Assessing welfare disparities in EU Regions

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Following the Stiglitz, Sen and Fitoussi commission, a signifcant number of papers has been published providing alternative measures of progress and well-being to Gross Domestic Product. Most of these papers difer in terms of their theoretical approach as well as their purpose and statistical methodology used to defne what welfare is and how to measure it. In this paper, we construct a new composite index of welfare, the Reframing Welfare Index (RWI), that aims to assess disparities across European regions. Building on multilevel data and a system of structural equations, we aim to precisely measure 21 aspects of welfare (pillars) that are categorized in four key foundational causes of welfare.

I. Introduction

For more than a half century, the most widely accepted measure of a country's economic progress has been the Gross Domestic Product (GDP). Over the last several years this indicator has been widely criticized on the basis that it is not a measure of the degree to which society's goals are met, rather a measure of the mere volume of marketed economic activity, which is only one means to that end (Stiglitz et al., 2009). The main problem with using the GDP indicator is how to measure well-being and economic progress (Bleys, 2012).

The applicability and robustness of GDP as a measure of prosperity has long been called into question (Kuznets, 1962). Even Kuznets (1934), GDP is simply an approximate measure of monetary flows, with the primary goal of estimating how much consumption and investment contributed to national income by assessing the level of industrial and agricultural production, he claimed that a measurement of national income can rarely be used to determine a nation's welfare.

Despite its flaws, GDP (along with its real and per capita variations) has been widely and consistently used in economic research to gauge development and well-being, allowing for across time and nations comparisons. The GDP measurement overlooks important aspects of social development[1], including income distribution

[1]Since 1970, the calculation of GDP has been guided by the agreed standards of the System of National Accounts. The SNA describes a coherent, consistent and integrated set of macroeconomic accounts in

(Stiglitz et al., 2009), educational attainment and access to healthcare (Drèze and Sen, 2013), political freedom (Van den Bergh, 2009), environmental impact (He et al., 2020), and gender equality (Gizelis, 2009). Incorporating these characteristics into welfare indices would also be pointless if they had no discernible impact on life satisfaction. In other words, it is equally important to measure and ensure people's comprehension of their prosperity.

Consequently, other relevant indicators of social progress have been proposed in the economic literature (Burchi and Gnesi, 2016). These indicators difer on a number of aspects with regards to the methodology adopted for their construction and the collection of relevant information used for measuring well-being. Some of these indicators (such as, the Index of Sustainable Economic Welfare, ISEW, or the Genuine Progress Indicator, GPI) take the standard GDP and correct it in order to refect the wide range of factors that matter to people and their well-being; others (the Human Development Index, HDI, the Better Life Index, BLI, or the Canadian Index of Wellbeing, CIW), to portrait the levels of well-being, include in the GDP both economic and social elements.

Nowadays, driven by the work of the Stiglitz's Commission (Stiglitz et al., 2009), it is widely accepted to consider well-being as a multi dimensional phenomenon. It means that different dimensions are measured on a micro or macro population (i.e. households, regions, countries) using a dashboard of indicators, often across time. The growing attention to the beyond-GDP measures has led to progressively include well-being indicators in the policy agenda. The European Commission has funded a new project MAKSWELL (MAKing Sustainable development and WELL-being frameworks work for policy, see Tinto et al. (n.d.)) that aims to improve data and methodologies to relate policy analysis and wellbeing. Most of these studies are carried out at country level and increasingly involve public institutions and local authorities, as well as the civil society.

In literature there is a wide debate and some researchers support the idea of deriving, from a multidimensional framework, a single metric that makes it easy to compute the progress/decline in well-being over time. But the identification of a metric, similar to the integrated system currently adopted to produce GDP measures, is a hard task. Meanwhile, a number of composite indices have been introduced both by international organizations (see for example UNDP, 2016) and by national Institutes of Statistics (Quality of Life Spain (INE – Spain, 2019), Bes Italy (Istat, 2015) and WBI Portugal (INE - Portugal, 2017)). The introduction of composite indices and their use to measure the effects of policy programs, require a framework that makes it possible to clearly assess their evolution between two different periods. This is the traditional approach for which GDP measure is useful, allowing comparisons both over time and across countries. Although there is not a common standard to measure well-being across countries, the various experiences share some common characteristics such as the definition

the context of a set of internationally agreed concepts, definitions, classifications and accounting rules. (United Nations, 2022) of domains and of the individual indicators. In this paper we consider as done the aforementioned steps but rather we focus on the methodology to compute composite indices, mainly on the normalization, aggregation and unbalance adjustment techniques by using regional data and a structural equation modeling approach

