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THE EUROPEAN MAP OF WELL-BEING: MEASURING WELL-BEING WITH ALTERNATIVE SYNTHETIC INDICES

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ABSTRACT

The last two decades have witnessed a proliferation of new indicators aimed at measuring well-being from a multifaceted perspective, more comprehensive than the one adopted by traditionally used indicators of production. This thesis proposes synthetic indices for seven dimensions of well-being and two overall well-being indices. The methodologies used are both the arithmetic mean aggregation and the principal component analysis. The main contribution of this study consists of expanding the range of domains and indicators through which most of the literature has measured well-being in Europe by combining a set of 30 variables. The two methodologies adopted follow a non-standard two step approach: in the first step, a composite index for each dimension is constructed to highlight the multidimensional nature of well-being; in the second step, the overall index provides a synthetic measure of the phenomenon. Similar results emerge from both methodologies. They depict a deep divide between Northern European countries and particularly Scandinavian countries which exhibit excellent levels of quality of life, and Eastern European countries which suffer low levels of well-being. Italy belongs to the latter group of countries, characterized by lower levels of well-being. Furthermore, the thesis is aimed at investigating the circumstances under which the two methodologies described above could lead to similar results. Even more, the work highlights how principal component analysis proves particularly useful for checking the internal consistency of the variables. Finally, the thesis discusses the importance of considering multidimensional indices of well-being, in order to flank GDP in assessing people's quality-of-life.

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1. *Introduction*

Throughout the twentieth century, economists and policymakers celebrated the triumph of productivity indicators as the most relevant measures to consider in order to account for the growth of a society. However, in order to evaluate the progress of a country, a proper measure of well-being is needed, which is able to collect together different aspects of quality of life. The quest for a measure of well-being has become more intensive after the recent economic crisis, as GDP, nowadays the most widely used indicator, proved to be an insufficient measure of the relevant aspects of people's well-being. The limits of the GDP, though, are not a recent discovery. Already in 1950s and 1960s, Simon Kuznets, Nobel Prize in Economic Sciences, pointed out that in the initial stage of economic growth in developing countries, an increase in GDP is usually associated to an increase in income inequality. Additionally, in 1974 Richard Easterlin showed that above a certain threshold the correlation between GDP growth and subjective well-being is surprisingly low. However, the most well-known critique to GDP comes from Robert Kennedy in his famous speech in 1968 at the University of Kansas, during which he objected that GDP "measures everything in short, except that which makes life worthwhile".

On 19th March 2014, on the occasion of the International Day of Happiness, Eurostat an online publication on Quality of Life indicators. Eurostat collects data on several dimensions of quality of life: material living conditions, productive or main activity, health, education, leisure or social interactions, economic and physical safety, governance and basic rights and natural and living environment.

This work aims at carrying forward the attempt to deliver a battery of synthetic indicators representing each dimension of well-being as indicated by Eurostat and an aggregate index including all the aspects of quality of life. The final goal is to make comparisons among European countries on the single dimensions of quality of life and on the overall level of well-being, with a particular emphasis on the Italian situation. Having a synthetic index for each dimension and an aggregate final index would be of extreme value for a policymaker in order to have track of the process of growth of the country. Such indices could also prove to be of great utility to citizens for a direct evaluation of the policies pursued by the government.

The idea underlying this work is therefore to aggregate the multiplicity of variables that Eurostat lists for each dimension of well-being into a single index for dimension, which best represents the set of information contained in the particular "field" of quality of life. Then, after assessing the feasibility, the research has the goal to transform the battery of dimension indices into a single synthetic well-being index. Two are the methodologies that the paper intends to follow: arithmetic mean aggregation and principal component analysis and both will follow a two-step approach. Arithmetic mean aggregation is likely the most widely used method to weight synthetic indices. Simplicity is the greatest advantage of this methodology but it is also its biggest flow. In fact, equal weighting is often interpreted as no weighting; however, one can easily observe that arithmetic mean aggregation implies equal importance of each dimension and it is a subjective weighting scheme. The many advantages and issues that this type of aggregation involves will be analysed later in the work. A number of studies (Ram 1982, Slottje 1991, Desai 1993, Ogwang 1994, Srinivasan 1994

and Lai 2000) proposed the use of Principal Components Analysis (PCA) as the most adequate aggregation method to create composite well-being indices. The reason behind this choice is that PCA reduces the dimensionality of the data set, with a small loss of relevant information. In particular, PCA allows the identification of the differentiating factors, namely the principal directions in which the data vary, by transforming a set of correlated variables into a set of uncorrelated components. Contrarily to the standard procedure of equal weights aggregation, a PCA approach would overcome the problem of assigning "subjective" weights by construction. This method is indeed data driven and could prove particularly useful in a comparison among European countries. Although the supremacy of PCA over equal weighting has been discussed in the above-mentioned studies from the theoretical point of view, none of these gave evidence that the two methodologies provide different results.

The goal of this paper is therefore to contribute to the existing literature on quality of life indices not only by constructing two innovative synthetic well-being indices, but also by showing whether, from an empirical point of view, meaningful differences in results exist between the two methodologies.

In general, few studies empirically adopt PCA to construct well-being indices and most of them rely on one-step approaches, where all selected indicators are not considered to be part of different aspects of quality of life and they are directly aggregated into a final index by means of principal component analysis (Maasoumi and Nickelsburg 1988; Boelhouwer and Stoop 1999; Somarriba and Pena 2009).

Ferrara and Nisticò (2014) use PCA in a two-step approach in a study about convergence in well-being across Italian regions in a multi-years setting. To the best of the author's knowledge, the latter is the sole study adopting a two step approach and will then be regarded as an example.

A final goal of this paper is to draw a map of well-being in Europe according to each of the indicated methodologies

The work is divided in sections. Section 2 reviews the related literature and the debate on composite indices. It briefly examines the main limitations of the most widely used existing indicators, providing an introduction to Section 3, which focuses on the methodologies pursued throughout the paper, with a special emphasis on the principal component technique. Section 4 describes the dataset, the adopted scaling methodology and the treatment of missing data. Section 5 deals with the results of the single dimensions of well-being as indentified by Eurostat. Section 6 presents the final results by discussing the composite well-being index, obtained by aggregating all different dimension indices into a single index. A European map of well-being emerges from the values of the index and the situation of Italy is particularly emphasized. Section 7 and 8 conclude by drawing the attention on the final remarks.

2. Literature Review

This section has the purpose to analyse the features, advantages and disadvantages of existing indicators, to introduce the reader to the vast literature on composite indices and to illustrate the reasons that motivate the research.

Gross Domestic Product

Before and mainly after the recent economic crisis, many economists claimed GDP's incapacity in capturing the well being of 21st century society and in general to "understand the world". Critiques to this indicator in this work are only briefly listed as a very large literature already focuses on this topic. These critiques might be concisely summarized in four points: 1- GDP does not take into account the sustainability of future GDP (i.e. the elimination of natural resources may induce an increase in current production at the expenses of future production); 2- an increase in production might not necessarily imply an increase in the well-being of a country (i.e. defensive expenses, etc..); 3- GDP provides no information on the income distribution of a country and 4- GDP does not take into account non-monetary aspects and fails to measure the well being of 21st century society. In this research it is argued that GDP probably never had the final goal to measure the well being of a society and that the latter mainly depends on the shift of paradigms in the society itself. According to the author's point of view, the true problem is not GDP itself, but the use that policy makers around the world made and still make of it. As a matter of fact, the use of GDP has "skewed global political objectives toward the single-minded pursuit of economic growth" (Habermann, 2011).

Too often scholars refer to the necessity to set aside GDP as a primary national goal and to replace it with a more inclusive indicator of well-being (i.e. De Vogli 2014, O'Neill 2014). Moreover, many policy makers (especially in countries where GDP growth is extremely low) might be attracted to the possibility to replace GDP with other tailored-specific indicators that position their own countries among the most virtuous ones.

The point of view taken in this research is that new measures of well-being are certainly needed, but GDP needs not to be abandoned. On the contrary, it is desirable that GDP, surely imperfect but well-established and comparable with international standards, will be paired with a battery of well being indicators and possibly with a single well-being index. In this case, progress in the society would be indicated by a simultaneous increase in both GDP and well-being indicators and the accountability of policy makers should be closely linked to the targets reached in both types of indicators.

Human Development Index

HDI is a the most famous composite well-being index and Haq was probably the first to have the intuition that a single measure of well-being was needed in order to convince policy-makers to promote policies not only aimed at improving economic growth, but also further dimensions of well-being, such as health and education. The Nobel laureate Sen was initially partially sceptical towards the idea that a single index could be capable to capture human development, but he soon was persuaded that only a single measure could strike the attention of public, media and most importantly policy-makers.

The main critiques moved towards the HDI focus on the fact that a scalar composite index intrinsically involves a high degree of subjectivity mainly due to the selection of component indicators, the choice of the functional model and of the weighting scheme.

A single measure of well-being: the debate on composite indices

The crucial question is whether it is possible to have a unique indicator of well-being. In this regard, it is opportune to take note of the sceptical answer of the Stiglitz Commission recognizing that the quest for a scalar measure of well being is not as fundamental as perceived by many statisticians. According to the Commission, rather than focusing on the construction of a single summary measure, statistical systems should provide reliable databases. Notwithstanding the correct arguments and position of the Commission, the story of MAP in Australia shows that even the best measures end up clashing with the need felt by the public of a comprehensive indicator clearly showing whether progress is effectively going on.

The debate between composite indicators supporters and detractors is long and probably never ending. Saisana et al. (2005) present an excellent summary of this debate, providing arguments both in favour and contrary to composite indices. These arguments can be briefly summarized as follows: composite indices prove to be useful in providing the big picture, summarizing complex and multidimensional concepts and they are particularly useful in attracting the attention of public interest, media and policy makers; they also considerably facilitate rankings and comparisons among countries (Saisana et al. 2005). On the other hand, composite indices may lead the policy makers to divert the focus from the single components and to draw simplistic conclusions (Saisana et al. 2005). It is therefore important to understand what is inside a composite index and the subjective judgements underlying the construction of the index itself.

This work takes an intermediate perspective and it supports both a multidimensional "dashboard" approach and a "composite index" approach. As previously mentioned, the primary goal of this work is to develop a single measure of well-being, but the further objective to obtain a battery of well-being indicators representing the different dimensions of well-being individuated by Eurostat still remains important and of course it represents a necessary step in order to fulfil the primary goal. The intention is to include into a single index a broad range of dimensions that might allow a high differentiation in a comparison among countries. The reason is that, as also recognized by Haq and Sen, the indicators selected in HDI are not anymore able to provide an adequate differentiation.

3. Methodology

This section explains the main features of the two weighting schemes adopted in this research. Following criteria of reasonableness, the discussion below concentrates on PCA technique, while the features of equal weighting are debated in contraposition to PCA.

Principal Component Analysis

Principal component Analysis (PCA) is an interdependence technique of multivariate analysis which analyzes the interrelationships among a number of variables and tries to define an underlying structure with the primary goal of data reduction. Broadly speaking, what PCA does is to condensate the information

contained in the original variables into a smaller set of new composite measures, the factors, with a minimum loss of information. As such, PCA can be looked at as a statistical technique providing objective groundwork for creating composite measures and proves particularly useful to measure concepts and phenomena that cannot be adequately explained by single measures.

After determining the internal consistency or factorability of the set of variables involved in the analysis, PCA aggregates them through orthogonal linear combinations. The weights of the linear combinations are empirically determined by the statistical technique itself. The resulting linear combinations are usually referred to as variates, factors or components.

To go deeper into the mathematics of PCA, suppose to have a vector of n variables. The first objective of PCA is to obtain the best linear combination, namely the one that manages to explain the highest amount of variance contained in the original set of variables. This linear combination is referred to as the first principal component and it is defined as:

$$PC_1 = b_{11}\overline{x}_1 + b_{12}\overline{x}_2 + \ldots + b_{1n}\overline{x}_n = \sum_{j=1}^{n} b_{1j}\overline{x}_j$$

Where $\overline{x}_1, \overline{x}_2, \ldots. \overline{x}_n$ are the original variables and $b_{11}, b_{12}, \ldots, b_{1n}$ are the constants that allow to maximize the variance. It turns out that these constants are the elements of the eigenvector corresponding to the largest eigenvalue of the correlation matrix among the original variables. Furthermore if $\overline{b}_1$ is selected to have unit length $\overline{b}_1^T \overline{b}_1 = 1$, which is the case in this study, then the variance of the first principal component is equal to the largest eigenvalue derived from the correlation matrix. Coming back to the intuition, the first principal component can be thought as the most representative linear combination of the original variables.

PCA extracts as many factors as the number of the original variables and each of those components explains smaller and smaller proportions of variance. However, as the main objective of PCA is data reduction and this study intends to create a single index for dimension of QoL and a single composite measure of well-being, only one factor is extracted in each of the single analyses, subject to the constraint that it is capable to explain at least half of the variability in the data.

Despite the fact that the weights are empirically determined by the statistical procedure, one should notice that the initial set of variables is selected by the researcher and that the latter is the one entitled to ensure that some underlying structure does exist in the dataset. In particular, variables that are to be considered for aggregation need to be facets of the same underlying latent concept. Therefore, in order to run a PCA some degree of inter-correlations among variables is required, but it is equally important that the correlations are meaningful. According to Hair et al. (2012), the assumptions that need to be fulfilled in order to perform a PCA are primarily conceptual and only secondarily statistical.

