w_{R1},\dots,w_{Rn}) \in R^n_+,\ w_{R1}+\dots+w_{Rn} = 1\}$)

where $OECD\_P^n_k$ is the matrix with the preferences expressed in the OECD website from the country a_k. We consider three distribution of weights: the observed distribution $f_{W_L}(w_L)$ on W_L (Local preferences in country a_k); the observed distribution of $f_{W_G}(w_G)$ on W_G (Global preferences); and a uniform distribution $f_{W_R}(w_R)$ on W_R (Random preferences).

Accordingly, for each country a_k and for each value that can be taken by the performance in BLI topics $\xi \in \chi$ (i.e., from the probability distribution $f_\chi(\xi)$) we compute three sets of weights that allow country a_k to get the rank r:

$$W^r_{Lk}(\xi) = \{w_L \in W_L: rank(k,\xi,w_L) = r\} \tag{3.2}$$

$$W^r_{Gk}(\xi) = \{w_G \in W_G: rank(k,\xi,w_G) = r\} \tag{3.3}$$

$$W^r_{Rk}(\xi) = \{w_R \in W_R: rank(k,\xi,w_R) = r\} \tag{3.4}$$

From equations (3.2), (3.3), and (3.4) one can then compute three rank acceptability indices, which are relative measures of (3.2), (3.3), and (3.4). In symbols:

$$b^r_{Lk} = \int_{\xi\in\chi} f_\chi(\xi) \int_{w_L \in W^r_{Lk}(\xi)} f_{W_L}(w_L)\, dw_L d\xi \tag{3.5}$$

$$b^r_{Gk} = \int_{\xi\in\chi} f_\chi(\xi) \int_{w_G \in W^r_{Gk}(\xi)} f_{W_G}(w_G)\ dw_G d\xi \tag{3.6}$$

$$b^r_{Rk} = \int_{\xi\in\chi} f_\chi(\xi) \int_{w_R \in W^r_{Rk}(\xi)} f_{W_R}(w_R)\, dw_R d\xi \tag{3.7}$$

Formulas (3.5), (3.6), and (3.7) give the probability that the country a_k has the r-th position in the ranking according - respectively - to Local preferences, Global preferences, and Random preferences. In words, b^r_{Lk}, b^r_{Gk}, and b^r_{Rk} are the ratio of the number of the vector of weights by which country a_k gets rank r to the total amount of considered weights. The considered weights are expressed by Local preferences in the case of b^r_{Lk}, by Global preferences in the case of b^r_{Gk}, and by Random preferences in the case of b^r_{Rk}. From a computational perspective, we estimate the multidimensional integrals by Monte Carlo simulations. To this purpose, Random estimates are the result of 100,000 random extractions of vectors w_R from a uniform distribution in W_R[70].

As suggested in Greco *et al.* (2017) the rank acceptability index (b_r^k) can be used to define a new multidimensional generalization of the Gini index (see Chapter 2 section 2.3.4 for details). First, for each rank we define the upward cumulative rank acceptability index of position l, the probability that an alternative a_k has a rank position l or higher (Angilella *et al.* 2016), that is:

$$b_k^{\geq l} = \sum_{s=k}^{m} b_s^k \tag{3.8}$$

The Gini index of the upward cumulative rank acceptability index of position l, is:

$$G^{\geq l} = \frac{\sum_{h=1}^{m} \sum_{k=1}^{m} \left| b_h^{\geq l} - b_k^{\geq l} \right|}{2ml} \tag{3.9}$$

$G^{\geq l}$ measures the concentration of probability to attain rank position l or higher among the considered alternatives. We estimate three different $G^{\geq l}$ based on the three rank acceptability indices ($b_{Lr}^k, b_{Gr}^k, b_{Rr}^k$ - taking into account respectively the Local, the Global, and the Random preferences). As suggested in Greco *et al.* (2017), an index analogous to $G^{\geq l}$ but measuring the concentration of probability to achieve rank l or lower among the considered alternatives is:

$$G^{\leq l} = \frac{\sum_{h=1}^{m} \sum_{k=1}^{m} \left| b_h^{\leq l} - b_k^{\leq l} \right|}{2m(m-l+1)} \tag{3.10}$$

where

$$b_k^{\leq l} = \sum_{s=1}^{l} b_s^k \tag{3.11}$$

is the downward cumulative rank acceptability index of position l for alternative a_k (Angilella *et al.* 2016).

[70] Tervonen and Ladhelma (2007) shows that 10,000 extractions are enough to get an error limit of 0.01 with a confidence interval of 95%.

3.3 The data

The Better Life Index has eleven topics. OECD estimates country-level performances in all the topics by means of 24 variables. Each topic is composed of one or more of the 24 variables, of which 16 have a positive (P) effect on well-being (e.g., rooms per person) and 8 have a negative (N) effect on well-being (e.g., long-term unemployment rate). Table 3.1 describes the composition, in terms of original variables, of each topic.

Table 3.1 - Topics and related variables of the BLI

Topics	Related variables
Housing	Dwellings without basic facilities (N) Housing expenditure (N) Rooms per person (P)
Income	Household net adjusted disposable income (P) Household net financial wealth (P)
Jobs	Employment rate (P) Job security (N) Long-term unemployment rate (N) Personal earnings (P)
Community	Quality of support network (P)
Education	Educational attainment (P) Student skills (P) Years in education (P)
Environment	Air pollution (N) Water quality (P)
Civic engagement	Consultation on rule-making (P) Voter turnout (P)
Health	Life expectancy (P) Self-reported health (P)
Life Satisfaction	Life satisfaction (P)
Safety	Assault rate (N) Homicide rate (N)
Work-Life Balance	Employees working very long hours (N) Time devoted to leisure and personal care (P)

In order to group 24 variables into 11 topics, the OECD first normalizes the value each variable takes, so that they all are within the $[0,1]$ range with the min max method:

$$index = \left(\frac{observed\ value - minimum\ value}{maximum\ value - minimum\ value}\right) \tag{3.12}$$

Secondly, variables that have a negative effect on well-being (N in table 3.1) undergo a unit translation $(1 - index)$ in order to make the complement to one comparable with the variables that have a positive effect on well-being. Thirdly, the indices so obtained are aggregated into 11 topics by simple average:

$$g_i(a_k) = \left(\frac{\sum_{j=1}^{s} index_j}{s}\right);\ k = 1, \dots, m \tag{3.13}$$

The final database covers 36 Countries on 11 topics. Table 3.2 summarizes the descriptive statistics of the performances for each topic.

Table 3.2 - Summary of the topic values

Topic	Average	StDev	Min	Max
Housing	5.51	1.48	2.06	8.21
Income	3.40	2.22	0.13	10
Jobs	6.54	1.85	1.49	9.53
Community	7.35	2.12	0	10
Education	6.40	1.93	0.52	9.13
Environment	6.78	1.99	2.07	9.62
Civic engagement	5.07	1.93	0	9.47
Health	6.83	1.95	0.58	9.35
Life Satisfaction	6.60	2.92	0	10
Safety	8.30	1.93	0.42	9.96
Work-Life Balance	6.66	1.88	0	9.77

Source: Author's elaborations on OECD (2016) BLI topics' performances.

In the dedicated website[71], persons can express their relative appreciation on each topic, by rating the topics according to their personal order of importance. The rates are in a score that is in the interval $[0, 5]$[72]. For each person expressing its opinion, the website builds its own Better Life Index, with an algorithm that estimates the weighted average of the country-level performances in the topics, using subjective scores as weights. This allows the visitors to see in real time how the BLI rank changes with the variation in the score associated to the topics. The microdata of individual responses (i.e., individual vectors of weights) can be downloaded from the website. In addition to the individual well-being preferences, microdata have the geolocation (country) of the visitors. In this study, we use the geolocations for grouping Local preferences. We have in total 92,980 preferences from all the 36 Countries where the BLI is measured (we do not consider the preferences from countries not included in BLI dataset)[73]. Table 3.3 reports the descriptive statistics of the weights. It is to some interest to note that for

[71] www.oecdbetterlifeindex.org

[72] In the SMAA estimates we normalize the weights as $\sum_{i=1}^{n} w_i = 1$, so that the rank acceptability indices are all comparable.

[73] We downloaded the microdata on 17th-18th February 2016.

all the topics, there are always some people weighting the topic with a zero importance and others giving a five points (the maximum) importance. Some information about the global relative appreciations among topics are in the average and median weights (second and third column in table 3.3). On this point, Civic engagement is, in average and in median the least preferred topic, while Education, Health, Life Satisfaction, and Work-Life Balance have the highest averages and medians.

Table 3.3 - Summary of the Weights for each Topic

	Average	Median	StDev	Min	Max
Housing	3.18	3	1.35	0	5
Income	3.10	3	1.39	0	5
Jobs	3.22	3	1.40	0	5
Community	2.94	3	1.44	0	5
Education	3.57	4	1.46	0	5
Environment	3.30	3	1.47	0	5
Civic engagement	2.42	2	1.41	0	5
Health	3.77	4	1.40	0	5
Life Satisfaction	3.76	4	1.45	0	5
Safety	3.32	4	1.48	0	5
Work-Life Balance	3.39	4	1.48	0	5

Source: OECD (2016); data extracted on 17-18 Feb 2016 from OECD.Stat

Admittedly, the weights extracted from the BLI dataset suffer from a selection bias as, for example, only people having access to IT facilities can indeed express their relative appreciation among the considered dimensions. Nonetheless, it is worth noticing that, at present, this dataset represents a unique opportunity to collect data on relative preferences worldwide. One that is worth preliminary exploring for its potential innovative methodological contribution.