To investigate these issues we consider data from European Regions that is based on a consolidated framework for the measure of well-being both at national and regional level (see Calcagnini and Perugini (2019); Casadio Tarabusi and Guarini (2013)). Following Melios and Papadimitriou (2002) we are deriving the four main foundations of welfare, namely: 1) individual wellbeing, 2) institutional and social progress, 3) economic welfare and 4) environment. The following section describes the methodology followed by results and discussion.

II. Methodology

What we measure affects our understanding of social and economic phenomena which subsequently affects how we design and implement policies. Ergo, if we measure the wrong thing or in the wrong way, we end up with wrong policy recommendations that negatively affect future outcomes. The effects of such spurious cycles of incomplete metrics and policies are tremendous for societies across the globe. Citizens' welfare is decreasing disproportionately through multiplier effects. Subsequently, people lose their faith in experts, science and politicians, decrease their support for national and international institutions and the spurious cycles go on.

Social and individual welfare is more than just material wealth at the individual and social levels. It is a holistic aspiration of modern societies that reaches into the social, economic, political, financial, cultural, and environmental character of a society that allows all individuals to realise their full potential in a fair and just way.

Such a composite and complex notion is extremely hard to capture in a holistic way into a universal linear metric. Welfare is multifaceted, heterogeneous across time and space and non-linear. To capture this multidimensional concept, we propose a new composite index that seeks to explore, understand, measure, and reframe welfare; the Reframing Welfare Index (RWI). The proposed RWI addresses both normative and methodological issues that previous metrics lack, aiming at a holistic and robust measure of welfare.

The framework of the Index captures welfare in four main categories, the Foundations of welfare:

- Just Societies
- Secured Livelihoods
- Sustainable Open Economies
- Nature and Green Future

The Just Societies foundation captures the interrelational structures that exist between individuals in a society with formal and informal institutions in the quest of an inclusive, fair, just and collective social growth. This foundation consists of five pillars: 1) Formal Institutions, 2) Human Rights, 3) informal Institutions, 4) Religions and 5) Social Capital. Each pillar consists of multiple indicators (See Appendix for full list and description).

The Secured Livelihoods foundation captures the levels, distribution and diffusion of the necessary means for human and societal flourishing. This foundation consists of six pillars: 1) Poverty, 2) Education, 3) Health, 4) Access, 5) Wealth and 6) Security. Each pillar consists of multiple indicators (See Appendix for full list and description).

The Sustainable Open Economies foundation captures the interrelational economic structures at the individual and aggregate level, looking both at the supply and demand perspectives. This foundation aims to understand and measure the extent to which an economy both at the micro and macro level is competitive, open to innovation, conducive to investments and trade and facilitates inclusive growth. It consists of five pillars: 1) Output, 2) Employment, 3) Business Environment, 4) Investment Environment and 5) Innovation. Each pillar consists of multiple indicators (See Appendix for full list and description).

The Nature and Green Future foundation captures the natural capital stock and green initiatives of each country. This foundation consists of five pillars: 1) Land, 2) Water, 3) Air, 4) Sustainable Productions and 5) Green Transformation. Each pillar consists of multiple indicators (See Appendix for full list and description).

Together, these foundations comprise of 21 weighted pillars. It is important to note that the pillars within each domain do not only associate with other pillars in the domain, but interrelate with pillars across the other foundations, and each pillar should therefore be understood in the wider context of the Index. For example, the Poverty pillar looks at the set of basic material conditions present in everyday life that provide the platform for members of society to attain wellbeing.

For each of the 21 pillars we have identified distinct indicators and interrelations that result a set of 178 distinct policy-focussed indices. Each index has been designed to reflect a discrete policy area that policymakers and others can influence, enabling actionable insight to be generated from the Index to help drive policy and other initiatives.

Following the conceptual framework for measuring welfare presented in the previous chapters, we have created a measured system that includes a complete standardized dataset and the construction of the index. This chapter describes the methodology for the development of the RWI by analyzing 1) the selection of indicators, 2) the compilation of the dataset, 3) the standardization process, 4) development of the index.