PCA indeed, similarly to many other statistical procedures, follows the "garbage in, garbage out" rule, meaning that if the selection of variables is not accurate, the results of the analysis tends to be distorted or even nonsensical. According to Hair et al. (2012) "It is responsibility of the researcher to ensure that the

observed patterns are conceptually valid and appropriate to study with factor analysis, because the technique has no means of determining appropriateness other than the correlations among variables". From a statistical standpoint, the application of PCA aggregation approach must be justified by a relevant number of significant correlations among the variables. There exist many empirical measures that contribute to check the factorability of the variables. The statistical package SPSS provides the correlation matrix, the anti-images correlation matrix, the Bartlett's test of sphericity and the measure of sampling adequacy. A visual inspection of the correlation matrix, namely the table showing all the inter-correlations among variables, represents a good starting point to check the internal consistency of the variables. A visual inspection should reveal that a substantial number of correlations above the value of 0.3 exists (Hair et al. 2012). Bartlett's test of sphericity tests the hypothesis that the correlation matrix is an identity matrix, implying no significant correlations and a p-value lower than the significance level implies that some significant correlations exist. A further tool to inspect the degree of interrelatedness inherent in the data is the measure of sampling adequacy. This index ranges between 0 and 1, where unity is reached when each variable is perfectly predictable by the others. According to Hair et al. (2012) "The researcher should always have an overall MSA value of above 0.50 before proceeding with the factor analysis". Furthermore, as suggested by Hair et al. (2012), this study extends the MSA guidelines to individual variables and it checks that each variable's MSA falls in the acceptable range (above 0.50). The individual variables' MSAs are reported on the diagonal of the anti-images correlation matrix.

Merits and limitations of PCA

The idea behind the use of principal component analysis is that indicators reflecting different facets of the same phenomenon are likely to be highly correlated. In this setting, if this considerations prove to reflect the reality of the data, PCA reveals to be an optimal methodology since it condensates the information contained in the original set of indicators into a smaller set of factors, with minimal loss of information.

The main advantage of PCA over equal weighting is to minimize the intrinsic degree of subjectivity involved in the construction of a composite index. In particular, the process of assigning weights to the original variables is overcome by the fact that PCA is a data driven procedure and the weights directly stem from the variability explained by the variables.

Another great advantage of PCA is that this methodology partially overcomes the problem of perfect inter-variables compensation inherent to equal weighting. The latter methodology indeed implies perfect substitutability, meaning that low scores in one dimension can be fully compensated by high scores in another dimension. As observed by Sager and Najam (1998) "the scheme of arithmetic averaging of the dimensions runs counter to the notion of their being essential and, therefore, non-substitutable". However, in PCA a relevant degree of substitutability still remains. PCA presents many further advantages and this paper will try to clarify them progressively in the following sections.

On the other hand, PCA also presents some limitations as indicated by Zarzosa (1996) and Mishra (2007). The two authors point out to four facts in particular: 1- indicators obtained by this procedure only have "ordinal" value, 2- the weights given to the variables (in the case of this research the eigenvectors of the correlation matrix) only have statistical meaning and have no socio-economic interpretation 3- some information is unavoidably lost as long as only the first component is taken into consideration and 4- this procedure yields good results only in the presence of high correlation.

The point of view taken in this paper is that in a multiplicity of scenarios the advantages of principal component analysis can outweigh the above mentioned disadvantages and that in the context of this research the latters are in fact not properly limitations. As a matter of fact, this paper is not concerned about the cardinality of the measures, while it only aims at making "ordinal" comparisons among European countries. However, it seems opportune to stress that with regard to this critique, equal weighting methodology recovers ground on PCA as this methodology allows for cardinal comparison, both cross-sectional and inter-temporal. As far as the interpretation of the weights is concerned, it is certainly true that the weights have mathematical-statistical interpretation but lack a transparent socio-economic interpretation. However, one should remind that PCA is the most "objective[2]" aggregation technique. Equal weighting scheme is often thought as absence of weights, but instead it is a subjective choice as well. As regards the last critiques, the two might be considered together. Both observations are somehow correct and lawful per se. However, it is necessary to clarify that the two observations are not to be considered disadvantages of PCA, but rather it would be fair to say that a good PCA requires some basic assumptions on the structure of the data, analyzed in the last paragraph.

4. Data

The reference dataset was published by Eurostat on 19th March 2014 on the occasion of the International Day of Happiness. The dataset can be found in the Eurostat website in the section dedicated to Quality of Life (from here on QoL) indicators. Most of the indicators presented in this section were collected by the European Statistical System (ESS), in particular by LFS (labour force survey), EHIS (European Interview Survey) and SILC (statistics on income and living conditions) and some other administrative sources internal to ESS. The remaining indicators come from external non-ESS sources such as EQLS (European Quality of Life Survey) and OECD-PISA. In general, 37 of the indicators included in the Eurostat data were analysed as possible candidates for inclusion in the synthetic index and 7 of them were excluded either because of missing values or because considered, by the exploratory factor analysis, inadequate to measure the underlying concepts. The reference year of this research is 2012.

[2] It is partially inappropriate to assess that PCA is an objective procedure as this methodology implies the ex-ante subjective choice to adopt an aggregation procedure with the explicit and sole purpose to maximize the percentage of variance to be explained by the index. A further element of subjectivity is introduced in the selection of the ex-ante dataset of variables.

Before proceeding with the analysis, one should notice that the different indicators initially have different units of measurement. This feature is corrected by scaling. Unfortunately, any statistical method, PCA in particular, is sensitive to the scaling procedure adopted. The Handbook on the Construction of Composite Indices (OECD, 2008) lists nine different methods of scaling, each with advantages and disadvantages. The method adopted in this research is to standardize all indicators such that they have zero mean and unit variance. This procedure is obtained by calculating the z-scores of the indicators by subtracting the observed mean value and dividing by the observed standard deviation of the indicator values. This method proves particularly useful as it allows a higher differentiation among countries by widening the range of indicators lying within a small interval.

Finally, a last issue is to be discussed. According to the Handbook on the Construction of Composite Indices (OECD, 2008) "there are three ways of dealing with missing data: deleting the case listwise or pairwise if any of the variables are missing, single imputation, or multiple imputation" (OECD, 2008).

In this research, the presence of missing values is extremely low (7 missing out of 930 entries) and there can be enough confidence to believe that the choice of imputation will not affect the results. However, in order to have clean results, countries with missing values were eliminated from the analysis (listwise deletion). For the sake of completeness, the whole analysis is further performed excluding the variables containing missing entries and imputing the missing values with the mean value of the variable. The main results of the different analyses are included in Appendix A and are to be considered important tools to validate the analysis.

5. *Results I: A synthetic index for each dimension of QoL*

The first step of factor analysis mainly consists in the use of Bartlett's test of sphericity and of the measure of sampling adequacy to assess the internal consistency of the indicators. A total of 7 indicators out of the 37 initially selected in the Eurostat database were excluded. Following the example of Ferrara and Nisticò (2014), each dimension of QoL is analysed separately. For each dimension, the final list of selected indicators and the application of the PCA are discussed. Ultimately, some considerations on the results are made with a special emphasis on the Italian situation. The eight dimensions of QoL that Eurostat individuates are: material living conditions, productive or main activity, health, education, leisure or social interactions, economic and physical safety, governance and basic rights and natural and living environment. Each of the listed dimensions are analyzed in the above mentioned order, with the exception of "Leisure and Social interaction", which is not included in the analysis as no data is available for 2012, the reference year of this research. Therefore the analysis presented in this paper consists of the remaining seven dimensions.

Material living conditions

This first dimension is often perceived as the fundamental component of QoL. Rather than influencing well-being per se, it can be thought as a necessary condition to the fulfilment of high levels of quality of life as

material conditions are means to "buy" high levels of QoL. According to OECD (2013), increases in this dimension are often associated with increases in other dimensions of well-being such as health and education. Eight are the indicators included in this dimension. Among them, three variables directly relate to income: household's median equalized income, income quintile share ratio defined as the ratio of the total income received by the top quintile to that received by the bottom quintile of the population and the share of people with an equalized disposable income below the at-risk-of-poverty threshold, set at 60 % of the national median equalized disposable income after social transfers. This work includes median disposable income and not GDP per capita, which is instead included in the HDI, for two main reasons: first, this choice is consistent with the recommendations of the Stiglitz Commission to focus on the household and secondly median income avoids pronounced distortions due to distributional effects. The remaining two listed indicators are both to be included as they measure different concepts: income inequality and poverty. Two are instead the indicators included in this dimension that focus on housing conditions the share of population living in a dwelling with a leaking roof, damp walls, floors and foundation and the share of total population having neither a bath, nor a shower, nor indoor flushing toilet in their household. The last three variables are the share of population expressing inability to afford some necessary items, self-reported difficulty to make ends meet and self reported ability to make ends meet very easily.

Before proceeding with the substantive analysis and prior to the construction of the synthetic index, it is crucial to assess the appropriateness of a principal component analysis with the data at hand. The first test used to verify that a sufficient number of correlations exists is Bartlett's test of sphericity. The latter tests the hypothesis that the correlation matrix is an identity matrix, implying no significant correlations. In this case, a p-value lower than 0.001 suggests the rejection of the null hypothesis of absence of correlations. Furthermore, an overall MSA of 0.731 shows a high degree of interrelatedness among the variables. All individual MSA values are also well-above 0.5, with six of the eight indicators reporting a MSA above 0.70.

Given the strong conceptual foundation underlying the aggregation of the variables upon the concerned dimension and the afore-mentioned statistical properties, it can be said with a high degree of confidence that a principal component analysis is indeed appropriate.

As a matter of fact, the first principal component is capable to explain 60% of the total variance in the data, where this percentage is derived by the eigenvalues[3] associated to the correlation matrix[4]. The weights of the index are represented by the eigenvectors of the correlation matrix. In order to understand which variables concur more and which concur less to the index, a look at the factor loadings is needed, namely the correlations between the original variables and the factors. Six of the indicators have extremely high values (above 0.8), implying that about two third of the variance contained in the original variables is explained by

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[3] The eigenvalues represent the amount of variance accounted for by a specific factor. In case of a single component extracted, the value of the eigenvalue associated to the first factor is obtained by summing up all communalities.

[4] In order to obtain the percentage of variance explained by a single factor, the eigenvalue associated to the factor itself is divided by the trace of the factor matrix, which is equal to the sum of the eigenvalues.

the factor[5].However, one variable, the share of population living in a dwelling with a leaking roof, damp walls, floors and foundation presents a low factor loading of 0.36. This value despite falling in the acceptable range[6] is meaningfully low. However, as this variable is important in order to best represent the sub-dimension “housing conditions”, it is retained in the analysis as its value of MSA would suggest.

Table 1 below reports the values of the two “material living conditions” indices constructed according to arithmetic mean aggregation and PCA.

Table 1 – Material Living Conditions Index

Position	**Country**	**PC Index**	**Country**	**Simple Mean**
1	Norway	4.06	Norway	1.43
2	Sweden	2.88	Sweden	1.05
3	Finland	2.61	Finland	0.98
4	Netherlands	2.53	Switzerland	0.84
5	Switzerland	2.45	Netherlands	0.84
6	Denmark	2.09	Denmark	0.67
7	Iceland	1.97	Luxembourg	0.64
8	Luxembourg	1.97	Iceland	0.63
9	Austria	1.61	Austria	0.58
10	Germany	1.25	Germany	0.44
11	Czech Republic	1.07	Czech Republic	0.42
12	France	1.00	France	0.36
13	Belgium	0.91	Belgium	0.27
14	United Kingdom	0.55	Slovakia	0.22
15	Slovakia	0.39	United Kingdom	0.17
16	Slovenia	0.35	Malta	0.10
17	Malta	0.09	Ireland	0.05
18	Ireland	0.03	Slovenia	-0.05
19	Poland	-0.83	Poland	-0.21
20	Cyprus	-0.93	Estonia	-0.38
21	Estonia	-0.97	Cyprus	-0.45
22	Italy	-1.24	Italy	-0.46
23	Portugal	-1.48	Spain	-0.46
24	Spain	-1.51	Portugal	-0.55
25	Hungary	-1.70	Croatia	-0.55
26	Croatia	-1.79	Hungary	-0.63
27	Lithuania	-2.04	Lithuania	-0.73
28	Greece	-3.05	Greece	-0.97
29	Latvia	-3.42	Latvia	-1.29
30	Bulgaria	-4.34	Bulgaria	-1.41
31	Romania	-4.50	Romania	-1.58

[5] Squared factor loadings indicate what percentage of the variance in the original variable is explained by the factor.
[6] According to Hair et al. (2012), all values above 0.30 are to be considered acceptable, but values greater than 0.50 are generally considered necessary for practical significance.

The two rankings are extremely similar. The countries with the highest values of the index are the Scandinavian countries. In general and as largely expected, there is a large divide between Northern Europe and Southern Europe. Italy positions itself at the 22nd place. The bottom of the ranking is occupied by countries of Eastern Europe, where Bulgaria and Romania occupy the lowest positions of the ranking.

Productive or main activity

This dimension was initially meant to refer to both paid and unpaid work. However, no data is available on the latter and the focus is therefore placed on the former. According to Eurostat (2014), work affects QoL through two separate channels: the most obvious one is the income that it generates, while the second one is represented by the role it plays "in giving people their identity and opportunities to socialize with others" (Eurostat 2014). This dimension was initially intended to refer to both quality and quantity (or lack) of employment. However, data for the former is not complete and the focus is shifted towards the latter. The two indicators selected to represent lack of employment are: unemployment rate and long-term unemployment rate measured as the proportion of total unemployment. According to the Stiglitz's Report, "people who become unemployed report lower life-evaluations, even after controlling for their lower income, and with little adaptation over time" and further "unemployed people also report a higher prevalence of various negative effects (sadness, stress and pain) and lower levels of positive ones (joy)".