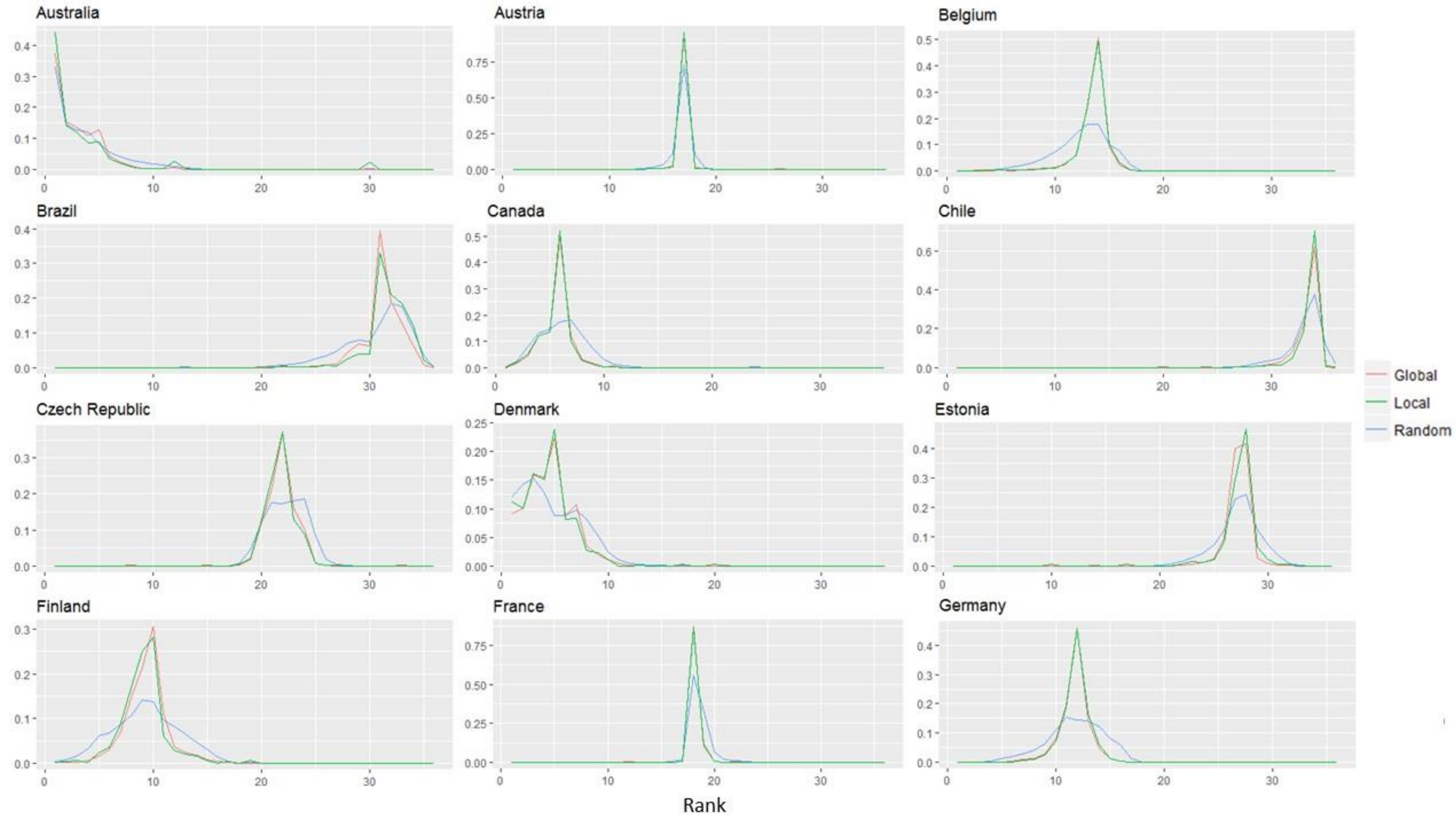
3.4 Results

For each of the three preferences considered (Local, Global, and Random), SMAA gives the probability of each country to have the r-th position in the ranking of the composite index of BLI. To save space, a comprehensive representation of the rank acceptability indices is in the Appendices (tables A3.1, A3.2, A3.3, A3.4, A3.5, and A3.6). Tables A3.1-A3.6 in the Appendices report the percentages of number of occurrences a country achieves each possible ranking from one to 36. For convenience, this section has four sub-components. In section 3.4.1, we present the general distributions and the correlations among the rank acceptability indices obtained by the three set of weights considered. In section 3.4.2, we focus on the differences among the main results of the three approaches. In section 3.4.3, we show the difference among the cumulative rank acceptability indices obtained with different weights. Finally, in section 3.4.4 we present the global inequality estimates.

3.4.1 The general effect of the Local relative appreciations in the BLI

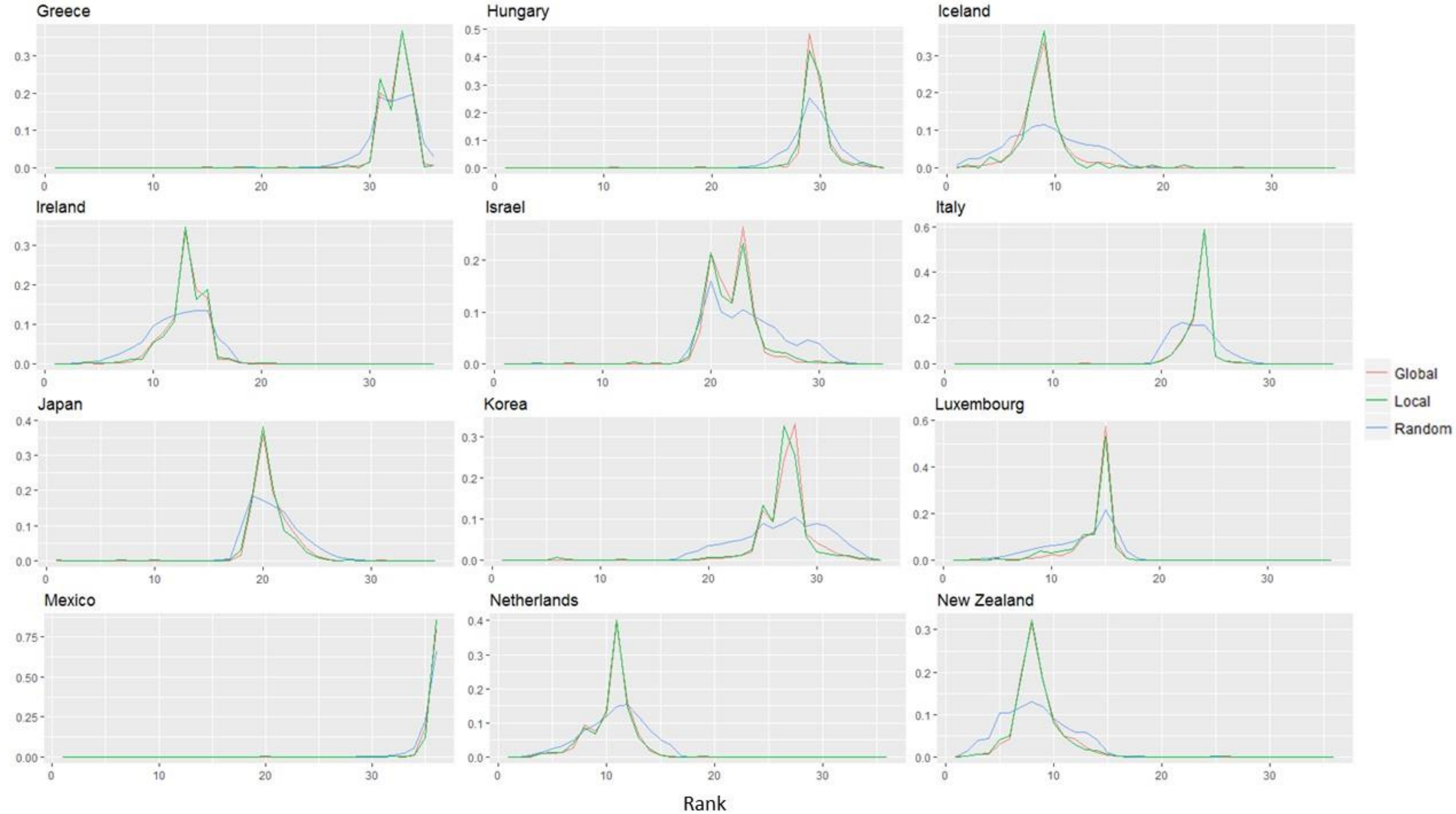
In this section, we present the overall results of SMAA and the general effects that Local preferences have in the evaluation. In figure 3.1, we show the distributions of the rank acceptability indices obtained respectively with Local, Global, and Random weights. The first evidence is that the distributions of rank acceptability indices obtained with Random weights are smoother than the distribution of rank acceptability indices obtained with Global and Local preferences. High probability to be in the top ranks are in Australia, Canada, Denmark, Norway, Sweden, and Switzerland. In these countries, there is a generalized positive performance in almost all the dimensions considered in the BLI. An opposite trend is in Chile, Greece, Mexico, and Russia, which show high probability to be on the bottom of the rank with all the three set weights considered.

Figure 3.1.a - Rank Acceptability Indices distributions (1/3)



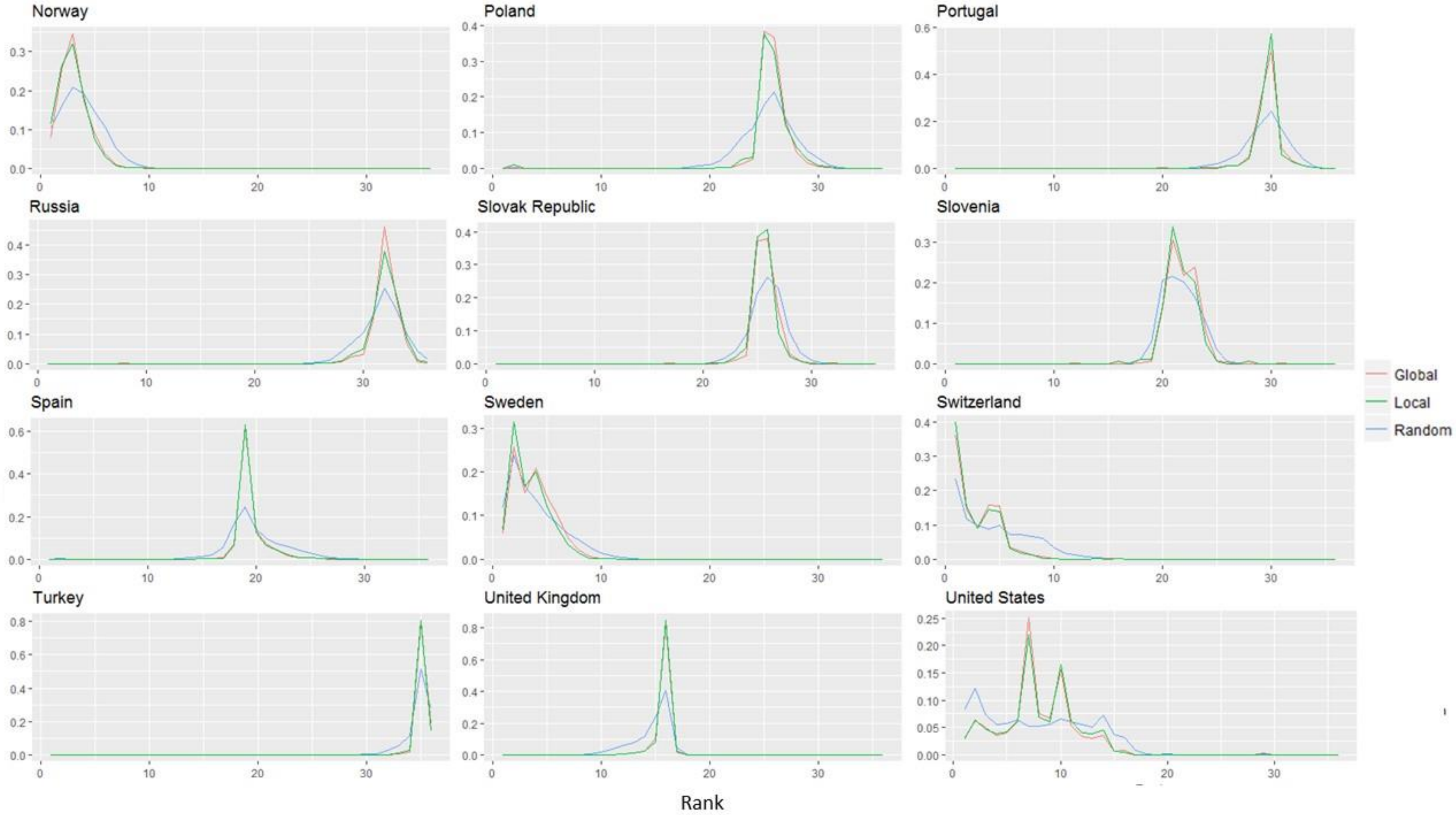
Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Figure 3.1.b - Rank Acceptability Indices distributions (2/3)



Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Figure 3.1.c - Rank Acceptability Indices distributions (3/3)



Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Overall, figure 3.1 shows high similarities among the distributions of rank acceptability indices obtained respectively with Local, Global, and Random weights. In order to give a representation of the difference among the rank acceptability indices obtained with different sets of weights, we follow the procedure adopted in Greco *et al.* (2017). More specifically, we estimate the Intraclass Correlation Coefficients (ICC) among rank acceptability indices obtained respectively with Random, Global and Local preferences. Greco *et al.* (2017) proposed the Consistency-of-Agreement ICC (CA-ICC), in order to test whether different measures give the same ranking to all the regions (Shrout and Fleiss, 1979; McGraw and Wong, 1996a, 1996b). With the same rational, we use the CA-ICC to test whether the Local preferences affect significantly the rank acceptability indices.