A. Selection of Indicators

The goal of selecting and organizing indicators underneath the framework defining welfare has been such as to enable accurate and holistic metrics that are available both at the country and regions level. One of the key characteristic determinants and advantage of the RWI in comparison to previously developed indicators is its context specificity. Stemming from work in anthropology, ethnography and sociology, the philosophy of the RWI considers the heterogeneous definitions and concepts of welfare not just across countries and time but also across regions within each country. To do so, we have collected all possible data at the lowest available disaggregation for European Countries (NUTS 2).

The first set of considerations when selecting indicators for each element is how well these indicators, both in isolation and as a collective grouping, create a good interpretation of the element in question. Both conceptual and statistical reasoning were taken into consideration to identify how well a set of indicators act as a proxy for each element:

- **Supported by academic literature**: We choose indicators where there is wide consensus that they captured the underlying meaning of the aspect of welfare we are interested in. This process involves a systematic literature review as well as a meta-analysis of existing relationships. In parallel, the choice of indicators has been discussed with a panels of global experts which advised indicators were best used;

- **Connection to productive capacity and Cantril's Ladder**: We choose indicators that are plausibly a causal factor of both wealth and wellbeing. To explore this link, we look at two things: (1) the degree of correlation each indicator has with proxies for economic and social wellbeing, namely productive capacity and Cantril's Ladder (see SEM methodology of this section), and (2) the research and academic literature around the causal paths of each indicator, and their connection to wealth and wellbeing. Considering both of these factors, we select indicators that are seen as plausible drivers of fundamental aspects of welfare;

- **Strong internal consistency**: Whilst testing indicators against productive capacity and Cantril's Ladder informs us of the properties of these indicators in isolation, a different type of test is needed to understand the collective qualities of these indicators as part of an overall measurement. Cronbach's alpha provides a measure of internal consistency across a grouping of indicators within each element, testing whether the indicators act as a collective whole. As a general rule of thumb, we look to have Cronbach's alpha values above 0.85 for a collection of indicators within each element, and only opt to break this rule for good conceptual considerations

B. Coverage of Indicators

In terms of coverage, the initial consideration of the Reframing Welfare Index covers the EU27 countries as well as the UK and Norway at the NUTS 2 level between 2000-2021. In order to ensure consistency we looked at:

- Wide coverage of countries: Because we are building a global Index, the data needs to cover a wide range of countries. We choose some indicators with a smaller coverage of countries if this coverage is focussed on lower and middle-income countries, and do not select indicators which have a focus on primarily higher-income countries – for example, indicators from OECD datasets;
- Coverage through time: We intended to create an Index that demonstrates how prosperity has shifted over time, rather than just the current state. To that end, we prefer indicators that capture change over time. We also prefer indicators that will be continue to be measured so that we can use updated data in future editions of the Index.

Using these criteria, we selected 178 indicators underpinning the four foundations of welfare. For a full list of indicators used in the construction of the RWI, please see Appendix. Before the Index could be calculated from these indicators, the issue of missing data points had to first be addressed

C. Complete dataset and Imputations

Reframing Welfare Index as with most composite Indexes, faces the problem of incomplete data. Some data points for some years might be missing for some countries, some indicators might be missing for some countries, and some indicators might be released with time lag. To complete our dataset, we prioritised real data in the following order. Firstly, where missing data are detected for a country, we first use the latest known value for that indicator. For example, indicators with missing data in 2015 are assigned the corresponding values of 2014. Secondly, where data are missing and no prior data or no reliable real data are available for a specific country from the main source for an indicator, augmentation and imputation are employed on a case-by-case basis, as explained in further detail below.

One way we deal with data missing for a country for all years is by inserting values directly based on other sources for the data. For example, the Bertelsmann Stiftung Index gives scores from 0 to 10 for many countries around the world. However, because this source is focused on developing a countries, there are a number of highly developed countries missing. In this case, we give these countries the highest possible score of 10, based on our assessment that this is the score they would receive if they were included. Additionally, in some cases data are not included in a dataset but are obtainable through different means. In these cases, we manually insert accurate data points in the most recent year available.