The other two indicators included in this dimension are measures of underemployment rather than of unemployment. They are: the share of population living in households with low work intensity and involuntary part-time employment measured as the proportion of total part-time employment. The four above-mentioned indicators are the components of this dimension. One must notice that defined as such and with the listed indicators, this dimension negatively affects well-being. The straightforward solution to this problem is to reverse the signs of the factor loadings such that the synthetic index will correlate negatively with the indicators in it and will therefore return a positive measure of well-being.

The Bartlett's test of sphericity yields a p-value lower than 0.0001, implying that the correlation matrix is not an identity matrix. The measure of sampling adequacy (0.70) together with the individual MSAs (all above 0.6) confirms the appropriateness of PCA.

After the extraction, the communalities, the percentage of variance in the original variables explained by the factor, range from 0.57 to 0.83 and the factor loadings range from 0.76 to 0.91, with the highest absolute value reached by unemployment rate. These values are extremely high and confirm that the four variables clearly have an underlying structure. A synthetic index in this context is therefore particularly appropriate and we observe that the first principal component is capable to explain 65% of the total variance in the data.

As for the results, Switzerland leads and Greece occupies the lowest position in both rankings. In general, the two methodologies yield almost identical results and only a few countries change positions between the two rankings. One example is Italy, which scores 24th and 25th with respect to PCA and equal weighting procedure. Few are the countries that score worse than Italy. Among them: Portugal, Latvia, Croatia,

Bulgaria, Spain and Ireland in addition to the above-mentioned Greece. On the contrary, the top positions are occupied by Northern countries.

Table 2 – Productive or main activity Index

Position	Country	PC Index	Country	Simple Mean
1	Switzerland	2.38	Switzerland	1.20
2	Norway	2.26	Norway	1.12
3	Austria	2.07	Austria	1.03
4	Luxembourg	1.87	Luxembourg	0.94
5	Iceland	1.71	Iceland	0.85
6	Sweden	1.64	Sweden	0.83
7	Netherlands	1.50	Netherlands	0.75
8	Finland	1.23	Finland	0.61
9	Denmark	0.99	Denmark	0.49
10	Czech Republic	0.94	Czech Republic	0.47
11	Slovenia	0.78	Slovenia	0.41
12	Germany	0.74	Germany	0.35
13	Malta	0.65	Malta	0.32
14	Poland	0.51	Poland	0.27
15	United Kingdom	0.44	United Kingdom	0.21
16	France	0.27	France	0.14
17	Belgium	0.26	Belgium	0.11
18	Cyprus	0.10	Cyprus	0.06
19	Estonia	-0.09	Estonia	-0.04
20	Romania	-0.11	Romania	-0.09
21	Hungary	-0.79	Lithuania	-0.41
22	Lithuania	-0.84	Hungary	-0.41
23	Slovakia	-1.06	Slovakia	-0.50
24	Italy	-1.23	Portugal	-0.63
25	Portugal	-1.30	Italy	-0.64
26	Latvia	-1.42	Latvia	-0.70
27	Bulgaria	-1.94	Croatia	-0.98
28	Croatia	-1.98	Bulgaria	-1.00
29	Spain	-2.95	Spain	-1.43
30	Ireland	-3.08	Ireland	-1.58
31	Greece	-3.54	Greece	-1.74

Health

The link between health and well-being is well-established in the literature. According to Eurostat (2014), health is a difficult concept to measure and a combination of objective and subjective indicators are needed in order to capture all the different facets of this phenomenon. Six are the indicators included in this dimension: three of them can be considered objective measures and the remaining are subjective indicators. The indicators appertaining to the former type are: life expectancy at birth, number of years a person is

expected to continue to live in healthy conditions and share of population suffering from a long-standing illness or health problem. Obviously, the former two positively affect health while the latter negatively influences it. Life expectancy at birth is the basic indicator widely used in the literature starting from HDI, while number of expected healthy years is a correction to the previous indicator. As discussed above and following the recommendations of the Stiglitz's Report, in order to measure a complex matter as health, subjective indicators need to be included as well. Among them: the share of population perceiving its health status as very bad, the share of population perceiving its health status as very good and the share of population perceiving long-standing limitations in usual activities due to health problems.

Table 3 - Health Index

Position	Country	PC Index	Country	Simple Mean
1	Iceland	2.92	Iceland	1.12
2	Ireland	2.49	Ireland	1.01
3	Sweden	2.46	Norway	0.91
4	Norway	2.45	Malta	0.89
5	Malta	2.36	Sweden	0.87
6	Switzerland	2.14	Switzerland	0.79
7	Cyprus	1.69	Greece	0.73
8	Greece	1.69	Luxembourg	0.71
9	United Kingdom	1.49	Cyprus	0.63
10	Luxembourg	1.45	Belgium	0.56
11	Belgium	1.21	United Kingdom	0.53
12	Spain	0.98	Spain	0.46
13	France	0.65	France	0.20
14	Austria	0.13	Austria	0.03
15	Netherlands	-0.07	Netherlands	-0.03
16	Denmark	-0.39	Bulgaria	-0.04
17	Italy	-0.42	Italy	-0.05
18	Bulgaria	-0.46	Denmark	-0.10
19	Czech Republic	-0.61	Romania	-0.10
20	Romania	-0.71	Czech Republic	-0.23
21	Portugal	-0.90	Portugal	-0.45
22	Poland	-1.04	Poland	-0.46
23	Germany	-1.25	Germany	-0.51
24	Croatia	-1.65	Croatia	-0.66
25	Slovenia	-1.70	Slovenia	-0.68
26	Finland	-1.77	Finland	-0.82
27	Hungary	-2.15	Slovakia	-0.83
28	Slovakia	-2.30	Hungary	-0.93
29	Lithuania	-2.57	Lithuania	-1.00
30	Estonia	-2.90	Estonia	-1.26
31	Latvia	-3.22	Latvia	-1.30

As for the appropriateness of PCA, the Bartlett's test rejects the null hypothesis of absence of correlations and the overall value of the measure of sampling adequacy is 0.55 with individual MSAs ranging from 0.52 to 0.77. The first principal component explains 55% of the variance of the data and as expected, it correlates positively with life expectancy at birth, number of healthy years and the share of population perceiving its health as very good, while it correlates negatively with the remaining variables. The factor loadings range, in absolute values, from 0.356 to 0.891, where the lowest and highest values are represented by self-perceived limitations and life expectancy at birth. The coefficient for self-perceived limitations is rather low and it implies that only 13% of this variable's variance is explained by the first principal component. However, given the conceptual importance of this variable, it seems opportune to keep it in the analysis.

The results show that the top five positions are occupied by Iceland, which leads the ranking with respect to both methodologies, Sweden and Norway as it usually happens, but also by Ireland and Malta which are often at the bottom of the ranking with respect to other dimensions of well-being. Some positive surprises in the top ten positions are represented by Cyprus and Greece, while negative surprises are represented by Germany 23rd and Finland 26th . Italy scores 17th in both rankings. The results obtained through the two different weighting procedures are in general marginally different.

Economic and Physical Safety

This dimension of well-being consists of two separate categories: economic safety and physical safety. Although it can be objected that the two do not necessarily represent the same concept, Eurostat decided to collect them together. Two are the indicators included in the domain of economic safety: the share of population unable to face unexpected financial expenses and the share of population in arrears on mortgages. On the other side, the indicator selected to represent physical safety is the share of population perceiving crime, violence or vandalism in its area of living. Crime indeed affects well-being both directly (victims of crimes) and indirectly, due to the fear that crimes inspire in people living close to the victims of crimes (family or neighbourhood). As observed by OECD (2013), the fear of crimes is indeed capable to reduce well-being by increasing levels of anxiety.

The appropriateness of PCA is verified by a p-value of the Bartlett's test lower than 0.0001 and by an overall and individual values of the MSA above 0.50. The principal component explains 58% of the total variance in the data. The factor loadings range from 0.251 to 0.919, where the variable referred to crime has the lowest value and the share of population in arrears on mortgages has the highest value. Since the former is the only variable in the dataset to measure physical safety, it is wise to keep it in the analysis despite of its low factor score. The signs of the factor loadings are inverted in order for the synthetic index to be a positive indicator of well-being.

Table 4 below shows that Norway leads both rankings, immediately followed by Sweden. In general, Northern countries occupy the top positions, while Eastern European Member States occupy the bottom of the rankings. Bulgaria is the country with the lowest score. Italy scores 19th with the principal component

methodology and only 21st with an equal weighting procedure, behind Lithuania, Poland and Slovenia, which instead score lower with PCA.

Along this dimension, the two methodologies yield rather different results. The motivation is that PCA in this context tend to attribute more weight to economic rather than to physical safety.

Table 4 – Economic and Physical Safety Index

Position	Country	PC Index	Country	Simple Mean
1	Norway	1.94	Norway	1.23
2	Sweden	1.58	Sweden	0.89
3	Switzerland	1.47	Austria	0.67
4	Austria	1.34	Finland	0.62
5	Luxembourg	1.29	Denmark	0.61
6	Netherlands	1.21	Iceland	0.58
7	Denmark	1.07	Luxembourg	0.53
8	Belgium	0.99	Switzerland	0.51
9	Germany	0.97	Slovakia	0.48
10	Finland	0.92	Germany	0.46
11	Malta	0.87	Malta	0.41
12	Slovakia	0.73	Belgium	0.38
13	Portugal	0.59	Portugal	0.35
14	France	0.53	Netherlands	0.30
15	Czech Republic	0.50	Spain	0.24
16	United Kingdom	0.38	Czech Republic	0.20
17	Iceland	0.34	France	0.15
18	Spain	0.29	Lithuania	0.14
19	Italy	-0.08	Poland	0.11
20	Estonia	-0.18	Slovenia	-0.03
21	Poland	-0.35	Italy	-0.15
22	Lithuania	-0.42	United Kingdom	-0.16
23	Slovenia	-0.49	Estonia	-0.24
24	Ireland	-1.19	Croatia	-0.45
25	Cyprus	-1.68	Ireland	-0.50
26	Romania	-1.69	Romania	-0.87
27	Croatia	-1.83	Hungary	-0.91
28	Greece	-1.97	Cyprus	-0.95
29	Hungary	-2.10	Latvia	-1.26
30	Latvia	-2.18	Greece	-1.30
31	Bulgaria	-2.83	Bulgaria	-2.04

Education

Education is a basic determinant of individuals' well-being. A vast literature highlights the role of education in the progress of society and many studies, especially focused on developing countries, try to estimate returns of education in terms of earnings (Duflo 2001). Education fosters productivity and innovation contributing to the growth of a country. However, many more are the channels through which education influences QoL. More educated people are more effective in preventing illnesses, they are more likely to find

good jobs, they show more respect for civil rights and for the environment in which they live and they generally report higher life satisfaction. Four are the variables selected in this work to represent the education dimension: the share of population having completed tertiary education, the share of population aged 18-24 participating in education or training in the four preceding weeks, lifelong learning defined as people aged 25-64 participating in training and 2012 PISA results.

The former three indicators are measures of the quantity of education in a country, while the latter is meant to capture the quality of the educational system and it is presumably the only indicator of quality that allows international comparisons. Unfortunately, no data is available for Malta with respect to PISA results and this country is indeed excluded from the analysis.

Table 5 – Education Index

Position	Country	PC Index	Country	Simple Mean
1	Denmark	2.67	Denmark	1.27
2	Switzerland	2.48	Finland	1.24
3	Finland	2.47	Switzerland	1.22
4	Netherlands	1.84	Estonia	0.91
5	Estonia	1.74	Netherlands	0.91
6	Iceland	1.53	Iceland	0.74
7	Norway	1.33	Norway	0.68
8	Sweden	1.30	Sweden	0.63
9	Slovenia	1.16	Luxembourg	0.55
10	Luxembourg	1.08	Slovenia	0.54
11	Germany	0.52	United Kingdom	0.28
12	United Kingdom	0.46	Germany	0.27
13	Poland	0.32	Poland	0.16
14	Ireland	0.04	Ireland	0.09
15	France	-0.06	France	-0.02
16	Spain	-0.15	Belgium	-0.04
17	Belgium	-0.18	Spain	-0.07
18	Austria	-0.26	Lithuania	-0.13
19	Lithuania	-0.30	Austria	-0.16
20	Czech Republic	-0.51	Latvia	-0.26
21	Latvia	-0.57	Czech Republic	-0.28
22	Portugal	-1.06	Portugal	-0.57
23	Hungary	-1.30	Hungary	-0.64
24	Italy	-1.38	Italy	-0.72
25	Greece	-1.72	Cyprus	-0.85
26	Cyprus	-1.78	Greece	-0.86
27	Croatia	-1.79	Croatia	-0.90
28	Slovakia	-1.95	Slovakia	-0.98
29	Bulgaria	-2.74	Bulgaria	-1.37
30	Romania	-3.20	Romania	-1.63

The Bartlett's test of sphericity yields a p-value lower than 0.0001, implying that the correlation matrix is not an identity matrix and that some correlations are statistically significant. MSA more effectively expresses the degree of inter-correlations in the data and its overall value of 0.60 together with the fact that all individual MSAs fall in the acceptable range suggests that an aggregation among these indicators is indeed appropriate. The percentage of variance that the first principal component manages to explain is 61%. The factor positively correlates with all the included variables and the factor loadings range from 0.69 (population with tertiary educational attainment) to 0.86 (lifelong learning). These values are exceptionally high and they imply communalities after extraction ranging from 0.47 to 0.74.