The results of the Consistency of Agreement are in table 3.4. They confirm that the correlation between the rank acceptability indices obtained with Local preferences and the rank acceptability indices obtained using Random and Global preferences, is significantly different from zero. Both the individual and the average correlation coefficients are never below 0.53 in the Random vs Local comparisons, and they are never below 0.95 in the Global vs Local comparisons.

Table 3.4 - Intraclass correlations

	Random vs Local				World vs Local			
RANK	Individual	Average	F-test(35,35)	p-value	Individual	Average	F-test(35,35)	p-value
1	0.914	0.955	22.31	0.000	0.989	0.994	173.77	0.000
2	0.929	0.963	27.15	0.000	0.990	0.995	206.23	0.000
3	0.938	0.968	31.21	0.000	0.996	0.998	494.50	0.000
4	0.943	0.971	34.11	0.000	0.994	0.997	348.18	0.000
5	0.785	0.880	8.32	0.000	0.987	0.994	153.87	0.000
6	0.596	0.747	3.95	0.000	0.997	0.998	604.58	0.000
7	0.704	0.826	5.75	0.000	0.983	0.991	114.36	0.000
8	0.664	0.798	4.94	0.000	0.996	0.998	564.68	0.000
9	0.650	0.788	4.71	0.000	0.992	0.996	246.39	0.000
10	0.780	0.876	8.08	0.000	0.996	0.998	453.11	0.000
11	0.706	0.828	5.81	0.000	0.992	0.996	249.12	0.000
12	0.623	0.767	4.30	0.000	0.997	0.999	703.73	0.000
13	0.759	0.863	7.30	0.000	0.997	0.998	618.71	0.000
14	0.651	0.788	4.73	0.000	0.998	0.999	857.58	0.000
15	0.683	0.812	5.31	0.000	0.995	0.998	440.35	0.000
16	0.753	0.859	7.11	0.000	0.999	1.000	2204.17	0.000
17	0.961	0.980	50.06	0.000	1.000	1.000	10483.06	0.000
18	0.887	0.940	16.70	0.000	1.000	1.000	6012.87	0.000
19	0.679	0.809	5.23	0.000	0.998	0.999	1331.83	0.000
20	0.819	0.901	10.07	0.000	0.998	0.999	1324.61	0.000
21	0.881	0.936	15.74	0.000	0.993	0.996	270.44	0.000
22	0.820	0.901	10.11	0.000	0.996	0.998	510.48	0.000
23	0.873	0.932	14.74	0.000	0.987	0.993	148.35	0.000
24	0.530	0.693	3.26	0.000	0.997	0.999	748.97	0.000
25	0.755	0.860	7.15	0.000	0.999	1.000	2027.56	0.000
26	0.883	0.938	16.15	0.000	0.995	0.998	432.58	0.000
27	0.722	0.838	6.19	0.000	0.948	0.973	37.34	0.000
28	0.756	0.861	7.20	0.000	0.980	0.990	99.22	0.000
29	0.869	0.930	14.24	0.000	0.987	0.993	149.49	0.000
30	0.731	0.845	6.44	0.000	0.989	0.995	188.25	0.000
31	0.765	0.867	7.51	0.000	0.982	0.991	108.01	0.000
32	0.911	0.953	21.47	0.000	0.981	0.990	105.04	0.000
33	0.882	0.937	15.94	0.000	0.990	0.995	205.08	0.000
34	0.835	0.910	11.15	0.000	0.989	0.994	174.58	0.000
35	0.878	0.935	15.46	0.000	0.997	0.998	598.52	0.000
36	0.955	0.977	43.19	0.000	0.996	0.998	543.07	0.000

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local preferences data

Both figure 3.1 and table 3.4 show that for any rank, we can exclude zero correlation among different assumptions on weights, and this may have two different explanations:

1. Both the Global and the Local preferences (as expressed in vectors of weights related to the eleven dimensions of BLI) are similar to Random uniform weights. In

other words, the preferences of people in terms of well-being are worldwide and country-level uniform distributed;

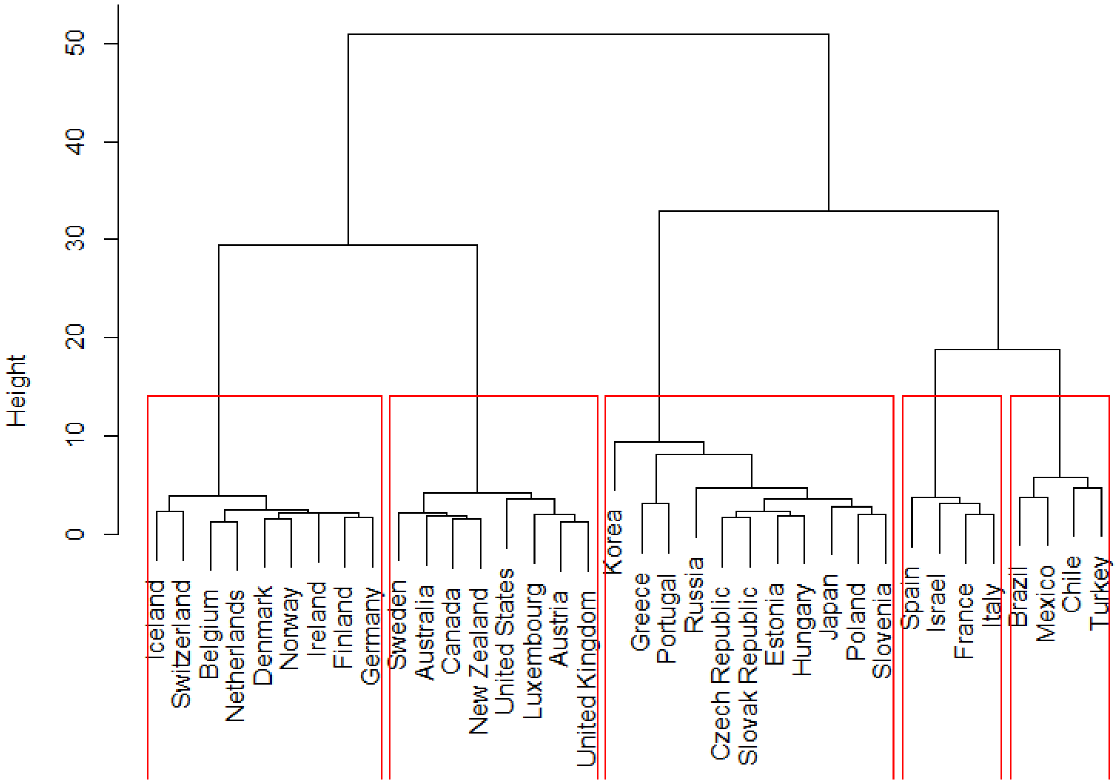
2. There are strong differences in the multidimensional performances among countries that cannot be compensated through the difference in the preferences. In other terms, there is a polarization in the multidimensional performance among countries, mainly because we are comparing systems at different stages of development.

With the aim of exploring these two points, we split the database in groups that share similar performances in terms of multidimensional well-being. To this intent, we perform a cluster analysis on the performances data. Figure 3.2 shows the cluster dendogram on the BLI performances data[74]. The number of clusters in figure 3.2 are chosen by the Elbow method[75].

[74] We clustered the data by the k-means method, which aims to partition the countries into k groups such that the sum of squares from countries to the cluster centres is minimized. The estimates are made in R with the 'stats' package (R Core Team, 2016), in which the algorithm of Hartigan and Wong (1979) is used.

[75] The Elbow is a visual method that looks at the percentage of variance explained as a function of the number of clusters. The idea is that one should choose a number of clusters so that adding another cluster doesn't give much better modelling of the data. Starting with K=2, and increasing K in each step by 1, at some value for K the cost (the difference in the variance explained) drops dramatically, and after that it reaches a plateau when it is increased further (Kodinariya, Makwana, 2013). In our case, this point is reached at five clusters.

Figure 3.2- Cluster dendogram on the Better Life Index topics' performances



Source: Authors' elaboration on OECD (2016) BLI topics' performances.
Note: On the y axes Height is the Euclidean distance

After the clusterization, we estimate again the rank acceptability indices within the clusters, and we repeat the CA-ICC. The results of CA-ICC within the clusters are in table 3.5. They tell us two different stories. First, there are some differences between the rank acceptability indices with Random preferences and the rank acceptability indices with Local preferences. The lower coefficients in table 3.5 confirm the polarization in the multidimensional performance of the 36 countries. In particular, this shows that some countries dominate the others in the majority of the dimensions of BLI, and this mitigates the effect of differentiating weights on the rank. The CA-ICC shows that there are significant differences between the rank acceptability indices in the cluster with Spain, Israel, France, and Italy. Part of this phenomenon is because Israel has more polarized Local preferences compared with the Local preferences of the other counties. Therefore, rank acceptability indices obtained with Random weights have some probability to be zero correlated with rank acceptability indices obtained with Local preferences in Israel. The second story is that the correlation between the rank obtained with the Global preferences and the rank obtained with the Local preferences are significantly positive even within clusters. Therefore, we observe some uniformity in the well-being preferences among different countries. The multidimensional idea of wellbeing seems to go beyond the national borders. This can be partially due to the self-selection of people voting on the OECD website, and to some extent, can extend to the Better Life Index framework the findings about the effects of globalizations on global values (among others: Tilly, 1995; Seita, 1997; Chase-Dunn, Gills, 2005).

Table 3.5 - Intraclass correlations within clusters

		Random vs Local				World vs Local			
Cl.	RANK	Individ.	Aver.	F-test	p-value	Individ.	Aver.	F-test	p-value
1	1	0.938	0.968	31.11	0.000	0.994	0.997	352.27	0.000
1	2	0.940	0.969	32.32	0.000	0.998	0.999	963.49	0.000
1	3	0.663	0.798	4.94	0.013	0.988	0.994	171.65	0.000
1	4	0.620	0.766	4.27	0.021	0.999	0.999	1677.71	0.000
1	5	0.593	0.745	3.92	0.027	0.982	0.991	112.57	0.000
1	6	0.685	0.813	5.36	0.010	0.994	0.997	354.17	0.000
1	7	0.538	0.700	3.33	0.044	0.990	0.995	198.02	0.000
1	8	0.624	0.768	4.31	0.020	0.998	0.999	1246.93	0.000
1	9	0.807	0.893	9.38	0.001	0.996	0.998	524.09	0.000
1	10	0.720	0.837	6.14	0.006	0.999	0.999	1852.08	0.000
2	1	0.901	0.948	19.27	0.001	0.997	0.998	572.72	0.000
2	2	0.828	0.906	10.63	0.006	0.975	0.987	77.94	0.000
2	3	0.886	0.940	16.62	0.002	1.000	1.000	17637.06	0.000
2	4	0.732	0.845	6.46	0.019	0.997	0.998	577.21	0.000
2	5	0.885	0.939	16.45	0.002	0.999	0.999	1751.84	0.000
2	6	0.929	0.963	27.35	0.000	0.999	1.000	3728.61	0.000
2	7	0.997	0.998	571.32	0.000	1.000	1.000	7675.47	0.000
3	1	0.932	0.965	28.53	0.000	0.996	0.998	481.19	0.000
3	2	0.928	0.963	26.68	0.000	0.982	0.991	113.14	0.000
3	3	0.919	0.958	23.56	0.000	0.985	0.992	128.77	0.000
3	4	0.655	0.791	4.79	0.010	0.997	0.998	632.69	0.000
3	5	0.941	0.970	32.92	0.000	0.997	0.998	632.60	0.000
3	6	0.672	0.804	5.10	0.008	0.943	0.971	33.99	0.000
3	7	0.702	0.825	5.72	0.005	0.969	0.984	62.91	0.000
3	8	0.920	0.959	24.15	0.000	0.988	0.994	159.48	0.000
3	9	0.749	0.857	6.97	0.003	0.993	0.996	275.89	0.000
3	10	0.832	0.909	10.93	0.000	0.989	0.995	188.99	0.000
3	11	0.986	0.993	146.83	0.000	0.997	0.998	597.84	0.000
4	1	0.908	0.952	20.73	0.017	1.000	1.000	15591.07	0.000
4	2	0.694	0.819	5.53	0.097	0.998	0.999	945.93	0.000
4	3	0.473	0.642	2.79	0.211	0.982	0.991	109.22	0.001
4	4	0.705	0.827	5.79	0.092	0.998	0.999	799.98	0.000
5	1	0.995	0.997	382.02	0.000	0.996	0.998	500.34	0.000
5	2	0.925	0.961	25.57	0.012	0.998	0.999	879.87	0.000
5	3	0.803	0.891	9.14	0.051	0.995	0.998	429.71	0.000
5	4	0.931	0.964	28.00	0.011	0.995	0.997	371.01	0.000

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local preferences data. Note: Cl. = Cluster.