If we cannot supplement missing data from an appropriate alternative source, we use linear regressions to impute an indicator value based on other independent variables. We use the following independent variables:

- Productive capacity;
- Country groupings;
- Relevant 'driver variables' that have an underlying relationship with the indicator we are seeking to impute.

We select these driver variables based on whether they have a strong conceptual and/or statistical relationship with productive capacity, the element itself, and the indicators needing imputation. In addition, they must have sufficient country coverage so that they cover countries that have indicators missing.

These regressions give us several imputation options. For each indicator, we choose the formula based on the degree of correlation and statistical significance of the driver variables. We have also applied a sense-check to ensure that the implied relationship is consistent with broader research and to avoid risks of overfitting. For example, in imputing data for the indicator "efficiency of seaport services", we used the logistics performance index as a driver variable. This had the advantage of covering a large number of countries, a strong statistical relationship with the efficiency of seaport services, and a strong conceptual argument.

As a result of this process, we choose a main imputation formula. In some cases, it may not be possible for that formula to be used for all countries because it contains a driver variable that covers only some. Therefore, for those countries we choose a fall-back imputation formula that uses a combination of productive capacity and country groupings.

The degree of imputation for each country with over 15% of its indicators imputed is available, broken down by pillar, in the Appendix.

The indicators in the Index are based on many different units of measurement, such as percentages and ordinal scales. These different units need to be normalised for comparisons between indicators and countries to be meaningful. One of the critical decisions is whether or not to take a logarithm of each indicator. In cases where the data distribution is skewed or has long tails, we log-normalise the indicator. For example, the cost in weeks of salary of redundancy for most countries is between 0 and 60 weeks. However, a select few countries have values much higher. Variation of this nature requires normalisation by taking the logarithm of the values, so that different observations can be compared within a narrower data range, and so that extreme variation in a single indicator does not unreasonably affect a countries overall performance. Forty-four indicators are transformed in this manner.

The next step is to normalise each of the 294 indicator values into values between 0 and 1. A distance-to-frontier (DTF) approach is used for this task. The distance-to-frontier approach compares a country's performance in an indicator with the values of the assumed best-case and the worst-case for the indicator. In this way, the country's relative position can be captured by the distance-to-frontier score generated.

For indicators which have logical upper and lower bounds, the best and worst cases might be set at, or close to, their highest and lowest possible values. This scenario mainly applies to indicators with ordinal scales as units of measurement. The indicator "political participation and rights", for instance, is limited to values between 1 and 7, thus its frontiers can be defined according to its logical boundaries.

However, where possible, we set the boundaries such that the normalised values (between 0 and 1) contain a relatively consistent standard deviation across indicators. For indicators with clearly defined logical bounds, this often means the DTF does not rely on 'logical bounds'. That is because, in many cases, the upper or lower logical bound is never actually achieved. This is particularly the case with survey variables.

For indicators whose values can vary on a spectrum that is unlimited at one or both ends, best and worst cases are imposed on the basis of the data collected for the Index since 2009. In cases where it is likely that the historical upper bound will be superseded in the future, as with internet bandwidth, we left room for improvement, incrementally extending the upper bound.

Another key consideration in applying distance-to-frontiers is to decide whether or not there were outliers that should be excluded when selecting best and worst cases. This is done primarily because selecting frontiers to include outliers would result in very little differentiation between the majorities of the other countries. We are typically guided by the 5% and 95% percentiles for observed values in excluding outliers. Selecting frontiers based on these percentiles means that each indicator's distance-to-frontier scores differentiate between states to a similar degree to other indicators, which is crucial when aggregating these scores to create element and pillar scores. We decided to opt for compatibility of distance-to-frontier scores for aggregation over avoiding penalisation of extremely high or low performers.

After we determine the frontiers, the next step is to calculate a country's distance-to-frontier score for each indicator. For a given indicator , if we write and for the frontiers established for this indicator, and for country 's raw value in indicator , then the country's normalised score is given by the following equation:

$$\frac{x_j^1 - V_{min}}{V_{min} - V_{max}} \tag{1}$$

Using distance-to-frontier scores allows direct comparison of values across indicators and countries, and also allows tracking and comparison of a country's performance across years. Since the upper and lower frontiers are fixed across years, changes in a country's year-to-year distance-to-frontier score reflect its improvement or deterioration in the same indicator, pillar, or overall score in absolute terms. Where greater values indicate worse outcomes — for instance, in the case of in the case of the "number of non-tariff measures" indicator — we invert the DTFs, such that higher scores always indicate better performance.