For what concerns the results, no matter which weighting procedure is used, the most and the least "educated" countries (according to the definition presented in the paper) are respectively Denmark and Romania. The top ten positions are occupied by the remaining Scandinavian countries, Switzerland, Estonia, the Netherlands, Iceland, Slovenia and Luxemburg. Italy ranks 24th , 9 positions lower than France, which is immediately followed by Spain and Belgium in both rankings. The five countries scoring lower than Italy are Cyprus, Greece, Croatia, Slovakia, Bulgaria and the above-cited Romania.

Natural and Living Environment

This dimension is closely linked to both sustainability and future generations' well-being and current quality of life. Some studies have proven a negative correlation between environmental problems and subjective well-being. Environmental problems have indeed a negative effect on health, which, as argued above, it is a basic driver of well-being. High levels of air pollution are often associated with respiratory diseases. Many are the environmental indicators, but they are often too specific to have a significant meaning from the point of view of quality of life. This study selects three indicators which mainly reflect individuals' perceived exposure to environmental problems. The indicators are: the share of people reporting exposure to pollution, grime and other environmental problems, the share of population perceiving exposure to noise pollution and urban population exposure to air pollution (the only "objective" indicator technically measured by the European Environmental Agency). Three countries, Greece, Croatia and Malta are excluded from the analysis as no data is available for these countries on the air pollution variable.

With the indicators at hand, a composite measure is deemed appropriate as suggested by the overall value of MSA (0.585) together with the individual values (ranging from 0.56 to 0.62). The Bartlett's test rejects the null hypothesis of absence of correlations. The principal component is able to explain 60% of the total variance in the data and the factor loadings, whose values are to be reversed (such that the index can be considered a positive driver of well-being), range from 0.72 (exposure to air pollution) to 0.86 (reported exposure to pollution and grime).

According to this study, the most "pleasant" environment is Ireland, followed by Iceland and all four Scandinavian countries and Estonia. Low levels of pollution are observed also in Spain, United Kingdom and

Hungary. High levels of pollution are instead present in the Netherlands, Portugal, Italy, Latvia, Bulgaria, Cyprus, Germany and Romania, which according to this work is the most polluted country.

Table 6 – Natural and Living Environment Index

Position	**Country**	**PC Index**	**Country**	**Simple Mean**
1	Ireland	2.58	Ireland	1.47
2	Iceland	2.13	Iceland	1.25
3	Sweden	1.74	Sweden	1.00
4	Finland	1.61	Finland	0.94
5	Norway	1.55	Norway	0.91
6	Denmark	1.32	Estonia	0.72
7	Estonia	1.18	Denmark	0.72
8	Spain	0.81	Spain	0.43
9	United Kingdom	0.80	United Kingdom	0.43
10	Hungary	0.47	Hungary	0.27
11	Switzerland	0.43	Switzerland	0.23
12	Lithuania	0.22	Lithuania	0.16
13	France	0.11	Luxembourg	0.08
14	Luxembourg	0.09	France	0.05
15	Austria	0.03	Austria	-0.01
16	Slovenia	-0.29	Slovenia	-0.14
17	Poland	-0.37	Czech Republic	-0.21
18	Czech Republic	-0.40	Poland	-0.26
19	Belgium	-0.60	Belgium	-0.33
20	Slovakia	-0.66	Slovakia	-0.37
21	Netherlands	-0.89	Netherlands	-0.52
22	Portugal	-1.17	Latvia	-0.62
23	Italy	-1.20	Italy	-0.68
24	Latvia	-1.22	Portugal	-0.69
25	Bulgaria	-1.28	Bulgaria	-0.77
26	Cyprus	-2.23	Germany	-1.25
27	Germany	-2.27	Cyprus	-1.33
28	Romania	-2.50	Romania	-1.47

Governance and basic rights

This last dimension is a further driver of quality of life. Respect for human rights, active citizenship and accountable governance are the hallmarks of modern democracies and they contribute to determine a country's level of quality of life. Only two indicators are included in this dimension as no additional data is available. They are: unadjusted gender pay gap and active citizenship. The former is defined as the average difference in gross hourly earnings between male and female employees. Eurostat specifies that the indicator is unadjusted, meaning that it is "not adjusted for individual characteristics that may explain part of the

earnings difference, because it aims to give a general picture of gender inequalities in terms of pay" (Eurostat, 2014). The second indicator included in this dimension, active citizenship is defined as the share of the population using the internet for interaction with public authorities. Greece and Switzerland are excluded from the analysis as no data is available for these countries.

Since there are only two indicators, the two different weighting procedures yield the exact same results by construction. Therefore Table 7 reports only the values of the index created with equal weighting procedure.

Table 7 – Governance and basic rights Index

Position	Country	PC Index
1	Slovenia	1.05
2	Denmark	0.99
3	Luxembourg	0.90
4	Norway	0.84
5	Sweden	0.77
6	Iceland	0.76
7	Malta	0.56
8	Belgium	0.48
9	Netherlands	0.38
10	France	0.34
11	Poland	0.28
12	Finland	0.26
13	Ireland	0.09
14	Latvia	0.08
15	Romania	-0.02
16	Italy	-0.11
17	Lithuania	-0.12
18	Portugal	-0.30
19	Spain	-0.33
20	United Kingdom	-0.47
21	Germany	-0.52
22	Austria	-0.55
23	Bulgaria	-0.55
24	Hungary	-0.58
25	Cyprus	-0.59
26	Slovakia	-0.70
27	Croatia	-0.85
28	Estonia	-1.04
29	Czech Republic	-1.07

Slovenia, which is the country with the lowest level of gender pay gap is at the top of the ranking followed by Denmark and Luxemburg. Italy ranks 16th with one of the lowest level of gender pay gap but an extremely low level of active citizenship. Latvia and Romania precede Italy, while Lithuania, Portugal and Spain follow. The lowest scoring countries in this dimension are Croatia, Estonia and Czech Republic.

6. *Final Results: Two Well-being Indices*

Up to this point, the work analyzed seven dimensions of QoL that Eurostat indicates as drivers of well-being. For each dimension a synthetic index was derived. This section has the final goal to build a composite index of well-being taking as inputs each of the seven obtained synthetic indices. Once again, the two methodologies that will be used for the rest of the paper are principal component analysis and arithmetic mean. At the beginning of each paragraph of the previous section, it was discussed why each specific dimension might be considered a facet of the concept of well-being. Therefore, in the discussion below, such arguments are skipped. The seven indicators that will be used as inputs for the well-being index are: material living conditions, productive or main activity, health, education, economic and physical safety, governance and basic rights and natural and living environment. These indicators are rescaled so that their values have zero mean and unit variance. Consistently to the first part of this work, countries presenting missing values for one or more dimensions are excluded from the analysis. The final analysis will therefore consist of 27 countries. The excluded countries are Croatia, Greece, Malta and Switzerland.

As anticipated in previous sections, for the sake of completeness, the whole analysis is replicated following different imputation methods: excluding those variables containing missing entries and imputing the missing values with the mean value of the variable. Appendix A will collect the main results of these different analyses and they are to be considered important tools in order to validate the current analysis. Before proceeding with the latter, it appears important to anticipate that the results do not substantially change with different imputation methods and this fact can be interpreted as a sign of robustness of the current analysis.

Similarly to what has been done in the previous section with the single dimension indices, the output of the exploratory factor analysis is discussed for two main reasons: to validate a PCA approach and to verify that the seven indices “get along with” each other and can be “synthesized” in a single index. The first tool that is employed throughout the paper is Bartlett’s test of sphericity. Given a p-value below 0.0001, the null hypothesis, indicating absence of significant correlations, can be rejected: the correlation matrix is not an identity matrix and at least some correlations among variables are significant. A more accurate measure of the level of inter-correlations among the variables (essential for a good PCA) is the measure of sampling adequacy. The reported overall value of the MSA is 0.70 and the individual values are well above 0.5 (four of the seven variables report values above 0.7). These results are extremely positive and they suggest that PCA is an appropriate technique in this context. Moreover, these numbers together with the arguments presented in the paragraphs above give to this analysis a strong statistical and conceptual foundation to the aggregation of the single dimension indices into a well-being index.

The first principal component manages to explain 56% of the total variance of the data at hand and it reflects a value of the first eigenvalue almost four times higher than that of the second largest eigenvalue. All values of the factor loadings are higher than 0.5. A close inspection is crucial in order to understand which variables concur more and which ones concur less to the index. Four of the indicators have extremely high values (above 0.7), implying that at least half of the variance individually contained in these variables is explained

by the factor. Material living condition index is the one concurring more to the final index with a factor loading value of 0.94. This exceptionally high value implies that almost 90% of the variance contained in the original index is explained by the factor. The first principal component further extracts a very high amount of variance of the education dimension (72%) and of the economic and physical safety dimension (68%). On the contrary, the dimensions natural and living environment and health have relatively low factor loadings, respectively 0.63 and 0.52, implying that only 39% and 27% of the variance contained in the original indices is explained by the factor. These values, although low, still fall in the acceptable range for a good PCA (see Hair et al. 2012) and therefore these variables are included into the final index. As expected, all values of the factor loadings have positive signs, implying that each indicator positively affects the final well-being index. Table 8 reports the values of the synthetic well-being index for both weighting procedures.

Table 8 – Well-being Index

Position	Country	PC Index	Country	Simple Mean
1	Norway	3.60	Norway	1.39
2	Sweden	3.07	Sweden	1.18
3	Iceland	2.69	Iceland	1.16
4	Denmark	2.55	Denmark	0.91
5	Luxembourg	2.30	Luxembourg	0.86
6	Finland	2.09	Finland	0.71
7	Netherlands	1.79	Netherlands	0.51
8	Austria	0.93	Belgium	0.29
9	Belgium	0.78	Austria	0.28
10	France	0.70	Slovenia	0.24
11	Slovenia	0.63	France	0.24
12	United Kingdom	0.60	United Kingdom	0.16
13	Germany	-0.10	Ireland	0.10
14	Ireland	-0.19	Poland	-0.02
15	Poland	-0.21	Germany	-0.17
16	Czech Republic	-0.30	Czech Republic	-0.18
17	Estonia	-0.55	Spain	-0.25
18	Spain	-0.92	Estonia	-0.32
19	Lithuania	-1.33	Lithuania	-0.42
20	Portugal	-1.37	Italy	-0.55
21	Slovakia	-1.41	Slovakia	-0.55
22	Italy	-1.45	Portugal	-0.56
23	Cyprus	-1.87	Cyprus	-0.68
24	Hungary	-2.20	Hungary	-0.78
25	Latvia	-2.75	Latvia	-1.04
26	Romania	-3.22	Romania	-1.10
27	Bulgaria	-3.86	Bulgaria	-1.40

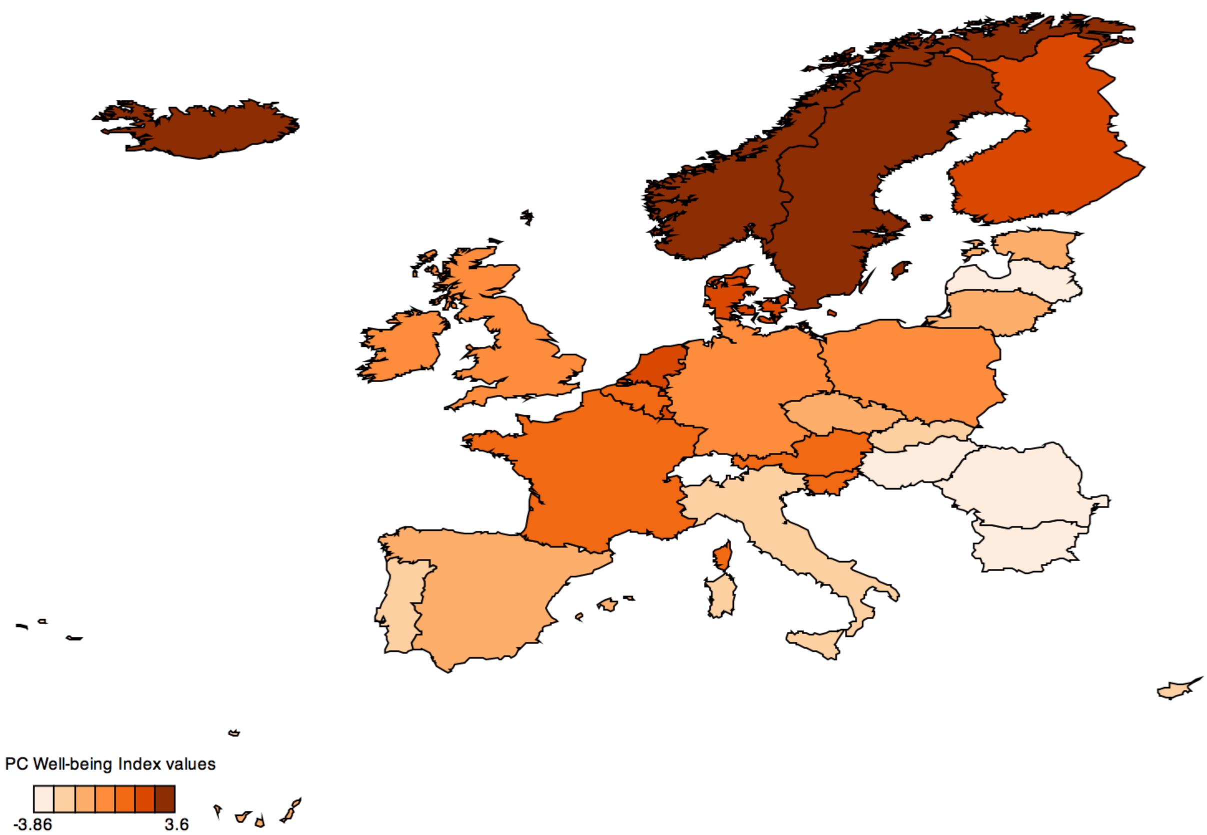
Results depict a deep divide between Northern European countries (and Scandinavian countries in particular) with an excellent level of quality of life and Eastern European countries with low levels of well-being.