3.4.2 Rank Acceptability Indices with Local, Global, and Random preferences

In this section, we focus on differences among the different assumptions. Table 3.6 and table 3.7 show a descriptive statistic of the attainable ranks for the 36 Countries of our analysis. Considering the sets of weights represented by Random, Global, and Local preferences, in tables 3.6 and 3.7 we show:

- Best is the rank that country obtains with the most favorable vector of weights;
- Worst is the rank that country obtains with the least favorable vector of weights;
- Mode is the rank that the country obtains more frequently;
- Median is the rank that the country obtains in median.

Although in general we observe a positive correlation among the different assumptions (see pervious section), there are non-negligible differences in the value assumed by Best, Worst, Mode, and Median attainable ranks. Table 3.6 shows that fifteen countries can get the first rank by taking a random set of weights[76]. All those countries would have the best score in terms of CI with BOD estimates. Indeed, these results are in line with Mizobuchi (2014) and Patrizii *et al.* (2017) who use DEA for their Composite BLI. The number of countries can get the first rank decreases to fourteen by taking into account the Global preferences[77], and it decreases to ten with Local preferences[78]. More specifically, four countries (Iceland, Ireland, New Zealand, and Spain) can get the first rank with the Global preferences, but they do not with the Local preferences. This means that, among OECD BLI voters, there are some persons in the world abroad from these countries believing that these countries are the best in terms of BLI, but no one inside these countries believe so. This imply that a CI estimated by BOD on these data would have reflected the abroad preferences more than the local societal preferences.

In the right side of table 3.6 emerges that nine countries can be on the 36-th rank according to Random preferences; they are Korea, Estonia, Hungary, Russia, Greece, Portugal, Turkey, Chile, and Mexico[79]. The number of countries that can get the last position remains unchanged when the Global preferences are considered, but there is a change in the set: Brazil replaces Hungary. When we consider the Local preferences, the number of countries that have some

[76] They are Australia, Belgium, Canada, Denmark, Finland, Iceland, Ireland, Luxembourg, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United States

[77] Belgium, Luxemburg, and Netherland go out, while Japan and Poland enter in the set of countries that are considered the best place according some preferences.

[78] Since the Local preferences are a subset of the Global preferences, the Best (Worst) ranks with Local preferences are always eater equal or higher (lower) than the Best (Worst) ranks with Global preferences.

[79] These countries are all in the bottom side of the rank also in Mizobuchi (2014) and Patrizii *et al.* (2016).

probability to be 36-th decreases to six. In fact, Korea, Hungary, and Portugal go out from the set of worst places. This means that only people not living in those countries perceive them as 36-th in terms of BLI.

Of some interest is the difference between the Best and the Worst rank in table 3.6. This information reflect how much a country can fluctuate in terms of perceived well-being. In this perspective, Spain is the country that have the highest range of the attainable ranks. Indeed, based on Global preferences, Spain can be either at the first or at the 35-th rank in terms of CI of BLI. High differences between Best and Worst ranks are also in Poland (34) and Japan (32). On the contrary, we observe low differences between Best and Worst rank for Sweden (10 with Local preferences), Slovak Republic (11 with Local preferences), and Slovenia (12 with Local preferences). These results reflect the variability among performances on different topics. In general, low variability mitigates the impact of differentiating weights used to aggregate performances into the composite BLI.

Table 3.6 - Best and Worst attainable ranks

	Best Rank			Worst Rank		
Preferences	Random	Global	Local	Random	Global	Local
Australia	1	1	1	24	30	30
Austria	7	7	7	26	27	23
Belgium	1	2	3	25	30	30
Brazil	17	13	13	35	36	36
Canada	1	1	1	16	25	24
Chile	21	20	20	36	36	36
Czech R.	8	7	8	32	33	33
Denmark	1	1	1	19	21	20
Estonia	11	4	10	36	35	32
Finland	1	1	1	21	22	19
France	10	9	9	28	28	27
Germany	2	2	2	22	27	27
Greece	18	14	15	36	36	36
Hungary	11	8	11	36	36	35
Iceland	1	1	2	26	29	22
Ireland	1	1	4	22	23	19
Israel	10	4	4	35	33	32
Italy	13	12	13	32	32	31
Japan	4	1	1	33	33	31
Korea	3	3	6	36	36	35
Luxembourg	1	2	3	30	30	17
Mexico	21	17	17	36	36	36
Netherlands	1	2	4	25	26	26
New Z.	1	1	2	25	27	26
Norway	1	1	1	15	18	17
Poland	4	1	1	34	34	31
Portugal	18	15	16	36	36	34
Russia	13	8	8	36	36	36
Slovak R.	14	11	21	34	34	32
Slovenia	13	12	16	30	31	28
Spain	1	1	2	35	35	35
Sweden	1	1	1	20	27	11
Switzerland	1	1	1	27	31	31
Turkey	19	9	9	36	36	36
United K.	3	3	4	26	29	25
United S.	1	1	1	30	31	30

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local preferences data.

Table 3.7 shows the median and the mode of the rank attainable by the 36 countries analyzed in terms of BLI. It is worth noting that the median rank reflects the opinion of the median voter, while the mode rank reflects the rank having the highest share of votes (highest number of appearances).

The median rank in table 3.7 shows that there are no countries in the first position. This means that there is no consensus with at least the 50% of the preferences, about the best country in terms of BLI. In other words, there is no country considered the best in terms of BLI by at least the 50% of feasible vectors of weights. The best result in terms of median rank with Random preferences is the third rank of Australia and Sweden; Australia shares the second rank with Switzerland by taking both the Global and the Local preferences. On the bottom side of the rank, there is more consensus. Indeed, Mexico is the worst country in terms of BLI for at least the 50% of vectors in all the sets of considered weights (Random, Global, and Local). More in details, as shown in tables A3.2, A3.4, and A3.6 in the Appendices, Mexico has 66%, 80%, and 85% of rank acceptability index in the rank 36, considering respectively Random, Global, and Local preferences. This signals that Mexico has the worst performance in the majority of topics included in the BLI.

The values of the Mode in table 3.7, show that are two countries (Australia and Switzerland) getting the best rank with all the three different set of weights considered. Thus, by a simple majority voting system, there is an *ex-aequo* on the first rank in terms of Better Life Index. It is interesting to note that the USA gets the second rank with Random preferences and drop to the seventh rank with Global and Local preferences. This means that the multidimensional performance in USA is unbalanced on topics in which people voting on OECD website care less. In the specific case, USA has a good performance on the topic Income, in which people voting in OECD website are usually giving less importance. Mexico gets the worst rank in the Mode with all the preferences taken into account.

More in general, from table 3.7 emerges that 17 of the 36 analyzed countries change the rank in mode when different set of weights are considered[80]. This reveals once again that, although the rank acceptability indices obtained by different weights are positively correlated, the attainable ranks are strongly dependent on the preferences taken.

[80] They are United States, Israel, Italy, Czech Republic, Denmark, Belgium, Brazil, Canada, Finland, Germany, Greece, Ireland, Japan, Korea, Netherlands, New Zealand, and Poland.

Table 3.7 - Median and Mode ranks

	Median Rank			Mode Rank		
Preferences	Random	Global	Local	Random	Global	Local
Australia	3	2	2	1	1	1
Austria	17	17	17	17	17	17
Belgium	13	14	14	13	14	14
Brazil	31	31	32	32	31	31
Canada	6	6	6	7	6	6
Chile	33	34	34	34	34	34
Czech R.	22	22	22	24	22	22
Denmark	4	4	4	3	5	5
Estonia	27	27	28	28	28	28
Finland	9	10	9	9	10	10
France	18	18	18	18	18	18
Germany	12	12	12	11	12	12
Greece	32	33	33	34	33	33
Hungary	29	29	29	29	29	29
Iceland	9	9	9	9	9	9
Ireland	13	13	13	14	13	13
Israel	20	22	22	20	23	23
Italy	23	24	24	22	24	24
Japan	21	20	20	20	20	20
Korea	27	27	27	28	28	27
Luxembourg	14	15	15	15	15	15
Mexico	36	36	36	36	36	36
Netherlands	11	11	11	12	11	11
New Z.	8	8	8	7	8	8
Norway	4	3	3	3	3	3
Poland	26	26	26	26	26	25
Portugal	30	30	30	30	30	30
Russia	32	32	32	32	32	32
Slovak R.	26	26	26	26	26	26
Slovenia	22	22	21	21	21	21
Spain	19	19	19	19	19	19
Sweden	3	4	3	2	2	2
Switzerland	4	2	2	1	1	1
Turkey	35	35	35	35	35	35
United K.	15	16	16	16	16	16
United S.	7	7	7	2	7	7

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local preferences data.

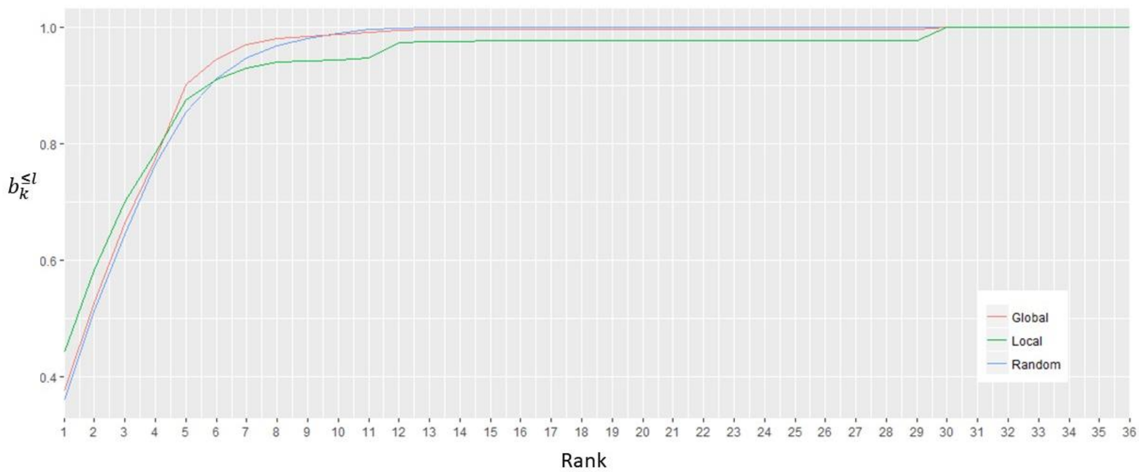
3.4.3 The direction in the differences

The difference between rank acceptability indices obtained with Random weights and rank acceptability indices obtained with Global and Local weights reveals the distance between a Random representation and a real representation of perceived multidimensional well-being. This is because the weights in the Global and Local sets are preferences expressed by people voting in the OECD website, while the Random preferences are vector of weights generated by a uniform distribution.