We employ the Structural Equation Modelling approach as it offers several desired characteristics in the construction of a composite index. As our goal is to measure an abstract concept, this implies that we need to find a way to tackle the latent nature of this score while at the same time we need to allow for each distinct item to have its own variance in order to develop a scale score that combines every element in a single dimension i.e. into a unidimensional index. Thus, the model we use to measure this unidimensional index i.e. the measurement model represents concepts that are either narrow or of broader interest (Acock, 2013). A structural equation model consists of the latent variable model and the measurement model (Bollen, 1989).

SEM has a set of desired properties that trigger further analysis and reality tests as the working hypothesis represents the (causal) model. Moreover, by using SEM there is no attempt to generalize the use of the model but to measure the fit between the data and the model. The approach enables hypothesis testing, model diagnostics and measures to assess the goodness of fit, based on statistical techniques. At this point we should mention that this differs from the PCA-based techniques as we do not combine many factors into a single one but rather we specify the factors to be combined allowing them to carry their own variance instead of assuming that the variance of the resulting block explains the variance of the items. Confirmatory factor analysis that is part of the SEM approach offers the advantage of a better treatment of the items' variances isolating their influence on the latent variable leading, potentially, to better results by removing the noise that only blurs the results with no actual explanatory power (Tenenhaus, 2009; Acock, 2013)

The first step to establishing welfare index is registering indicators is matching the indicators, pillars and domains to data available at NUTS-2 level. We compiled a dataset from multiple sources including the Eurobarometer, Eurostat Regional Indicators, National Accounts for public spending across different countries, World Bank and Gallup International.

Then, Indicators in each dimension are transformed into indexes ranged from 0 to 10 in order to get standard value for each indicator using the normalisation method described above. The indicators' indexes are statistically tested by Structural Equation Modeling (SEM) This test is conducted to evaluate the current index welfare calculation as well as the additional indicators. From this step, we can get the final indicators on each dimension by evaluating loading factors of SEM analysis for each individual region.

D. Model and algorithm

Given the nJ data matrix $\mathbf{X}$, the n × K membership matrix $\mathbf{U}$, the K × J centroids matrix C, the J × P loadings matrix $\Lambda = [\Lambda_H, \Lambda_L]$, the n × P latent variables matrix $\mathbf{Y} = [\Xi, H]$, and the errors matrices $\mathbf{Z}$, $\mathbf{E}$ and $\mathbf{D}$, the Partial Least Squares K-Means model can be written as follows:

$$H = HB^T + \Gamma^T \Xi + Z \tag{2}$$

$$X = Y\Lambda^T + E = \Xi\Lambda_H^T + H\Lambda_L^T + E \tag{3}$$

$$X = UC\Lambda\Lambda^T = UC\Lambda_H\Lambda_H^T + UC\Lambda_L\Lambda_L^T + E \tag{4}$$

subject to constraints:

1) $\Lambda\Lambda^T = I$
2) $U \in 0, 1, U1_K = 1_n$

Thus, the PLS-SEM-KM approach includes the PLS-SEM and the clustering method. In fact, the third set of equations is the Reduced K-means model (De Soete and Carroll 1994) and the three sets of equations will produce a partitioning of the units and the corresponding SEM, simultaneously. Moreover, gap method discussed in Tibshirani et al. (2001) is embedded in the PLS-SEM-KM algorithm in order to automatically select the optimal number of clusters. Note that, in the PLS-SEM-KM algorithm the centroid matrix C and the loadings matrix Λ simultaneously converge to an optimal solution that turns out to be at least a local minimum. It is important to remember that the algorithm, given the clustering constraints on U, can be expected to be rather sensitive to local optima. For these reasons the use of a multi-start procedure is recommended, i.e., PLS-SEM-KM is randomly started several times and the best solution is retained (for details on this methodology the reader can refer to Fordellone and Vichi 2020). In fact, in our application we have used 2000 random starts and the results seem to be more stable.