Being the leader in three of the seven single dimension indices (material living condition, productive or main activity and economic and physical safety), Norway obtains the highest scores in the well-being indices with both methodologies. The result is not only driven by the three first positions obtained by the Scandinavian country in the three sub-indices, but also from the fact that Norway always appears in the top 6 positions in each of the remaining single dimension indices. Right below Norway, Sweden occupies the second position. Despite the fact that Sweden does not lead any of the rankings dedicated to the single dimensions, it manages to score second on the overall index thanks to two second positions on the single dimensions material living conditions and economic and physical safety.

Iceland occupies the last step of the podium, thanks to the fact that it leads the ranking in the health index. Despite being the leader in the education dimension and scoring second on governance and basic rights, Denmark is excluded from the podium. The reason is that, although this country is exceptionally virtuous in the above mentioned dimensions, in the remaining ones it rarely appears in the top 5 positions. Luxemburg, Finland, the Netherlands, Austria, Belgium, France and Slovenia round out the top ten.

On the other hand and according to both methodologies, the last four positions are all occupied by Eastern European countries: Hungary, Latvia, Romania and finally Bulgaria which exhibits the lowest score of the index. The mid-positions of the rankings are occupied in mixed order by the remaining Northern European countries, the remaining Eastern European countries and all Mediterranean countries.

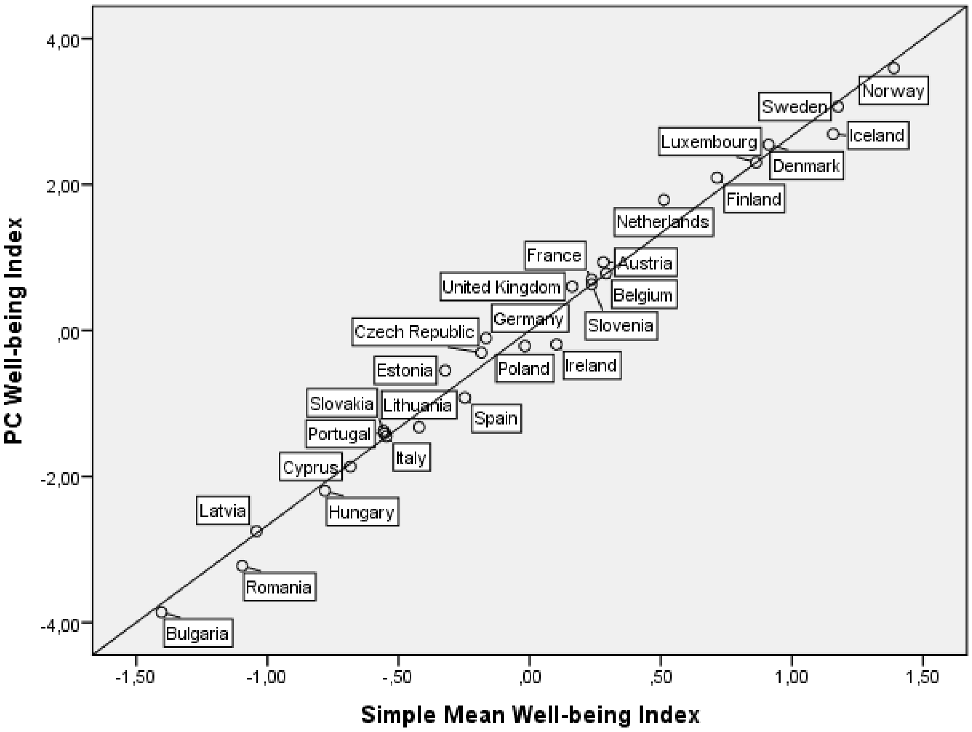
Map 1: Principal Component Well-being Index for 27 European countries (2012)



Overall, the two methodologies yield similar results. In particular, it appears evident that the top seven and the bottom five positions are identical with respect to the two methodologies. On the other hand, a slightly different story emerges from the central part of the rankings, where some differences exist. However, these differences do not dramatically revolutionize the rankings as countries usually move only by one or two position between the two methodologies. Obviously, some countries are favoured by one of the two methodologies while some others by the opposite methodology.

A clear example is given by Germany and Italy. The former scores 13th according to the index derived by PCA and 15th with equal weighting aggregation. On the other hand, Italy scores 20th according to the index built through equal weighting and 22nd with the PCA approach. The two above mentioned countries are the only ones together with Portugal whose ranks change by two positions between the two methodologies.

Figure 1: PC vs Simple Mean Well-being Index



The case of Italy is certainly curious. Italy "looses" two positions with the principal component approach, despite the fact that in the single dimension indices it never scores lower with the PC index. Although these arguments may sound counterintuitive, the explanation is extremely simple: Italy reaches its highest performance in the dimension with the lowest weight on the overall PC index, health. On the contrary, it performs rather poorly in those dimensions which concur more to the principal component well-being index, namely material living conditions and education. The case of Germany is interestingly very similar to the Italian one. Germany usually scores lower in the single dimension PC indices; nonetheless, it scores higher on the overall PC index. The explanation is given by the fact that Germany outperforms (with respect to its own standard) in the material living conditions index, which is the one with the highest weight on the overall

PC index and it performs rather poorly in the two dimensions with lowest weights: natural and living environment and health.

Having examined the differences that arise between the two methodologies from the empirical perspective, it is now opportune to discuss the two methodologies from a theoretical standpoint.

7. *Discussion*

A main result emerges from the previous section: the two aggregation schemes yield fairly similar results. Minor differences obviously exist, but they are not as relevant as many would expect. As explicitly stated in the introduction, this work intended to further contribute to the existing literature on quality of life indicators by analyzing whether the important differences that the two methodologies present from a conceptual standpoint are translated into the empirical ground. With the results obtained, the answer to this research question appears to be negative. However, no misunderstanding should arise with respect to this point as an incautious reader might come to believe that the debate on aggregation methods is largely a useless intellectual exercise. Obviously, this belief would be extremely wrong. Results must be interpreted carefully. Probably, the debate on different methodologies is not as fundamental as perceived by many statisticians and economists, but it is not as sterile as a quick look to the previous section would suggest for some main reasons. Firstly, this study is only valid for the countries analyzed and for a specific year, 2012; therefore any generalization of results would be incorrect. Understanding both the origins and the consequences of the differences that might arise is therefore crucial. Secondly, the current study still presents some minor differences which must not be totally neglected. Thirdly, every empirical study must be justified by a strong conceptual framework. Consequently, the theoretical arguments presented in the first part of the thesis cannot be questioned by purely empirical results. Finally, one consideration is particularly important. According to Annoni and Weziak-Bialowolska (2012), the fact that the two methodologies yield roughly similar results is doubtlessly positive information as it implies that the weights derived in the index built with the PCA approach are all very similar. According to the authors "all the indicators should contribute roughly to the same extent and direction to the most relevant component. If this is not the case, it means that more than one latent phenomenon is underlying the set of variables and these additional phenomena are described by those variables which are not contributing mostly to the first PCA component" (Annoni P. and Weziak-Bialowolska D., 2012). Summing up this line of thought, the fact that the two methodologies give similar result is not only positive, but also necessary and it further legitimates the use of PCA as a tool to validate the results obtained through arithmetic mean aggregation. As a consequence, some obvious questions emerge from the previous arguments: Are eventual differences in results between the two methodologies bad news? When do they appear? Which of the two aggregation procedures is to be preferred in these cases?

With this regard, the above quotation of Annoni and Weziak-Bialowolska (2012) results useful once again. Differences between the two aggregation procedures mainly appear when the set of information "waiting" for aggregation is not particular homogeneous and a single index would not be appropriate to describe a

single phenomenon. This happens when the correlations between some of the variables and the principal component are low. In this case, a principal component analysis would recommend not synthesizing all variables into a single index as the latter would not be representative of the latent phenomenon that the researcher wishes to measure. Oppositely, an arithmetic mean would neglect these considerations. Furthermore, PCA surely presents some advantages over arithmetic mean or other types of weighted means. PCA indeed, by maximizing the percentage of variance in the data to explain by means of the index, it minimizes the loss of relevant information. Moreover, PCA is a data driven procedure and therefore weights are not subjectively chosen as it is the case in different aggregation methods.

On the other hand, there might also exist contexts in which the use of arithmetic mean would be more appropriate than a PCA approach. Arithmetic mean, not only is to be appreciated thanks to its simplicity and ease of interpretation, but it also allows cross-sectional and inter-temporal comparisons, without requiring any assumptions on the correlation structure of the data.

According to the spirit of this research, no stand firm will be taken on which of the two methodologies is to prefer. According to this work, the only conclusion that can be reached is that no universal way to build composite indices exists and that different contexts may require different aggregation methods, different weighting schemes and even different scaling procedures. Theoretical together with empirical considerations should time to time suggest which aggregation method is the most appropriate given the selected indicators and the data at hand.

However, one important merit should be recognized to PCA. One must indeed remember that PCA is primarily an explorative technique and only secondarily a method to construct synthetic indices. With this in mind, Annoni and Dijkstra (2013) recognizes that the main utility of PCA actually consists in checking the internal consistency of the data. According to their study, PCA should not be seen as an aggregation method but rather PCA plays its most important role in the step preceding the aggregation, namely during the selection of the indicators to include in the synthetic index.

In this study, PCA was used both as a “selection tool” and as an aggregation technique. This work fully shares the vision in Annoni and Dijkstra (2013) and a particular emphasis was devoted to highlight how PCA indicates whether different indicators are suitable to measure a unique latent concept. On the other hand, this research highly values the contribution of PCA as an aggregation technique. Nonetheless, it recognizes that many are the valid aggregation methods while the role that PCA plays as explorative technique is unique.

Among the many aggregation methods, some are noteworthy. McGillivray and Noorbakhsh (2004) propose a differential weighting scheme, where the weights are decreasing functions of the level of well-being achievement. Although consistent with economic theory that suggests that some variables are less important in societies which have high achievement in them (Booyesen 2001), this aggregation method presents some issues due to the difficulty to build inter-temporally sound weight functions. An alternative approach would be to directly ask people about their priorities regarding the different dimensions of well-being and directly stem the weights from those answers. However, this approach is not as easy as one would imagine, as different countries prioritize different aspects of QoL, according to wealth effects and cultural

considerations. The comparability of results is therefore compromised. Summing up, there does not exist a universal optimal aggregation method, but each one presents its advantages and disadvantages.

No matter the aggregation method, one point must be clear: well-being is a multidimensional concept and an internationally comparable well-being index, reflecting this multidimensionality, must be developed and paired to GDP, as the latter indicator measures the sole economic dimension of well-being and it is therefore not suitable to measure well-being in all its facets.

Between GDP and a multidimensional synthetic well-being index there exist not only a deep conceptual distinction, but also empirical differences.

Table 9 reports the GDP per capita in PPP of the countries included in the analysis in order to allow a comparison with the previously reported results of the synthetic well-being index obtained by PCA. The choice of the well-being index, between the two types presented in the previous section is randomly made and it can be considered representative of both well-being indices as they are extremely correlated.

Table 9 – Well-being Index vs. GDP per capita

Position	Country	PC Index	Country	GDP per capita (PPP $)
1	Norway	3.60	Luxembourg	89,577 $
2	Sweden	3.07	Norway	64,839 $
3	Iceland	2.69	Netherlands	45,414 $
4	Denmark	2.55	Ireland	45,282 $
5	Luxembourg	2.30	Austria	44,692 $
6	Finland	2.09	Sweden	43,622 $
7	Netherlands	1.79	Germany	43,171 $
8	Austria	0.93	Denmark	42,880 $
9	Belgium	0.78	Belgium	41,076 $
10	France	0.70	Iceland	40,031 $
11	Slovenia	0.63	Finland	39,730 $
12	United Kingdom	0.60	France	37,115 $
13	Germany	-0.10	United Kingdom	36,942 $
14	Ireland	-0.19	Italy	35,571 $
15	Poland	-0.21	Spain	32,303 $
16	Czech Republic	-0.30	Cyprus	29,718 $
17	Estonia	-0.55	Slovenia	28,459 $
18	Spain	-0.92	Czech Republic	28,397 $
19	Lithuania	-1.33	Portugal	26,151 $
20	Portugal	-1.37	Slovak Republic	25,721 $
21	Slovakia	-1.41	Estonia	24,352 $
22	Italy	-1.45	Lithuania	23,813 $
23	Cyprus	-1.87	Poland	22,623 $
24	Hungary	-2.20	Hungary	22,586 $
25	Latvia	-2.75	Latvia	21,048 $
26	Romania	-3.22	Romania	18,120 $
27	Bulgaria	-3.86	Bulgaria	15,672 $