In this section, we focus on the direction of the differences among rank acceptability indices. These differences provide information about the relationships between relative performances of countries and the relative preferences of people. In particular, they can reveal whether the country-level multidimensional performances are in line with people's relative appreciations of the different dimensions. Assuming that the proportions among the performances in different topics of the Better Life Index depends only on the policy makers' activity, our database can help us understand the extent to which policy makers act to provide a mix of well-being that is in line with the societal priorities. For instance, the rank that the country a_k obtains using Global preferences reflects the perceived well-being of the Global community, while the rank that the country a_k obtains using Local preferences reflects the perceived well-being of the Local community. The difference between the rank that the country a_k obtains with Local preferences, and the rank that the country a_k obtains with Global preferences, reflects the difference between the perceived well-being of Local people, and the perceived well-being of Global community in the country a_k. Taking the Global preferences as baseline (i.e., a supra-national idea of well-being), a move up (or move down) in the rank when Local preferences are taken into account reflect a match (or mismatch) between local people's priorities and local policy makers' activity.

In the SMAA context, the direction of the aforementioned differences can be estimated by the downward cumulative rank acceptability indices (see equation (3.11)). In other words, the downward cumulative rank acceptability indices show for any rank, the probability for the country of achieving a rank lower than that rank, i.e., the share of preferences by which that country is at least first, second, third and so on… A graphical example for the Australian case is in figure 3.3. For instance, comparing Australian rank acceptability indices for rank 1, we can see that the share of Local (i.e. Australians) voters ranking Australia first, are more than the share of Global (all voters in OECD website) voters ranking Australia first, which are more than the Random weights ranking Australia first (see left side in figure 3.3). Therefore, in percentage, there are more Australians ranking Australian first, than Global voters ranking Australia first and also than random weights ranking Australia first. Cumulating those shares with the shares of weights ranking Australia second and following ranks, we have the downward cumulative rank acceptability indices for rank two and following. Comparing the downward cumulative rank acceptability indices obtained with Local preferences, with the downward cumulative rank acceptability indices obtained with Global preferences, we can see whether there is a dominance in the perceived well-being of the Local societal preferences compared with the Global societal preferences. For the Australian case, the Local perceived well-being dominates the Global perceived well-being just until the fourth rank. Indeed, starting from the fourth rank, there are in percentage more people in the Global voters ranking Australia in the first five (six, seven, and so on…) ranks than in Australia.

Figure 3.3 - Downward cumulative rank acceptability indices for Australia



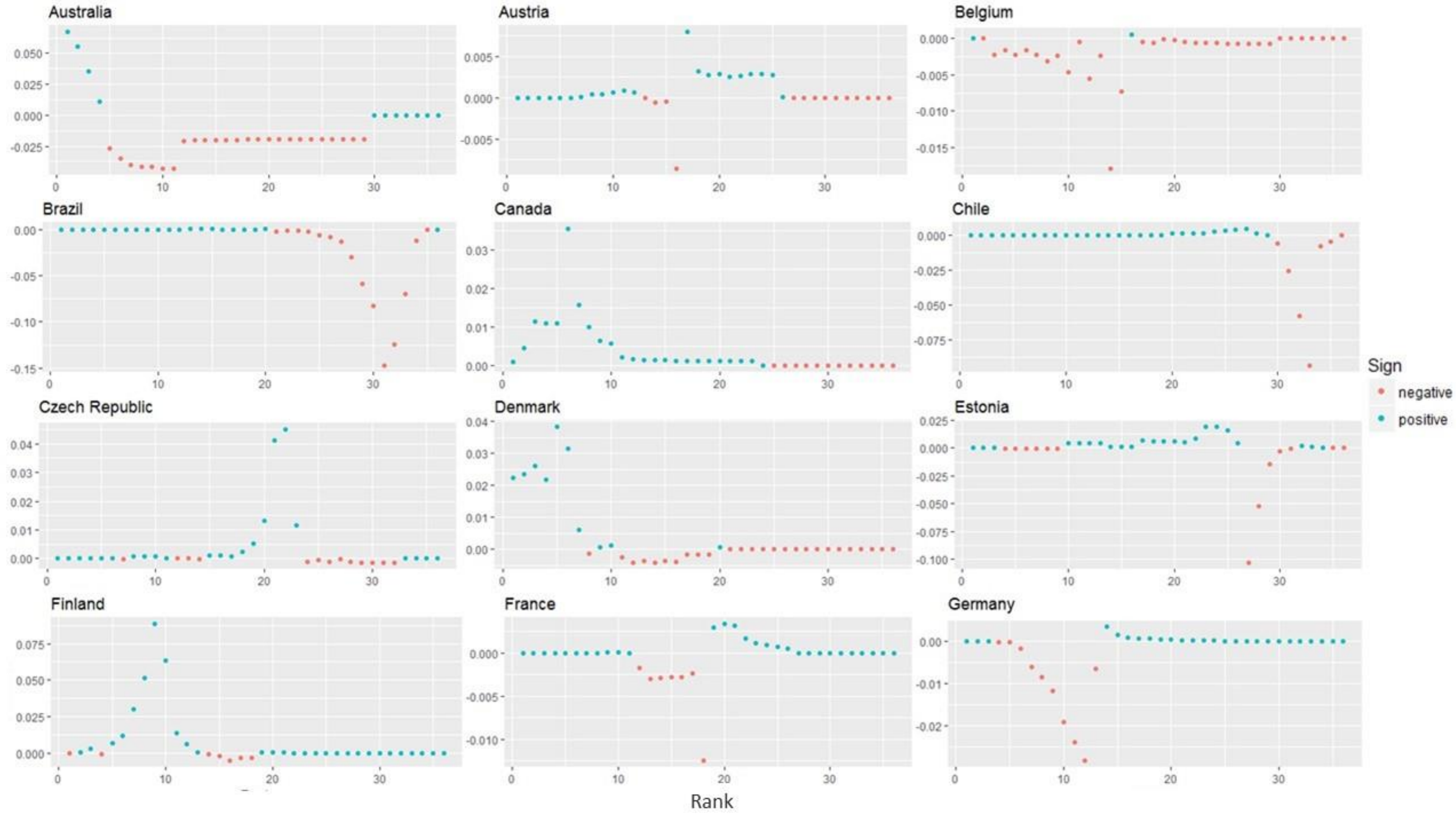
Source: Authors' elaboration on OECD (2016) BLI topics and local Preferences data.

The values of the difference between the downward cumulative rank acceptability indices obtained by Local and by Global weights for all the countries considered are in figure 3.3 (detailed values are in tables A3.7 and A3.8 in the Appendices). The difference allows estimating whether there is dominance, by looking the values above and below the zero. In the Australian case (upper left side of figure 3.4.a), as already noted, the local perceived well-being dominates the global perceived well-being until the fourth rank, and it is dominated from the fifth to the 30-th rank. This means that there is no clear direction in the relations between the societal Local preferences and the multidimensional performance in Australia.

Ideally, if consumer-voters are fully mobile and consumer-voters have full knowledge of differences among countries, the downward cumulative rank acceptability indices with local preferences must always dominate the downward cumulative rank acceptability indices with global preferences. In other words, people living in the country should have a perceived well-being higher than people living abroad. This because of the local match between people preferences and policy makers' activity, driven by people voting with their feet (Tiebout, 1957), and by the 'voice' of people living in the Country (Hirschman, 1970). With our results, we can empirically test this hypothesis in the BLI framework. More specifically, with the hypothesis that local policy makers are the only responsible for the mix performances of BLI, negative (positive) values in the columns in figure 3.4 reflect a mismatch (match) between societal priorities and policy makers' activity at country-level.

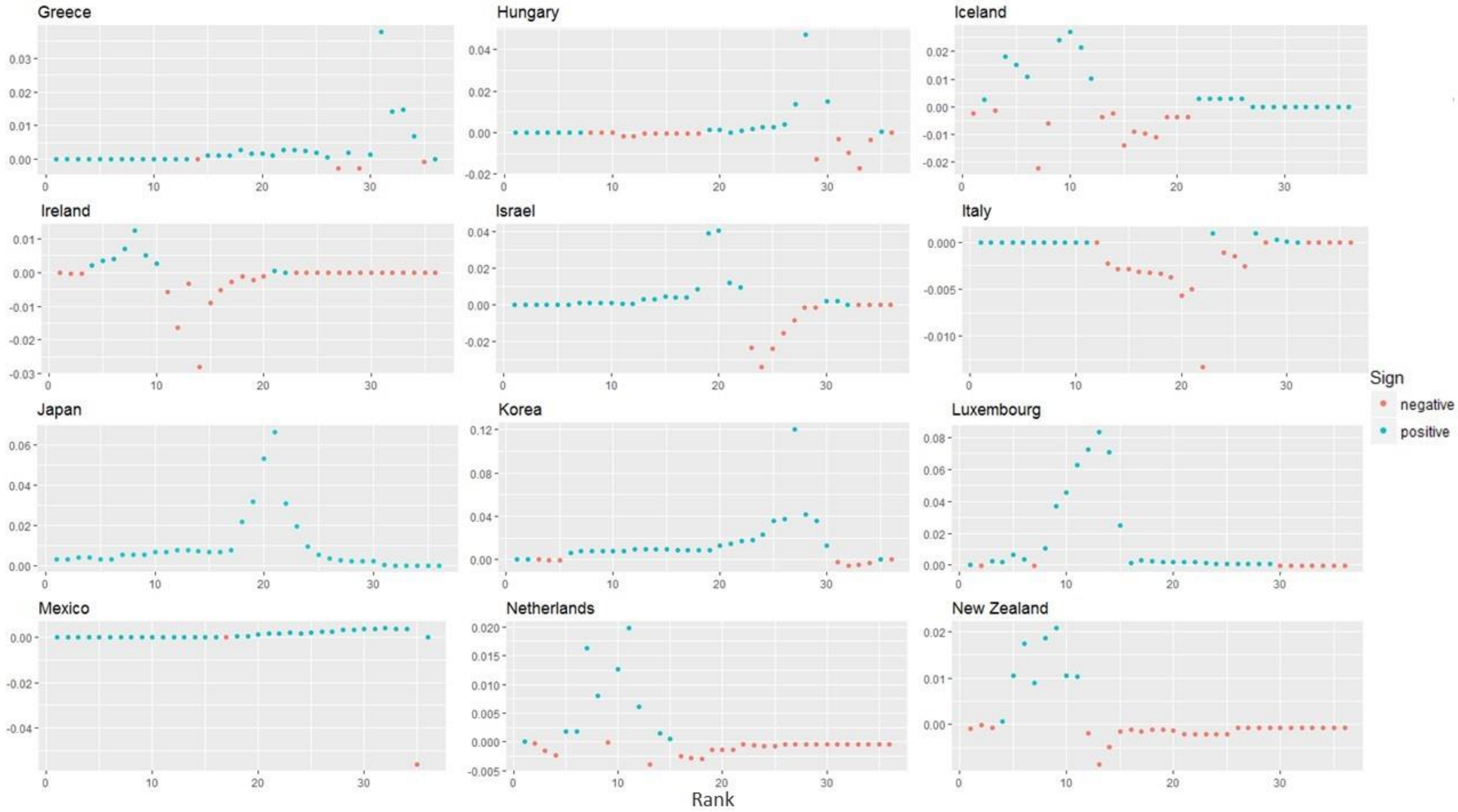
In figure 3.4 the light blue dots are the ranks where the downward cumulative rank acceptability index obtained with Local preferences dominates the downward cumulative rank acceptability index obtained with Global preferences, the other way around are the red dots. In only four of the 36 countries (Japan, Norway, Sweden, and Turkey), people living in the country always perceive the country well-being better than people living abroad. In these countries, Local societal preferences match with the proportions among the multidimensional performances. In other words, these countries have a multidimensional performance in line with the priorities of people living there, i.e., they perform better in topics in which local people care more. In the rest of the countries, the direction of the differences between downward cumulative rank acceptability indices obtained with Global and Local preferences is not monotone. Nevertheless, we observe that there are no countries, in which the downward cumulative rank acceptability index obtained with Global preferences dominates the downward cumulative rank acceptability index obtained with Local preferences. This means that no country has a mix of well-being performances that reflect Global relative appreciations more than Local relative appreciations.

Figure 3.4.a - Differences between downward cumulate rank acceptability indices (1/3)



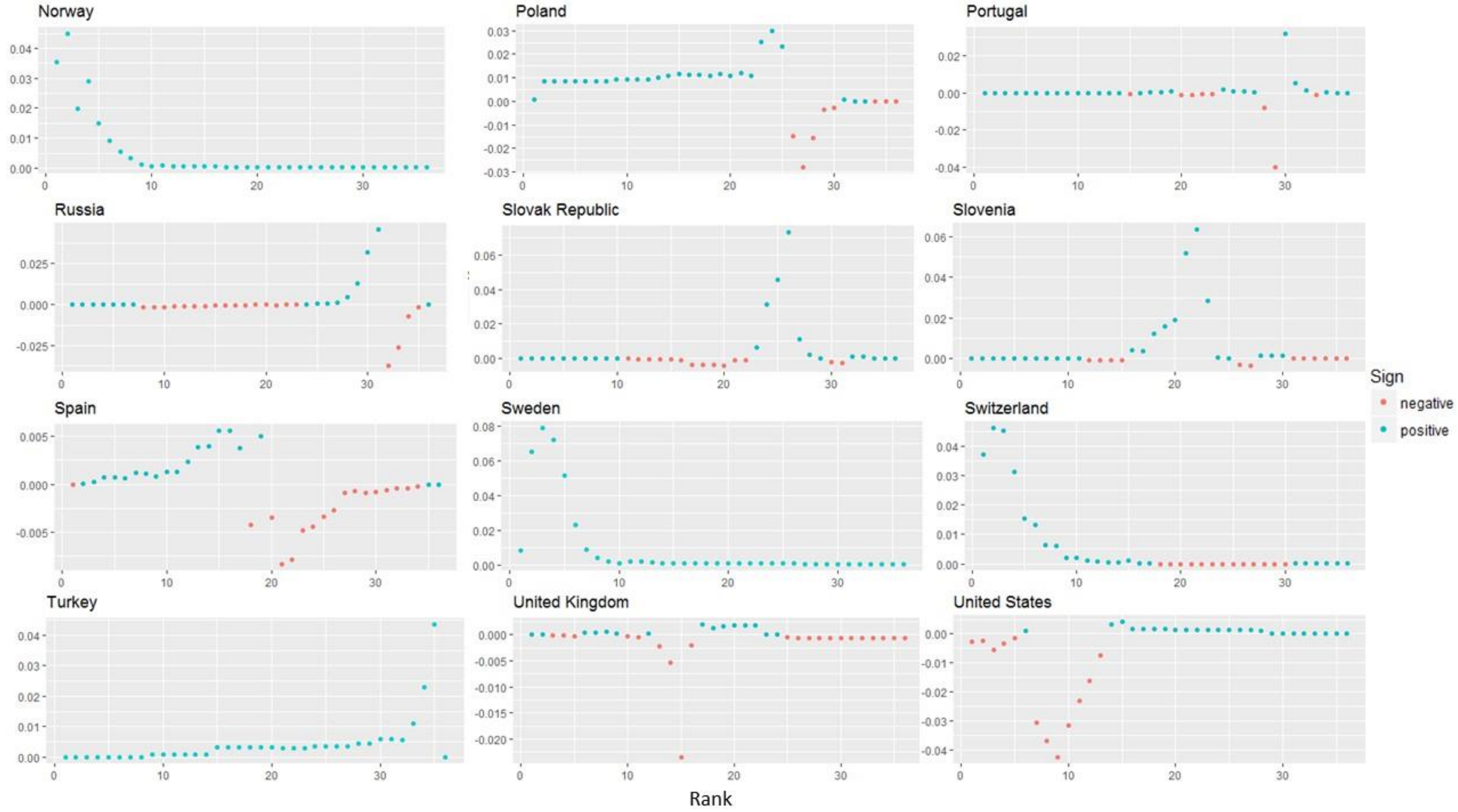
Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local preferences data. Notes: Differences between downward cumulate rank acceptability indices with Local Preferences, and downward cumulate rank acceptability index with Global Preferences; Light blue positive, red negative.

Figure 3.4.b - Differences between downward cumulate rank acceptability indices (2/3)



Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local preferences data. Notes: Differences between downward cumulate rank acceptability indices with Local Preferences, and downward cumulate rank acceptability index with Global Preferences; Light blue positive, red negative.

Figure 3.4.c - Differences between downward cumulate rank acceptability indices (3/3)



Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local preferences data. Notes: Differences between downward cumulate rank acceptability indices with Local Preferences, and downward cumulate rank acceptability index with Global Preferences; Light blue positive, red negative.

3.4.4 The Multidimensional Inequality

In this section, we estimate the global inequality in the Better Life Index. To this intent, we use the generalized measure of inequality proposed in Greco *et al.* (2017). This is the first evaluation of inequality in the OECD BLI framework considering both the individual preferences and the topic performances at country-level. In table 3.8, we present the $G^{\geq l}$ and the $G^{\leq l}$ indices for the Random, Global and Local cumulative rank acceptability indices. In all the three cases, they confirm a great concentration, especially for the best ranks, as shown by the very high values of $G^{\leq l}$ for small l. A high concentration is also valid for the worst ranks, as shown by the very high values of $G^{\geq l}$ for a big l.

Comparing the inequality indices among different preferences, it emerges that the inequality in the cumulative rank acceptability indices with the Random preferences is lower than the inequality in the cumulative rank acceptability indices with the Global and Local preferences in almost all the ranks both in $G^{\geq l}$ and $G^{\leq l}$[81]. This means that the weighted averages of country performances using real individual preferences as weights are more polarized than the weighted averages of performances using a set of random uniform distributed weights. In other words, countries that have good performances in multidimensional well-being have also a proportion among the different dimensions of BLI more balanced on the priorities of people. On the contrary, the bad performer countries have also a mix of well-being unbalanced on topics in which people care less. This causes that when real preferences are taken into account, the distance among good performers' and bad performers' countries increases, and probability to get the best and the worst positions are more polarized. The main consequence is that the inequality in the perceived well-being (regarding people voting in OECD website) is higher than the inequality observed in the multidimensional performances of countries.

[81] More in detail, $G^{\leq l}$ with Random preferences is lower than $G^{\leq l}$ with Global preferences in all the ranks excluding the 17-th. $G^{\leq l}$ with Random preferences is lower than $G^{\leq l}$ with Local preferences in almost all the ranks excluding the 16-th, 17-th, 18-th, 19-th, 20-th, and 21-th. $G^{\geq l}$ with Random preferences is lower than $G^{\geq l}$ with Global preferences in all the ranks excluding the 18-th. $G^{\geq l}$ with Random preferences is lower than $G^{\geq l}$ with Local preferences in all the ranks excluding the 17-th and 18-th.

Table 3.8 - Multidimensional inequality G-indices

	Random preferences		Global preferences		Local preferences	
	$G^{\leq l}$	$G^{\geq l}$	$G^{\leq l}$	$G^{\geq l}$	$G^{\leq l}$	$G^{\geq l}$
1	0.900	0.000	0.930	0.000	0.930	0.000
2	0.870	0.026	0.897	0.027	0.894	0.031
3	0.853	0.051	0.884	0.053	0.881	0.060
4	0.838	0.078	0.871	0.080	0.868	0.087
5	0.818	0.105	0.858	0.109	0.853	0.115
6	0.799	0.132	0.836	0.138	0.831	0.143
7	0.778	0.160	0.809	0.167	0.806	0.171
8	0.756	0.188	0.780	0.196	0.776	0.196
9	0.733	0.216	0.754	0.223	0.749	0.224
10	0.707	0.244	0.728	0.251	0.723	0.254
11	0.682	0.272	0.702	0.280	0.698	0.282
12	0.658	0.300	0.675	0.309	0.672	0.310
13	0.636	0.329	0.648	0.338	0.644	0.338
14	0.615	0.360	0.623	0.366	0.621	0.367
15	0.592	0.391	0.596	0.396	0.595	0.396
16	0.569	0.423	0.569	0.426	0.568	0.425
17	0.542	0.455	0.541	0.455	0.540	0.454
18	0.512	0.485	0.512	0.484	0.510	0.484
19	0.482	0.512	0.483	0.512	0.479	0.512
20	0.450	0.538	0.452	0.539	0.447	0.542
21	0.419	0.562	0.422	0.565	0.417	0.568
22	0.390	0.586	0.394	0.591	0.389	0.595
23	0.362	0.613	0.367	0.619	0.364	0.624
24	0.335	0.641	0.340	0.650	0.337	0.652
25	0.307	0.670	0.311	0.681	0.308	0.681
26	0.279	0.697	0.283	0.706	0.280	0.708
27	0.250	0.724	0.254	0.735	0.255	0.736
28	0.222	0.751	0.227	0.763	0.227	0.762
29	0.194	0.778	0.197	0.793	0.200	0.791
30	0.166	0.804	0.170	0.818	0.169	0.815
31	0.138	0.831	0.141	0.848	0.143	0.848
32	0.111	0.857	0.112	0.872	0.118	0.868
33	0.083	0.885	0.084	0.898	0.089	0.891
34	0.056	0.915	0.057	0.929	0.057	0.921
35	0.028	0.949	0.028	0.968	0.029	0.965
36	0.000	0.974	0.000	0.987	0.000	0.989

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data.

More generally, table 3.8 clearly shows that there are pervasive inequalities among countries in the multidimensional performance of Better Life Index. The probabilities to get the best and the worst rank are polarized in few countries, and the distance between good and bad performers increases when relative appreciations of people are taken into account.

3.5. Conclusions

This paper proposes a Composite Index of well-being, which takes into account the societal preferences in the OECD Better Live Index framework. To the best of our knowledge, this is the first attempt in this direction. From a methodological perspective, we use the Stochastic Multi-Objective Acceptability Analysis approach, which allow considering all the feasible ranks of the countries with all the individual preferences. In this way, the methodology determines the probability that each country is the first, the second, the third, and so on in the ranking. As proxy of societal preferences, we use the opinions collected by the OECD website since 2011, which are individual vectors of weights related to the eleven topics of BLI.

The analysis offers interesting points to be addressed in further research involving both methodological aspects and positive analysis. To begin with, the correlation between rank acceptability indices obtained by Local preferences, and the rank acceptability indices obtained by Global and Random preferences are significantly different from zero. Among the good performers' countries, the rank acceptability indices reveal that some systems (Australia and Switzerland in particular) show good performances with all the three different sets of weights considered (Random, Global, and Local). On the contrary, USA loses some ranks when real preferences of people are taken into account. On the bottom side of the rank, Mexico is considered the worst country in terms of BLI for at least the 50% of vectors in all considered the sets of weights. This signals that Mexico has the worst performance in the majority of topics included in the BLI.

The high Intraclass Correlation Coefficients among the three rank acceptability indices reveals that the rank are robust. These results could be, in principle, explained in terms of a similarity in country-level preferences that goes beyond national borders. Moreover, we found pervasive differences in the country-level performances that cannot be compensated through differences in preferences. Finally, yet importantly, SMMA confirmed to be a valid support for taking into account the differentiations in individual preferences.

Rank acceptability indices obtained with different sets of weights (Random, Global, and Local) are then used to explore the relationship between relative performances and people's preferences at country-level. More in details, when there is a gain in the downward cumulative rank acceptability indices obtained with Local preferences, the country mix of BLI is in line with the preferences of local people, when there is a loss, the country performance mix does not reflect the relative priorities given by people on OECD website. To this respect, in only four out of the 36 countries considered, we find that people living in the country always perceive the country well-being better than people living abroad.