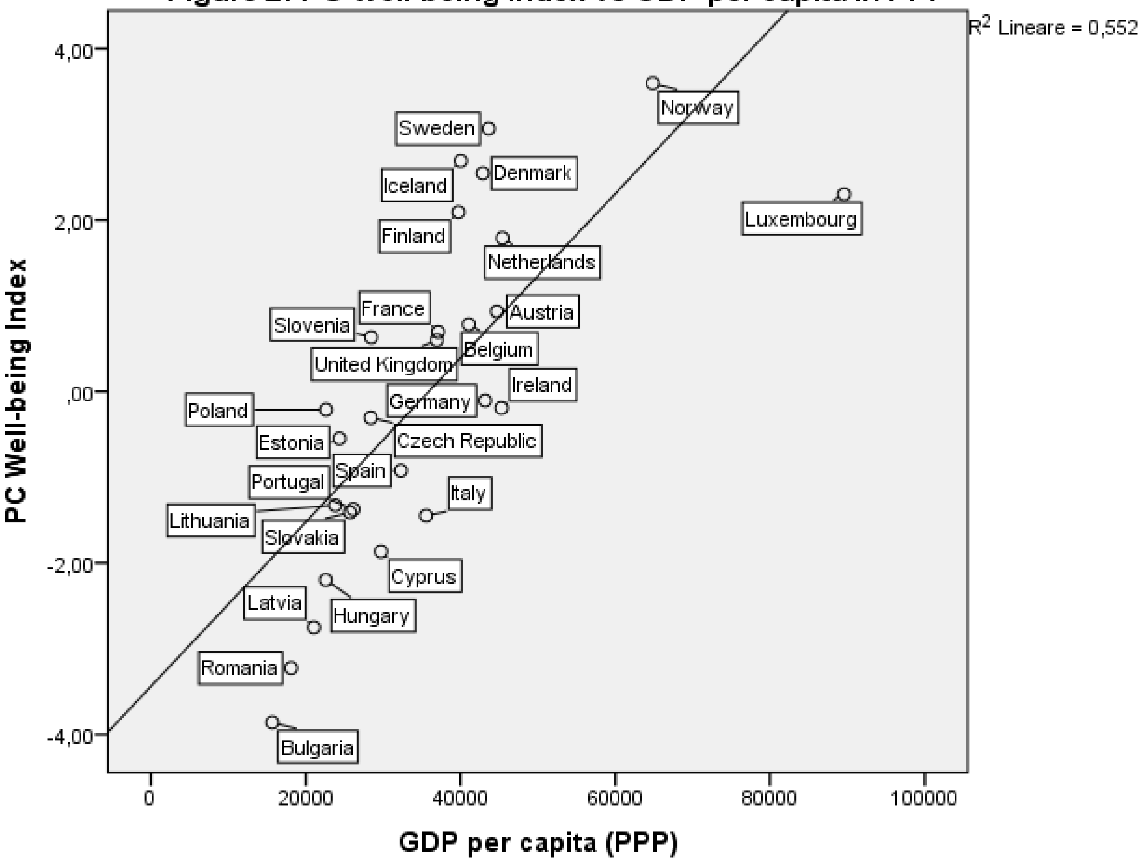
Looking at the table, it can be observed that some countries demonstrate their ability to translate their abundance of economic resources in high levels of well-being (i.e. Norway), while some other countries only prioritize the economic aspect of well-being (i.e. Ireland).

Interestingly, some other countries manage to obtain high levels of QoL without high levels of GDP per capita. A striking example of this latter category is Poland, which despite reporting one of the lowest GDP per capita among the countries analyzed, it shows a middling level of quality of life.

Oppositely, Italy, despite having a GDP per capita much higher than that of Poland, reports substantially lower levels of well-being. Notwithstanding its prosperous economical situation, the case of Ireland is similar: with one of the highest GDP per capita, its level of QoL is middling.

The differences between the two rankings are therefore very pronounced, but still the two indicators are positively correlated, as effectively shown in the figure below. Economic prosperity is indeed a fundamental aspect of well-being and therefore it is normal to expect a positive correlation. However, a coefficient of correlation of 0.552 is not as strong as one would imagine ex-ante and the low value of the coefficient is not entirely driven by the presence of Luxemburg, presumably an outlier.

Figure 2: PC Well-being Index vs GDP per capita in PPP



As a matter of fact, even after excluding this country, the new coefficient remains middling with a value of 0.696. These numbers provide a further justification to the current study. They prove that a synthetic well-being index is indeed needed and this work contributes to the literature by building two different indices with two alternative and valid aggregation methods.

8. Conclusions

After the recent economic crisis, the quest for a measure of well-being has become more intensive as many international institutions and a large portion of academia acknowledged the multidimensionality intrinsic to the notion of well-being.

This work adds to a large body of literature focusing on well-being indices. Using a large new data set on quality of life indicators published by Eurostat and considering a sample of European countries, this paper intended to contribute to such literature by constructing two innovative composite indices of well-being. Starting from the awareness of the multidimensionality of the concept of well-being, the obtained indices try to incorporate all relevant aspects of well-being into a single index. One of the greatest merit of this study consists of expanding the range of domains and indicators through which most of the literature has measured well-being in Europe. Two are the methodologies adopted to aggregate the indicators, carefully selected by means of exploratory factor analysis: arithmetic mean and principal component analysis. Both methodologies are implemented following a two-step approach, where first all variables are aggregated into seven dimension indices, each representing a different domain of quality of life and then the latters are aggregated into a single synthetic well-being index.

In general, results show a deep divide between Northern European countries and particularly Scandinavian countries with excellent levels of quality of life and Eastern European countries with low levels of well-being. Italy positions itself among the countries with low levels of well-being. Interestingly, the results hold for both aggregation procedures. This work had the further aim to contribute to the existing literature on quality of life indicators not only by developing two innovative indices but also by analyzing whether the important differences that the aggregation procedures present from a conceptual standpoint are translated into the empirical ground. The main results emerging from this study show that the two schemes yield fairly similar results and the reason is attributed to the fact that when indicators are highly correlated, the choice of the weighting scheme marginally changes the results. With this in mind, this work shares with Annoni and Dijkstra (2013) the vision that PCA proves particularly useful in checking the internal consistency of the data. The paper also examined in which contexts PCA results the most appropriate aggregation technique and the current seems to meet the contextual requirements.

Finally, this work adds to a body of literature aiming at demonstrating that new multidimensional measures of well-being are necessary, that can complement the precious information provided by well-established measures such as GDP. Having a synthetic index for each dimension and an aggregate final index would be of extreme value both for policymakers and citizens for a transparent assessment and evaluation of the policies pursued.

References

Annoni, P., & Dijkstra, L. (2013). EU Regional Competitiveness Index. *Scientific and Policy Reports, Joint Research Centre of European Commission.*

Annoni P., & Weziak-Bialowolska, D. (2012). Quality of Life at the sub-national level: an operational example for the EU. *Report by the Joint Research Centre of the European Commission.*

Bandura, R. (2008). A survey of composite indices measuring country performance: 2008 update. *New York: United Nations Development Programme, Office of Development Studies (UNDP/ODS Working Paper).*

Bleys, B. (2012). Beyond GDP: Classifying alternative measures for progress. *Social Indicators Research*, 109(3), 355-376.

Boelhouwer, J., & Stoop, I. (1999). Measuring well-being in the Netherlands: The SCP index from 1974 to 1997. *Social indicators research*, *48*(1), 51-75.

Booysen, F. (2002). An overview and evaluation of composite indices of development. *Social indicators research*, *59*(2), 115-151.

Clark, A. E. (2006). A note on unhappiness and unemployment duration, *Applied Economics Quartely*, 52(4), 291-308.

Cnel-Istat (2013), BES/2013. Il benessere equo e sostenibile in Italia, Roma. http://www.istat.it

Costanza R., Hart M., Posner S., Talberth J. (2009). Beyond GDP: The Need for New Measures of Progress, *The Pardee Papers*, *Boston University*.

De Vogli, R. (2014). The financial crisis, health and health inequities in Europe: the need for regulations, redistribution and social protection. *International journal for equity in health*, 13(1), 58.

Desai, M. (1993). Income and Alternative Measures of Well-Being, In: D. G. Westendorff and D. Ghai (eds), Monitoring Social Progress in the 1990s. Aldershot: *United Nations Research Institute for Social Development*, Avebury.

Duflo, E. (2001). Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment, *American Economic Review*, 91(4), 795-813

Easterlin, R. A. (1974). Does economic growth improve the human lot? Some empirical evidence. *Nations and households in economic growth*, 89, 89-125.

Eurofound (2013). Third European Quality of Life Survey – Quality of life in Europe: Subjective well-being. *Publications Office of the European Union, Luxembourg.*

Eurostat (2009). Feasibility study for Well-Being Indicators: Executive summary of Task 1-3.

Eurostat (2010). Feasibility study for Well-Being Indicators. Task 4: Critical review. *Eurostat Publication*

Ferrara, A. R., & Nisticò, R. (2014). Measuring Well-Being In A Multidimensional Perspective: A Multivariate Statistical Application To Italian Regions *(No. 201406)*.

Ferrara, A. R., & Nisticò, R. (2013). Well-being indicators and convergence across Italian regions. *Applied Research in Quality of Life*, *8*(1), 15-44.

Fleurbaey, M. (2009). Beyond GDP: The quest for a measure of social welfare. *Journal of Economic Literature*, 1029-1075.

Habermann, H. (Ed.). (2011). Facilitating Innovation in the Federal Statistical System:: Summary of a Workshop. *National Academies Press.*

Hair J. F., Black W. C., Babin B. J., Anderson R. E. (2012), Multivariate Data Analysis, *Pearson International Edition.*

Joint Research Centre-European Commission. (2008). Handbook on constructing composite indicators: methodology and user guide. *OECD Publishing.*

Joliffe, I. T., & Morgan, B. J. T. (1992). Principal component analysis and exploratory factor analysis. *Statistical methods in medical research*, *1*(1), 69-95.

Kovacevic, M. (2010). Review of HDI critiques and potential improvements. *Human development research paper*, 33.

Lai, D. (2000). Temporal analysis of human development indicators: principal component approach. *Social Indicators Research*, 51(3), 331-366.

Maasoumi, E., & Nickelsburg, G. (1988). Multivariate measures of well-being and an analysis of inequality in the Michigan data. *Journal of Business & Economic Statistics*, 6(3), 327-334.

Mazziotta, M., & Pareto, A. (2013). Methods For Constructing Composite Indices: One For All Or All For One?. *RIEDS- Italian Review of Economics, Demography and Statistics*, 67(2), 67-80.

McGillivray, M. (1991). The Human Development Index: Yet Another Redundant Composite Development Indicator?. *World Development*, 19(10): 1461–68.

McGillivray, M., & Noorbakhsh, F. (2004). Composite indices of human well-being: past, present, and future *(No. 2004/63). Research Paper, UNU-WIDER, United Nations University (UNU).*

Mishra, S. K. (2007). Construction of maximin and non-elitist composite indices—alternatives to elitist indices obtained by the principal components analysis. *MPRA Paper, 3338 (University Library of Munich: Germany).*

OECD (2011) Compendium of OECD well-being indicators.

OECD (2013) How's Life? 2013. Measuring Well-being, *OECD Publishing*.

Ogwang, T. (1994). 'The Choice of Principal Variables for Computing the Human Development Index'. *World Development*, 22(12): 2011–114.

Osberg, L., & Sharpe, A. (2005). How should we measure the "economic" aspects of well-being?. *Review of Income and Wealth*, 51(2), 311-336.

Ram, R. (1982). Composite indices of physical quality of life, basic needs fulfilment, and income: A principal component representation. *Journal of Development Economics*, *11*(2), 227-247.

Sagar, A. D., & Najam, A. (1998). The human development index: a critical review. *Ecological economics*, *25*(3), 249-264.

Saisana, M., Saltelli, A., & Tarantola, S. (2005). Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators. *Journal of the Royal Statistical Society: Series A (Statistics in Society*), 168(2), 307-323.

Sharpe, A., & Smith, J. (2005). Measuring the Impact of Research on Well-being: A Survey of Indicators of Well-being *(No. 2005-02). Centre for the Study of Living Standards.*

Slottje, D. (1991). Measuring the Quality of Life Across Countries. *The Review of Economics and Statistics*, 73(4): 684–754.

Smith, J. (2003). Guide to the Construction and Methodology of the Index of Economic Well-being. *Centre for the Study of Living Standards*.

Somarriba, N., & Pena, B. (2009). Synthetic indicators of quality of life in Europe. *Social Indicators Research*, *94*(1), 115-133.

Srinivasan, T. N. (1994). 'Human Development: A New Paradigm or Reinvention of the Wheel?'. *American Economic Review Papers and Proceedings*, 84, 238–243.

Stiglitz, J. E., Sen, A., & Fitoussi, J. P. (2010). Report by the commission on the measurement of economic performance and social progress. *Paris: Commission on the Measurement of Economic Performance and Social Progress*.

Appendix A

Although the presence of missing data in the dataset at hand is extremely low with 7 missing values out of 930 entries, the analysis pursued throughout the paper excluded those countries reporting at least one missing value. Excluding cases listwise is probably the most conservative way to treat missing data. However, according to the Handbook on the Construction of Composite Indices (OECD, 2008), there are different ways of dealing with missing data in the context of a principal component analysis and each of them might be considered valid depending on the situation. Doubtlessly, it would be interesting to find out whether different analyses with alternative methods of treatment of missing values show similar results. Furthermore, with regard to this study, it appears newsworthy to gather more information about the well-being of those countries excluded from the analysis, Croatia, Greece, Malta and Switzerland. Each of them does not have more than 2 missing values out of the 30 required in the complete analysis. The Handbook on the Construction of Composite Indices (OECD, 2008) indicates as a possible alternative to impute missing values with the mean of the indicator concerned. Column 2 and 3 in Table 10 report the values of the well-being index where the imputation with mean is the selected method (figure below). Oppositely to the approach adopted throughout the paper where countries reporting missing values were excluded, another method is to exclude the incomplete variables. The indicators to be excluded are: Pisa results, air pollution,

unadjusted gender pay gap and active citizenship. The values of the well-being index excluding the above mentioned variables are reported in column 4 and 5 of Table 10. It is important to highlight that in the latter approach, the dimension "Governance and basic rights" is not present, given the fact that both its components report missing values.