The chapter proposes a contribution towards a new way to compare the perceived well-being across different countries, and an innovative tool to measure the inequality by taking into account both different individual preferences and multidimensional performances at country-level. The global inequality estimates clearly that there is a pervasive polarization in the multidimensional performances of countries. Moreover, the distance between good and bad performers increases when relative appreciations of people are taken into account. This could be interpreted in the sense that good performers' countries have also a proportion among the different dimensions of BLI more balanced on the priorities of people, while bad performers' countries have a mix of well-being unbalanced on topics about which people care less. Regarding people voting in OECD website, the inequality in the perceived well-being is higher than the inequality observed in the multidimensional performances.

To what extent these results are affected by the admitted selection bias affecting the data is unknown. Nonetheless, we argue that this analysis could play a crucial role in stimulating research involving proper sampling procedure. Furthermore, future research in economics should manage the multi-dimensionality of the phenomena interacting with societal behavior in a holistic approach. The UN Sustainable Development Goals (SDGs) clearly go in this direction (Costanza *et al.* 2016). The new tools proposed in this research combined with the new source of big data that are nowadays increasing (see di Bella *et al.* 2017 for a review of Big data and social indicators), can certainly be a valid support for these objectives.

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Appendices

Table A3.1 - Rank acceptability index with Random Preferences (1/2)

Rank	Australia	Austria	Belgium	Brazil	Canada	Chile	Czech R.	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Iceland	Ireland	Israel	Italy
1	0.33	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
2	0.15	0.00	0.00	0.00	0.03	0.00	0.00	0.14	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
3	0.13	0.00	0.00	0.00	0.08	0.00	0.00	0.15	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
4	0.12	0.00	0.00	0.00	0.13	0.00	0.00	0.13	0.00	0.03	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00
5	0.08	0.00	0.01	0.00	0.15	0.00	0.00	0.09	0.00	0.06	0.00	0.01	0.00	0.00	0.05	0.01	0.00	0.00
6	0.06	0.00	0.01	0.00	0.17	0.00	0.00	0.09	0.00	0.07	0.00	0.02	0.00	0.00	0.08	0.02	0.00	0.00
7	0.04	0.00	0.02	0.00	0.18	0.00	0.00	0.10	0.00	0.09	0.00	0.03	0.00	0.00	0.09	0.03	0.00	0.00
8	0.03	0.00	0.03	0.00	0.12	0.00	0.00	0.08	0.00	0.11	0.00	0.04	0.00	0.00	0.11	0.04	0.00	0.00
9	0.02	0.00	0.05	0.00	0.07	0.00	0.00	0.05	0.00	0.14	0.00	0.06	0.00	0.00	0.12	0.06	0.00	0.00
10	0.02	0.00	0.07	0.00	0.03	0.00	0.00	0.02	0.00	0.14	0.00	0.11	0.00	0.00	0.10	0.09	0.00	0.00
11	0.01	0.00	0.10	0.00	0.01	0.00	0.00	0.01	0.00	0.10	0.00	0.16	0.00	0.00	0.08	0.11	0.00	0.00
12	0.01	0.00	0.14	0.00	0.01	0.00	0.00	0.01	0.00	0.08	0.00	0.14	0.00	0.00	0.07	0.12	0.00	0.00
13	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.14	0.00	0.00	0.06	0.13	0.00	0.00
14	0.00	0.01	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.12	0.00	0.00	0.06	0.14	0.00	0.00
15	0.00	0.03	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.08	0.00	0.00	0.05	0.14	0.00	0.00
16	0.00	0.11	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.06	0.00	0.00	0.03	0.07	0.00	0.00
17	0.00	0.73	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.01	0.04	0.00	0.00
18	0.00	0.10	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.56	0.00	0.00	0.00	0.00	0.00	0.03	0.00
19	0.00	0.01	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.08	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.16	0.08
21	0.00	0.00	0.00	0.01	0.00	0.00	0.17	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.10	0.16
22	0.00	0.00	0.00	0.01	0.00	0.00	0.17	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.09	0.18
23	0.00	0.00	0.00	0.01	0.00	0.00	0.18	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.17
24	0.00	0.00	0.00	0.01	0.00	0.00	0.19	0.00	0.04	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.09	0.17
25	0.00	0.00	0.00	0.03	0.00	0.00	0.08	0.00	0.07	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.08	0.11
26	0.00	0.00	0.00	0.03	0.00	0.00	0.02	0.00	0.12	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.07	0.07
27	0.00	0.00	0.00	0.05	0.00	0.01	0.00	0.00	0.23	0.00	0.00	0.00	0.01	0.07	0.00	0.00	0.04	0.04
28	0.00	0.00	0.00	0.07	0.00	0.01	0.00	0.00	0.24	0.00	0.00	0.00	0.02	0.13	0.00	0.00	0.04	0.02
29	0.00	0.00	0.00	0.08	0.00	0.03	0.00	0.00	0.12	0.00	0.00	0.00	0.04	0.25	0.00	0.00	0.05	0.00
30	0.00	0.00	0.00	0.08	0.00	0.04	0.00	0.00	0.07	0.00	0.00	0.00	0.08	0.21	0.00	0.00	0.04	0.00
31	0.00	0.00	0.00	0.13	0.00	0.05	0.00	0.00	0.04	0.00	0.00	0.00	0.19	0.14	0.00	0.00	0.02	0.00
32	0.00	0.00	0.00	0.18	0.00	0.11	0.00	0.00	0.01	0.00	0.00	0.00	0.18	0.07	0.00	0.00	0.01	0.00
33	0.00	0.00	0.00	0.18	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.04	0.00	0.00	0.00	0.00
34	0.00	0.00	0.00	0.11	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.01	0.00	0.00	0.00	0.00
35	0.00	0.00	0.00	0.03	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
36	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Table A3.2 - Rank acceptability index with Random Preferences (2/2)

Rank	Japan	Korea	Luxembourg	Mexico	Netherlands	New Z.	Norway	Poland	Portugal	Russia	Slovak R.	Slovenia	Spain	Sweden	Switzerland	Turkey	U. K.	U. S.
1	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.23	0.00	0.00	0.08
2	0.00	0.00	0.00	0.00	0.00	0.01	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.12	0.00	0.00	0.12
3	0.00	0.00	0.00	0.00	0.00	0.04	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.10	0.00	0.00	0.07
4	0.00	0.00	0.01	0.00	0.01	0.04	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.09	0.00	0.00	0.06
5	0.00	0.00	0.01	0.00	0.02	0.10	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.10	0.00	0.00	0.06
6	0.00	0.00	0.02	0.00	0.03	0.10	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.07	0.00	0.00	0.06
7	0.00	0.00	0.03	0.00	0.05	0.12	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.07	0.00	0.00	0.05
8	0.00	0.00	0.04	0.00	0.08	0.13	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.07	0.00	0.00	0.05
9	0.00	0.00	0.05	0.00	0.09	0.12	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.06	0.00	0.01	0.06
10	0.00	0.00	0.06	0.00	0.12	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.00	0.02	0.07
11	0.00	0.00	0.07	0.00	0.15	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.03	0.06
12	0.00	0.00	0.08	0.00	0.15	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.06	0.05
13	0.00	0.00	0.10	0.00	0.12	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.07	0.05
14	0.00	0.00	0.12	0.00	0.08	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.12	0.07
15	0.00	0.00	0.22	0.00	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.24	0.04
16	0.00	0.00	0.14	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.41	0.03
17	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.05	0.01
18	0.09	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.17	0.00	0.00	0.00	0.00	0.00
19	0.18	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.06	0.25	0.00	0.00	0.00	0.00	0.00
20	0.17	0.04	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.21	0.14	0.00	0.00	0.00	0.00	0.00
21	0.16	0.04	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.22	0.10	0.00	0.00	0.00	0.00	0.00
22	0.14	0.04	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.02	0.20	0.07	0.00	0.00	0.00	0.00	0.00
23	0.09	0.05	0.00	0.00	0.00	0.00	0.00	0.09	0.01	0.00	0.04	0.17	0.06	0.00	0.00	0.00	0.00	0.00
24	0.07	0.06	0.00	0.00	0.00	0.00	0.00	0.11	0.01	0.00	0.09	0.10	0.04	0.00	0.00	0.00	0.00	0.00
25	0.04	0.09	0.00	0.00	0.00	0.00	0.00	0.18	0.02	0.00	0.21	0.03	0.03	0.00	0.00	0.00	0.00	0.00
26	0.02	0.08	0.00	0.00	0.00	0.00	0.00	0.21	0.03	0.00	0.26	0.01	0.02	0.00	0.00	0.00	0.00	0.00
27	0.01	0.09	0.00	0.00	0.00	0.00	0.00	0.14	0.06	0.01	0.23	0.00	0.01	0.00	0.00	0.00	0.00	0.00
28	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.09	0.12	0.04	0.09	0.00	0.01	0.00	0.00	0.00	0.00	0.00
29	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.05	0.19	0.07	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.03	0.25	0.11	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31	0.00	0.08	0.00	0.01	0.00	0.00	0.00	0.01	0.17	0.16	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
32	0.00	0.06	0.00	0.01	0.00	0.00	0.00	0.00	0.09	0.25	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00
33	0.00	0.04	0.00	0.02	0.00	0.00	0.00	0.00	0.04	0.19	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00
34	0.00	0.02	0.00	0.06	0.00	0.00	0.00	0.00	0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00
35	0.00	0.00	0.00	0.23	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.51	0.00	0.00
36	0.00	0.00	0.00	0.66	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.27	0.00	0.00

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Table A3.3 Rank acceptability index with Global Preferences (1/2)

Rank	Australia	Austria	Belgium	Brazil	Canada	Chile	Czech R.	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Iceland	Ireland	Israel	Italy
1	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.15	0.00	0.00	0.00	0.02	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.14	0.00	0.00	0.00	0.04	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.11	0.00	0.00	0.00	0.12	0.00	0.00	0.15	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
5	0.13	0.00	0.00	0.00	0.14	0.00	0.00	0.22	0.00	0.02	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
6	0.04	0.00	0.00	0.00	0.50	0.00	0.00	0.09	0.00	0.03	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00
7	0.02	0.00	0.00	0.00	0.12	0.00	0.00	0.11	0.00	0.07	0.00	0.01	0.00	0.00	0.11	0.00	0.00	0.00
8	0.01	0.00	0.01	0.00	0.03	0.00	0.00	0.04	0.00	0.15	0.00	0.01	0.00	0.00	0.22	0.01	0.00	0.00
9	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.02	0.00	0.21	0.00	0.03	0.00	0.00	0.34	0.02	0.00	0.00
10	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.31	0.00	0.08	0.00	0.00	0.12	0.06	0.00	0.00
11	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.11	0.00	0.19	0.00	0.00	0.06	0.08	0.00	0.00
12	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.46	0.00	0.00	0.03	0.12	0.00	0.00
13	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.15	0.00	0.00	0.01	0.33	0.00	0.00
14	0.00	0.00	0.51	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.05	0.00	0.00	0.01	0.19	0.00	0.00
15	0.00	0.01	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.17	0.00	0.00
16	0.00	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
17	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
18	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.87	0.00	0.00	0.00	0.00	0.00	0.01	0.00
19	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.06	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.21	0.02
21	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.04
22	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.11
23	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.19
24	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.59
25	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.03
26	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01
27	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
28	0.00	0.00	0.00	0.04	0.00	0.01	0.00	0.00	0.41	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00
29	0.00	0.00	0.00	0.07	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.48	0.00	0.00	0.00	0.00
30	0.00	0.00	0.00	0.06	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.30	0.00	0.00	0.00	0.00
31	0.00	0.00	0.00	0.39	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.09	0.00	0.00	0.00	0.00
32	0.00	0.00	0.00	0.19	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.18	0.03	0.00	0.00	0.00	0.00
33	0.00	0.00	0.00	0.13	0.00	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.02	0.00	0.00	0.00	0.00
34	0.00	0.00	0.00	0.07	0.00	0.62	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.01	0.00	0.00	0.00	0.00
35	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Table A3.4 Rank acceptability index with Global Preferences (2/2)

Rank	Japan	Korea	Luxembourg	Mexico	Netherl.	New Z.	Norway	Poland	Portugal	Russia	Slovak R.	Slovenia	Spain	Sweden	Switz.	Turkey	U.K.	U S.
1	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.36	0.00	0.00	0.03
2	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.14	0.00	0.00	0.06
3	0.00	0.00	0.00	0.00	0.00	0.01	0.35	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.09	0.00	0.00	0.05
4	0.00	0.00	0.00	0.00	0.01	0.01	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.16	0.00	0.00	0.04
5	0.00	0.00	0.00	0.00	0.01	0.03	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.16	0.00	0.00	0.04
6	0.00	0.00	0.00	0.00	0.01	0.04	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.03	0.00	0.00	0.06
7	0.00	0.00	0.00	0.00	0.03	0.19	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.03	0.00	0.00	0.25
8	0.00	0.00	0.01	0.00	0.09	0.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.08
9	0.00	0.00	0.01	0.00	0.08	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.07
10	0.00	0.00	0.02	0.00	0.12	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16
11	0.00	0.00	0.02	0.00	0.39	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05
12	0.00	0.00	0.04	0.00	0.16	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03
13	0.00	0.00	0.10	0.00	0.07	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03
14	0.00	0.00	0.12	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.03
15	0.00	0.00	0.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.01
16	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.83	0.01
17	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00
18	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00
19	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.62	0.00	0.00	0.00	0.00	0.00
20	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.13	0.00	0.00	0.00	0.00	0.00
21	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	0.07	0.00	0.00	0.00	0.00	0.00
22	0.12	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.04	0.00	0.00	0.00	0.00	0.00
23	0.08	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.24	0.02	0.00	0.00	0.00	0.00	0.00
24	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.02	0.08	0.01	0.00	0.00	0.00	0.00	0.00
25	0.01	0.12	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.37	0.01	0.01	0.00	0.00	0.00	0.00	0.00
26	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.36	0.01	0.00	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00
27	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.14	0.01	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00
28	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.05	0.05	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.01	0.28	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.01	0.50	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
34	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
35	0.00	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.79	0.00	0.00
36	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.19	0.00	0.00

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Table A3.5 Rank acceptability index with Local Preferences (1/2)

Rank	Australia	Austria	Belgium	Brazil	Canada	Chile	Czech R.	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Iceland	Ireland	Israel	Italy
1	0.44	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.14	0.00	0.00	0.00	0.02	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
3	0.12	0.00	0.00	0.00	0.05	0.00	0.00	0.16	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.09	0.00	0.00	0.00	0.12	0.00	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00
5	0.09	0.00	0.00	0.00	0.14	0.00	0.00	0.24	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
6	0.04	0.00	0.00	0.00	0.52	0.00	0.00	0.08	0.00	0.04	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00
7	0.02	0.00	0.00	0.00	0.10	0.00	0.00	0.08	0.00	0.09	0.00	0.01	0.00	0.00	0.07	0.01	0.00	0.00
8	0.01	0.00	0.00	0.00	0.03	0.00	0.00	0.03	0.00	0.17	0.00	0.01	0.00	0.00	0.24	0.01	0.00	0.00
9	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.02	0.00	0.25	0.00	0.03	0.00	0.00	0.37	0.01	0.00	0.00
10	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.28	0.00	0.07	0.00	0.00	0.13	0.05	0.00	0.00
11	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.19	0.00	0.00	0.05	0.07	0.00	0.00
12	0.03	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.46	0.00	0.00	0.01	0.11	0.00	0.00
13	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.17	0.00	0.00	0.00	0.35	0.00	0.00
14	0.00	0.00	0.49	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.06	0.00	0.00	0.01	0.16	0.00	0.00
15	0.00	0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.19	0.00	0.00
16	0.00	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00
17	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
18	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.86	0.00	0.00	0.00	0.00	0.00	0.01	0.00
19	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.12	0.00	0.00	0.00	0.01	0.00	0.09	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.22	0.01
21	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.04
22	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.12	0.10
23	0.00	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.21
24	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.59
25	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.03
26	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.01
27	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.01
28	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.46	0.00	0.00	0.00	0.01	0.09	0.00	0.00	0.01	0.00
29	0.00	0.00	0.00	0.04	0.00	0.01	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.42	0.00	0.00	0.00	0.00
30	0.02	0.00	0.00	0.04	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.02	0.33	0.00	0.00	0.01	0.00
31	0.00	0.00	0.00	0.33	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.24	0.07	0.00	0.00	0.00	0.00
32	0.00	0.00	0.00	0.21	0.00	0.05	0.00	0.00	0.01	0.00	0.00	0.00	0.15	0.02	0.00	0.00	0.00	0.00
33	0.00	0.00	0.00	0.18	0.00	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.01	0.00	0.00	0.00	0.00
34	0.00	0.00	0.00	0.13	0.00	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.02	0.00	0.00	0.00	0.00
35	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
36	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Table A3.6 Rank acceptability index with Local Preferences (2/2)

Rank	Japan	Korea	Luxembourg	Mexico	Netherl.	New Z.	Norway	Poland	Portugal	Russia	Slovak R.	Slovenia	Spain	Sweden	Switz.	Turkey	U.K.	U S.
1	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.40	0.00	0.00	0.03
2	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.01	0.00	0.00	0.00	0.00	0.00	0.31	0.15	0.00	0.00	0.06
3	0.00	0.00	0.00	0.00	0.00	0.01	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.09	0.00	0.00	0.05
4	0.00	0.00	0.00	0.00	0.01	0.01	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.14	0.00	0.00	0.04
5	0.00	0.00	0.01	0.00	0.01	0.04	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.14	0.00	0.00	0.04
6	0.00	0.01	0.00	0.00	0.01	0.05	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.03	0.00	0.00	0.06
7	0.00	0.00	0.00	0.00	0.04	0.18	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02	0.00	0.00	0.22
8	0.00	0.00	0.02	0.00	0.09	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.07
9	0.00	0.00	0.04	0.00	0.07	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06
10	0.00	0.00	0.03	0.00	0.14	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17
11	0.00	0.00	0.04	0.00	0.40	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06
12	0.00	0.00	0.05	0.00	0.15	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04
13	0.00	0.00	0.11	0.00	0.06	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04
14	0.00	0.00	0.11	0.00	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.05
15	0.00	0.00	0.53	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.08	0.01
16	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.85	0.01
17	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00
18	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.00	0.00	0.00	0.00	0.00
19	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.63	0.00	0.00	0.00	0.00	0.00
20	0.38	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.12	0.00	0.00	0.00	0.00	0.00
21	0.20	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.07	0.00	0.00	0.00	0.00	0.00
22	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.04	0.00	0.00	0.00	0.00	0.00
23	0.06	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.02	0.20	0.02	0.00	0.00	0.00	0.00	0.00
24	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.05	0.05	0.01	0.00	0.00	0.00	0.00	0.00
25	0.01	0.13	0.00	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.38	0.01	0.01	0.00	0.00	0.00	0.00	0.00
26	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.33	0.01	0.00	0.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00
27	0.00	0.33	0.00	0.00	0.00	0.00	0.00	0.12	0.01	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00
28	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.06	0.04	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
29	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.03	0.25	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.57	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.25	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
34	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00
35	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.81	0.00	0.00
36	0.00	0.00	0.00	0.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local Preferences data

Table A3.7 - Differences between Downward Cumulate rank acceptability indices (1/2)

Rank	Australia	Austria	Belgium	Brazil	Canada	Chile	Czech R.	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Iceland	Ireland	Israel	Italy
1	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
5	-0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.04	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00
6	-0.04	0.00	0.00	0.00	0.04	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
7	-0.04	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.03	0.00	-0.01	0.00	0.00	-0.02	0.01	0.00	0.00
8	-0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.05	0.00	-0.01	0.00	0.00	-0.01	0.01	0.00	0.00
9	-0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.09	0.00	-0.01	0.00	0.00	0.02	0.01	0.00	0.00
10	-0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.06	0.00	-0.02	0.00	0.00	0.03	0.00	0.00	0.00
11	-0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.02	0.00	0.00	0.02	-0.01	0.00	0.00
12	-0.02	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.03	0.00	0.00	0.01	-0.02	0.00	0.00
13	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
14	-0.02	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	0.00	0.00
15	-0.02	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00
16	-0.02	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00
17	-0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00
18	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	0.01	0.00
19	-0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00
20	-0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	-0.01
21	-0.02	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	-0.01
22	-0.02	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	-0.01
23	-0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	0.00
24	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	0.00
25	-0.02	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	0.00
26	-0.02	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	0.00
27	-0.02	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.10	0.00	0.00	0.00	0.00	0.01	0.00	0.00	-0.01	0.00
28	-0.02	0.00	0.00	-0.03	0.00	0.00	0.00	0.00	-0.05	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00
29	-0.02	0.00	0.00	-0.06	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00
30	0.00	0.00	0.00	-0.08	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
31	0.00	0.00	0.00	-0.15	0.00	-0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00
32	0.00	0.00	0.00	-0.12	0.00	-0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.01	-0.01	0.00	0.00	0.00	0.00
33	0.00	0.00	0.00	-0.07	0.00	-0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.01	-0.02	0.00	0.00	0.00	0.00
34	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Authors' elaboration on OECD (2016) BLI topics' performances, and local preferences data.

Notes: Differences between Downward Cumulate rank acceptability index with Local Preferences, and Downward Cumulate rank acceptability index with Global Preferences; In green the positive values and in red the negative values.

Table A3.8 - Differences between Downward Cumulate rank acceptability indices (2/2)

Rank	Japan	Korea	Luxembourg	Mexico	Netherl.	New Z.	Norway	Poland	Portugal	Russia	Slovak R.	Slovenia	Spain	Sweden	Switz.	Turkey	U.K.	U S.
1	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.07	0.05	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.08	0.05	0.00	0.00	-0.01
4	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.07	0.03	0.00	0.00	0.00
5	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.05	0.02	0.00	0.00	0.00
6	0.00	0.01	0.00	0.00	0.00	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.00
7	0.01	0.01	0.00	0.00	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	-0.03
8	0.01	0.01	0.01	0.00	0.01	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	-0.04
9	0.01	0.01	0.04	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.04
10	0.01	0.01	0.05	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03
11	0.01	0.01	0.06	0.00	0.02	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02
12	0.01	0.01	0.07	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02
13	0.01	0.01	0.08	0.00	0.00	-0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
14	0.01	0.01	0.07	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00
15	0.01	0.01	0.03	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	-0.02	0.00
16	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
17	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
19	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
20	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
21	0.07	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.05	-0.01	0.00	0.00	0.00	0.00	0.00
22	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.06	-0.01	0.00	0.00	0.00	0.00	0.00
23	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00
24	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	0.01	0.04	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00
26	0.00	0.04	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00
27	0.00	0.12	0.00	0.00	0.00	0.00	0.00	-0.03	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
28	0.00	0.04	0.00	0.00	0.00	0.00	0.00	-0.02	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00	-0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
32	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.04	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
35	0.00	0.00	0.00	-0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00
36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Authors’ elaboration on OECD (2016) BLI topics’ performances, and local Preferences data.

Notes: Differences between Downward Cumulate rank acceptability index with Local Preferences, and Downward Cumulate rank acceptability index with Global Preferences; In green the positive values and in red the negative values.