Table 10 – Alternative treatments of missing data

	Imputation with mean		Excluding variables where missing		Excluding cases where missing	
Position	**Country**	**PC Index**	**Country**	**PC Index**	**Country**	**PC Index**
1	Norway	3.53	Norway	3.27	Norway	3.60
2	Sweden	2.95	Switzerland	2.84	Sweden	3.07
3	Switzerland	2.69	Sweden	2.77	Iceland	2.69
4	Iceland	2.52	Iceland	2.25	Denmark	2.55
5	Denmark	2.49	Denmark	2.13	Luxembourg	2.30
6	Luxembourg	2.38	Luxembourg	2.10	Finland	2.09
7	Finland	2.05	Netherlands	1.84	Netherlands	1.79
8	Netherlands	1.96	Finland	1.81	Austria	0.93
9	Austria	1.02	Austria	1.35	Belgium	0.78
10	Belgium	0.94	United Kingdom	0.79	France	0.70
11	Slovenia	0.82	Belgium	0.64	Slovenia	0.63
12	France	0.77	France	0.56	United Kingdom	0.60
13	United Kingdom	0.57	Germany	0.51	Germany	-0.10
14	Germany	0.24	Czech Republic	0.42	Ireland	-0.19
15	Malta	-0.04	Slovenia	0.28	Poland	-0.21
16	Poland	-0.06	Malta	-0.22	Czech Republic	-0.30
17	Czech Republic	-0.13	Estonia	-0.25	Estonia	-0.55
18	Ireland	-0.42	Poland	-0.35	Spain	-0.92
19	Estonia	-0.54	Slovakia	-0.78	Lithuania	-1.33
20	Spain	-0.95	Ireland	-0.87	Portugal	-1.37
21	Portugal	-1.16	Spain	-0.88	Slovakia	-1.41
22	Slovakia	-1.17	Cyprus	-0.92	Italy	-1.45
23	Lithuania	-1.19	Portugal	-1.06	Cyprus	-1.87
24	Italy	-1.20	Lithuania	-1.22	Hungary	-2.20
25	Cyprus	-1.59	Italy	-1.24	Latvia	-2.75
26	Hungary	-2.09	Hungary	-1.98	Romania	-3.22
27	Croatia	-2.43	Croatia	-2.27	Bulgaria	-3.86
28	Latvia	-2.45	Latvia	-2.71		
29	Romania	-2.88	Romania	-2.74		
30	Greece	-3.04	Greece	-2.86		
31	Bulgaria	-3.60	Bulgaria	-3.21		

Looking at Table 10, the differences among the three methodologies do not appear particularly prominent as the rankings all look very similar. In particular, the analysis obtained by imputation with mean appears to be the most similar to the analysis with listwise exclusion. This is confirmed by the figure 3.A below.

The graphs below show the pairwise correlations among the three methods. The first two graphs obviously exclude the 4 missing countries, while Figure 3.C shows the correlation between the two methodologies that can count on the entire sample. It can be observed that the highest correlation (0.996) appears in Figure 3.A, showing the correlation between imputation with mean and excluding cases listwise. However, it can be easily noticed that all correlations are very high and above 0.95.

Figure 3.A : Imputation with mean vs Excluding cases listwise

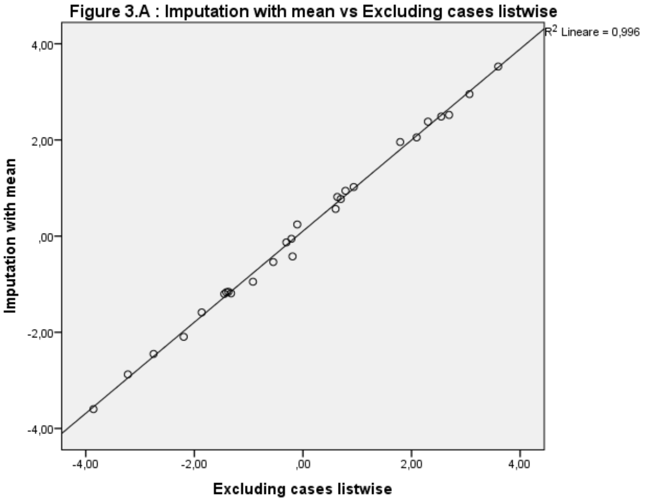


Figure 3.B : Excluding variables vs Excluding cases listwise

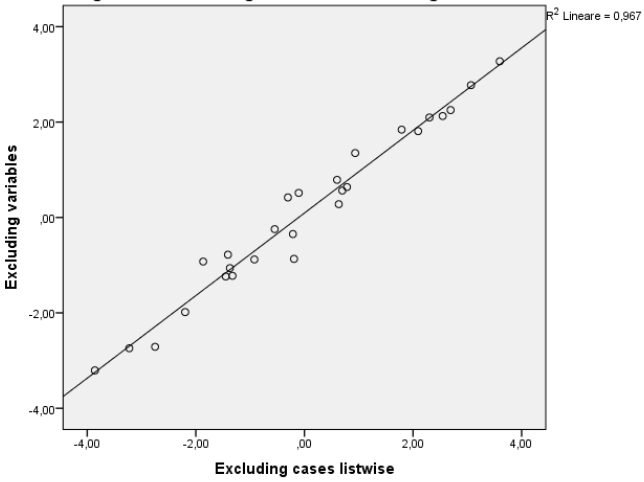
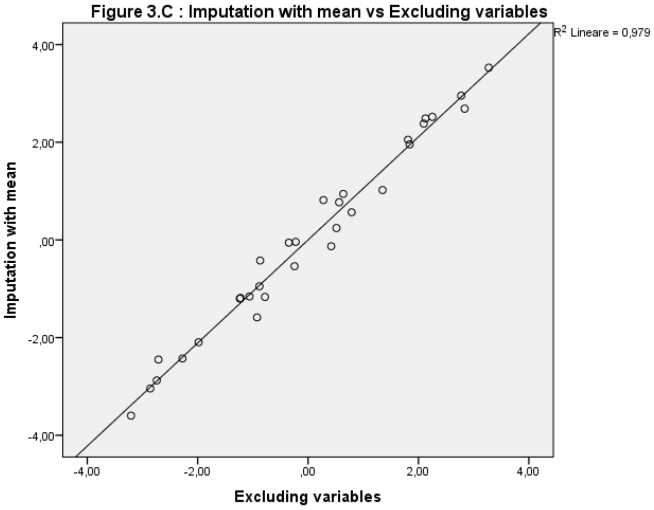


Figure 3.C : Imputation with mean vs Excluding variables



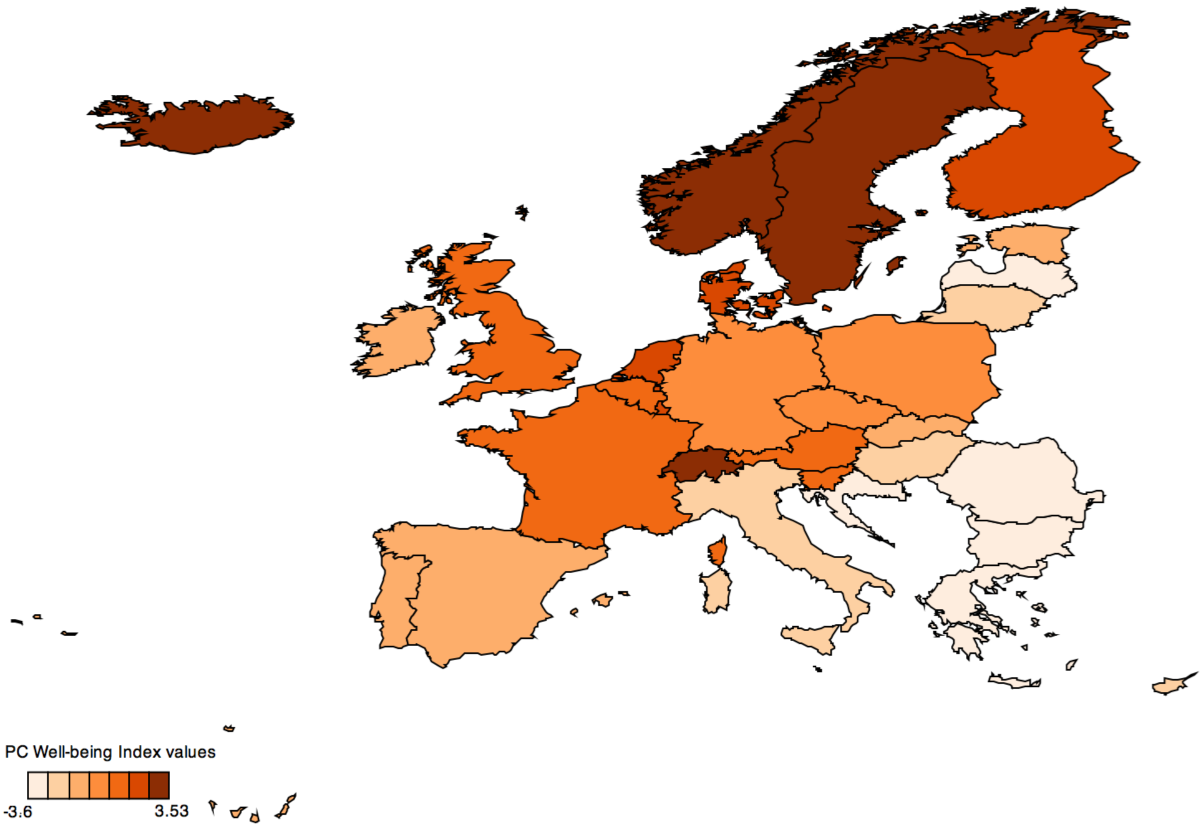
Thanks to these results, the analysis developed throughout the paper awards significant robustness. Given the low percentage of missing values, the choice of how to treat missing data turns out to have marginal importance. Nonetheless, the decision to exclude cases listwise seemed ex-ante the most conservative one

and was therefore the one adopted. Hence, these results can also be interpreted as robustness checks and as a way to find out more about the well-being of Croatia, Greece, Malta and Switzerland.

One last point is to be discussed: some might think that imputation with mean is not an optimal imputation method as it assigns "random" values (the mean of the concerned indicator) to the countries reporting missing values. The same analysis has hence been replicated for different imputation methods. Similar results emerged.

Map 2: Principal Component Well-being index in 31 European countries

(Imputation with mean)



Appendix B

The analysis pursued in this work followed a two-step principal component approach. First, a multiplicity of indicators was aggregated to build an index for each dimension of well-being and then the obtained indices were aggregated into a composite well-being index. The adopted approach reflected the decision to assign particular importance to the several dimensions of well-being. An alternative approach, more often adopted

in the literature[7], is to follow a one-step principal component approach where all the selected indicators are directly aggregated into a synthetic well-being index. This approach does not recognize a fundamental value to the single dimensions of well-being and its sole scope is to construct a synthetic well-being index. A one-step principal component analysis has advantages and disadvantages over its two-step counterpart. One of the main advantages of a one-step PCA is that it allows the direct selection of the indicators to include in the final index. However, this can be a double edged sword. If, on the one hand, the direct selection of the indicators can lead to the inclusion of the most adequate variables to measure the intended concept, on the other hand it can induce the researcher to include variables measuring a different concept. In the case of well-being, it is well possible that a one-step approach would lead to the exclusion of important dimensions of well-being. For these reasons, the decision to use a two-step analysis seemed ex-ante the safest and the most appropriate. Furthermore, a one-step PCA certainly demands some stringent preliminary conditions: the list of variables among which PCA selects its indicators must be carefully chosen by the researcher and must include in a balanced way all the different facets of the phenomenon intended to be measured. This means that, when measuring well-being, it is opportune that the number of indicators referring to economic conditions is similar to the number of variables referred to health. As a matter of fact, with a one-step approach, the number of indicators referring to one particular dimension does matter and any asymmetry might compromise the overall analysis. In a two-step approach this issue is overcome by the fact that all dimensions enter into the final index with the same ex-ante weight.

Table 11 contains the main results of a one-step principal component analysis on well-being. Missing values are replaced with the mean value of the concerned variable. The starting dataset consists of the 30 variables selected in the two-step methodology, some of which turns out to be inadequate to directly measure well-being and are therefore excluded. Hence, before commenting on results, a brief discussion on the exploratory factor analysis seems appropriate.

According to Hair et al. (2012). the overall MSA value should always be above 0.50 in order to proceed with the PCA. The same authors suggests that “If the MSA value falls below 0.50. then the variable-specific MSA values can identify variables for deletion to achieve an overall value of 0.50” and further “In deleting variables. the researcher should first delete the variable with the lowest MSA and then recalculate the factor analysis”. As far as this study is concerned. this process is therefore repeated seven times excluding one variable at a time until the overall MSA value of 0.50 is reached. The indicators excluded are in order of exclusion “Gender pay gap”. “Noise”. “Leaking roof”. ”Limitations”. “Crime”. “Grime” and “Low work intensity”. Finally. the indicator “Illness” is excluded from the analysis since it correlates positively with the well-being index. despite negatively affecting well-being per se. At the end of this process. the overall MSA value is 0.77 and no variables have individual MSA values below the threshold. The principal component

[7] See Maasouni and Nickelsberg (1988) for a QoL analysis in the State of Michigan, Boelhouwer and Stoop (1999) for a well-being study in the Netherlands and Somarriba and Pena (2009) for a QoL analysis in Europe.

explains 51% of the total variance. which is a barely satisfactory result. The signs of the factor loadings are all reversed as the variables positively influencing well-being negatively correlate with the final index and vice versa. A reversion of signs guarantees that the obtained final index is indeed an index of well-being.The variable “deprived” has the highest value of factor loading. in absolute value. while “good health” has the lowest value. As explained in previous sections of the paper. the factor loadings do not tell anything about the relative importance of the various indicators on well-being. They are just functional to find the main directions of variability in the dataset.

Table 11 – One-step principal component index vs. Two-step principal component index

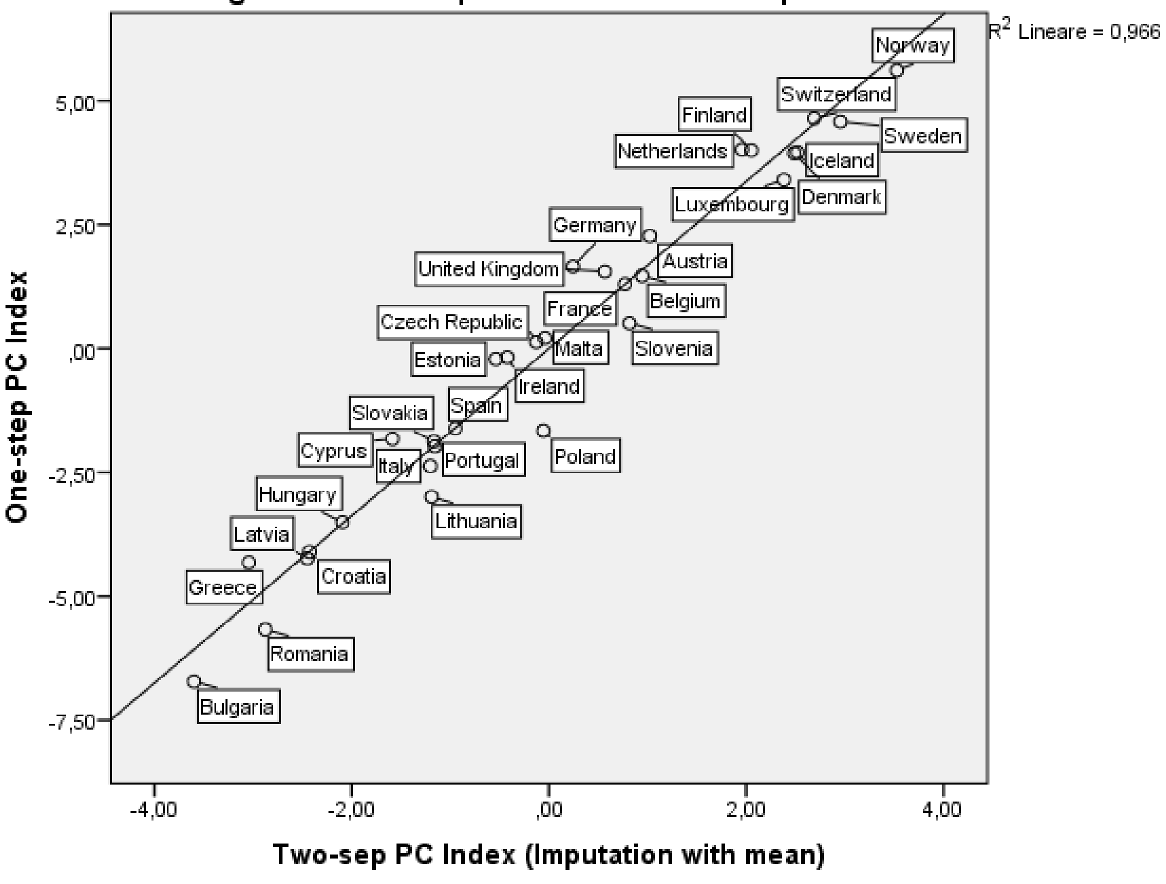
Position	**Country**	**One-step PC Index**	**Country**	**Two-step PC Index**
1	Norway	5.61	Norway	3.53
2	Switzerland	4.65	Sweden	2.95
3	Sweden	4.58	Switzerland	2.69
4	Netherlands	4.01	Iceland	2.52
5	Finland	4.00	Denmark	2.49
6	Iceland	3.96	Luxembourg	2.38
7	Denmark	3.94	Finland	2.05
8	Luxembourg	3.41	Netherlands	1.96
9	Austria	2.27	Austria	1.02
10	Germany	1.66	Belgium	0.94
11	United Kingdom	1.55	Slovenia	0.82
12	Belgium	1.47	France	0.77
13	France	1.30	United Kingdom	0.57
14	Slovenia	0.51	Germany	0.24
15	Malta	0.21	Malta	-0.04
16	Czech Republic	0.13	Poland	-0.06
17	Ireland	-0.18	Czech Republic	-0.13
18	Estonia	-0.21	Ireland	-0.42
19	Spain	-1.61	Estonia	-0.54
20	Poland	-1.66	Spain	-0.95
21	Cyprus	-1.82	Portugal	-1.16
22	Slovakia	-1.87	Slovakia	-1.17
23	Portugal	-1.97	Lithuania	-1.19
24	Italy	-2.37	Italy	-1.20
25	Lithuania	-2.99	Cyprus	-1.59
26	Hungary	-3.51	Hungary	-2.09
27	Croatia	-4.10	Croatia	-2.43
28	Latvia	-4.24	Latvia	-2.45
29	Greece	-4.32	Romania	-2.88
30	Romania	-5.67	Greece	-3.04
31	Bulgaria	-6.72	Bulgaria	-3.60

Table 11 reports the values of the one-step principal component index and of its two-step counterpart in order to allow a comparison between the two methodologies. Results show that the two approaches yield very similar results. In both rankings Norway occupies the first position. while Bulgaria occupies the last. Italy occupies the 24th place. The two countries mainly benefitting from the one-step PC ranking are Germany and Cyprus. climbing the ranking by 4 positions. respectively from the 14th to the 10th position and from 25th to the 21st place. Oppositely. Poland looses 4 positions going from the 16th to the 20th position.

Overall. some differences do exist. but they are not very pronounced. Figure 4 shows that the correlation between the two methodologies is indeed very high and it assumes a value of 0.97.

The two approaches are therefore very similar in this scenario. However. conceptual differences are relevant. The one-step methodology gives a larger weight to the economic aspects of well-being since among the indicators selected by that the explorative factor analysis. seven out of 22 appertain to the dimension "Material living conditions". Oppositely. the two-step approach seems more balanced and it tries to incorporate in the index all relevant aspects of Qol. Therefore. it is likely to provide a better picture of well-being in Europe.

Figure 4 : One-step PC Index vs Two-step PC Index



Appendix C

The section "Methodology" dealt with the definition of principal component and the interpretation of the statistical output. Particular emphasis was devoted to the interpretation of eigenvalues and eigenvectors. This section intends to discuss the derivation of the eigenvalues and corresponding eigenvectors from an algebraic point of view.

Consider the definition of the first principal component: $PC_1 = \overline{b}_1^T \overline{x}$.

The vector $\overline{b}_1$ maximizes $Var\left[\overline{b}_1^T \overline{x}\right] = \overline{b}_1^T R \overline{b}_1$. where R is the $(n*n)$ correlation matrix.

Obviously. a normalization constraint must be imposed. The assumption here is that $\overline{b}_1$ has unit length $\overline{b}_1^T \overline{b}_1 = 1$. This implies that the squares of the coefficients sum to one.

The maximization problem is:

$$\max \quad \overline{b}_1^T R \overline{b}_1 \quad sub \quad \overline{b}_1^T \overline{b}_1 = 1$$

To solve the maximization problem. the Lagrangian solution is adopted. The new maximization problem is:

$\overline{b}_1^T R \overline{b}_1 - \lambda(\overline{b}_1^T \overline{b}_1 - 1) = \overline{0}$ where λ is the Lagrangian multiplier.

By differenciating with respect to $\overline{b}_1$. the following expression is obtained:

$R\overline{b}_1 - \lambda \overline{b}_1 = \overline{0}$ or equivalently $\left(R - \lambda I_n\right)\overline{b}_1 = \overline{0}$

Where λ_1 is the eigenvalue of R and $\overline{b}_1$ its corresponding eigenvector.

Recalling that the eigenvalue maximizing the variance is such that: $\overline{b}_1^T R \overline{b}_1 = \overline{b}_1^T \lambda \overline{b}_1 = \lambda \overline{b}_1^T \overline{b}_1 = \lambda$.

then λ_1 must be the largest of all possible λ_s. Consequently. $\overline{b}_1$ is the eigenvector associated to the largest eigenvalue λ_1.

Appendix D

Table I - List of selected Indicators

Label	Indicator	Description	Source
Material Living Conditions			
Median	Median Income	Household's median equivalised[8] disposable income	EU-SILC (statistics on income and living conditions)
S80/S20 rati	Income quintile share ratio	Ratio of the total income received by the top quintile to that received by the bottom quintile	EU-SILC
Risk-of-poverty	At risk of poverty9 rate	Share of people with an equivalised disposable income (after social transfer) below the at-risk-of-poverty threshold. which is set at 60 % of the national median equivalised disposable income after social transfers	EU-SILC
Deprived	Severely materially deprived people	Share of population that expresses the inability to afford some items considered by most people to be desirable or even necessary to lead an adequate life	EU-SILC
Not make ends meet	Inability to make ends meet	Self-reported difficulty to make ends meet; measurement of poverty in terms of the household's experienced feeling of poverty	EU-SILC
Make ends meet	Make ends meet very easily	Self reported ability to make ends meet	EU-SILC

[8] The concept of equivalised disposable income is used to reflect the fact that incomes of individuals are shared in a household.
[9] This indicator does not automatically measure wealth or poverty, but low income in comparison to other residents in that country, which does not necessarily imply low standards of living.

Leaking roof		Share of population living in a dwelling with a leaking roof. damp walls. floors. foundation. or rot in window frames or floor	EU-SILC
No bath		Share of total population having neither a bath. nor a shower. nor indoor flushing toilet in their household	EU-SILC
Productive or main activity			
Unemployment	Unemployment rate	Share of population aged 15 to 74 without work during the reference week. available to start work within the next two weeks. actively having sought employment at some time during the last four weeks	EU-LFS (Labour Force Survey)
Long term unemployment	Long-term unemployment rate	Long term unemployment as a proportion of total unemployment	EU-LFS
Low work	People living in households with very low work intensity	Share of population living in households having a work intensity below a threshold set at 0.20	EU-LFS
Involuntary part-time	Involuntary part-time employment as percentage of the total part-time employment	Involuntary part-time employment as a proportion of total part-time employment	EU-LFS
Health			
LE	Life Expectancy at the age of 1	Mean number of years a child aged 1 can expect to live if subjected throughout his or her life to the current mortality conditions	EU-SILC (statistics on income and living conditions)
HLY	Healthy Life Years	Number of years a person is expected to continue to live in a healthy condition	EU-SILC

Illness	People having a long-standing illness or health problem	Share of population suffering from a long-standing illness or health problem	EU-SILC
Limitations	Long-standing limitations	Self-perceived long-standing limitations in usual activities due to health problem	EU-SILC
Good health	Self-perceived very good health	Share of population perceiving its health status as very bad	EU-SILC
Bad health	Self-perceived very bad health	Share of population perceiving its health status as very bad	EU-SILC
Education			
Tertiary	Population with tertiary education	Share of working age population having completed tertiary education. namely the highest level of education that can be attained (ISCED levels 5 and 6)	EU-LFS
Early leavers	Early leavers from education and training	Percentage of population aged 15-24 having attained at most lower secondary education and not being involved in further education or training in the four weeks preceding the survey	EU-LFS
Long-life training	People that participated in education or training in the four preceding weeks	% of the population aged 25 to 64 having participated in education and training in the four weeks preceding the survey	EU-LFS
PISA	Pisa score 2012	Score in the PISA test in 2012 obtained by summing the scores in the section "Math". "Reading" and "Science"	OECD- PISA 2012
Economic and Physical Safety			
Inability expenses	Inability to face unexpected financial expenses	Share of population unable to face unexpected financial expenses	EU-SILC

Arrears	Population in arrears	Share of population in arrears on mortgages. rents. utility bills or hire purchases	EU-SILC
Crime	Crime. violence or vandalism in the area	Share of population perceiving crime. violence or vandalism in its area	EU-SILC
Natural and Living Environment			
Air pollution	Urban population exposure to air pollution	Population-weighted concentration of PM10[10] in micrograms per cubic metre to which the urban population is potentially exposed	EEA (European Environment agency)
Grime	Pollution. grime or other environmental problems	Share of people who report that they have been exposed to pollution. grime and other environmental problems	EU-SILC
Noise	Noise from neighbours or from the street	Share of population perceiving exposure to noise pollution defined as exposure to ambient sound levels beyond comfort levels	EU-SILC
Governance and basic rights			
Gender pay gap	Unadjusted gender pay gap	Difference between average gross hourly earnings of male paid employees and of female paid employees as a percentage of average gross hourly earnings of male paid employees[11]	Eurostat
Active citizenship	Interaction with public authorities	Share of population using the internet for interaction with public authorities within the last three months before the survey.	Eurostat

[10] Fine particulates (PM10), i.e. particulate matter whose diameter is less than 10 micrometers, can be carried deep into the lungs where they can cause inflammation and a worsening of the condition of people with heart and lung diseases
[11] The population consists of all paid employees in enterprises with 10 employees or more in NACE Rev. 2 aggregate B to S (excluding O).