III. Results

As explained in the previous section, the twenty one (21) dimensions in the regional RWI, which derived from a three-phase consultation process and based on Melios and Papadimitriou (2002), were defined with the purpose of providing a tool for policy makers. However, the pillars refect the shared vision of sustainable welfare, i.e., the quality of development. This in turn characterizes a region in which the economic dimension (production, distribution, consumption) is compatible with environmental and social factors, where the social and health services adequately meet the needs of all the citizens, where participation in cultural life is alive, where economic, social and political rights and equal opportunities are guaranteed and where environment is protected. In other words, the selected variables used to construct the RWI, which are dependent upon the interpretation of the representatives of civil society organizations, define the real definition of welfare.

From the results of the RWI indicator it is worth noting that:

1) The distribution of the well-being indicator is symmetrical: the same number of regions are located below and above the average zero-mean. Above the zeromean there is a strong predominance of regions located in the North. Southern provinces with a well-being value above the average are only 19. This result seems to confirm the existence of the dualism between the Northern and the Southern European divergence hypothesis, which is well documented in the economic literature
2) Among the top 15 regions ranked, 7 are Norwegian with scores above 8/10 for 2021.
3) Among the worse 15 regions ranked, 7 are Greek with scores below 4/10 for 2021.
4) The RWI indicators are well-balanced in their dimensions, as suggested by the low values of the mean absolute rank differences. These are calculated as:

$$\frac{1}{n}\sum_{i=1}^{N}|x_i^d - x_i^Q| \tag{5}$$

   where n is the number of regions i, xd is the rank of region i in the dimension d, and xQ is the rank of region i in the overall RWI Q indicator.

The geographical pattern of the RWI indicator is shown Fig. 1, where the distribution of the welfare indicator has been divided in deciles. The darker areas, associated with higher values of the indicator, are mainly located in the North. The map clearly shows the existence of two macro regions and their frontier is geographically represented by the Central regions, with a larger number of lighter areas located in the South. However, the map also shows the presence of intra-region variability in the values of regional welfare indicators within the above-mentioned macro regions. To understand the distribution of the index values across regions, Figure 2 shows the stochastic kernel counter plot between 2020 and 2021. We see that values significantly but symmetrically differ.

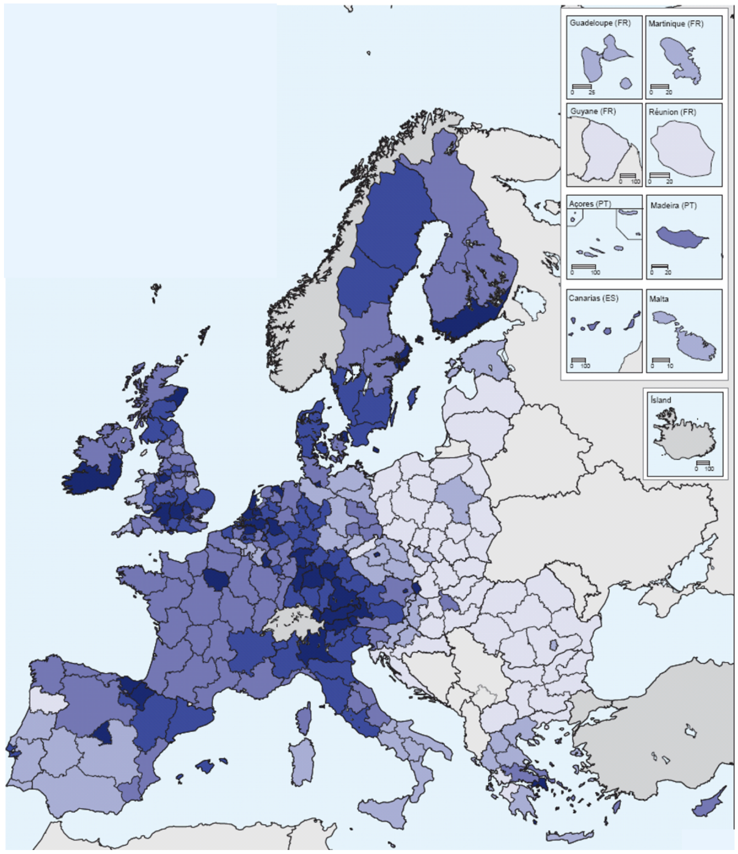

Figure 1. : RWI by region

IV. Sensitivity Analysis

Besides the issue related to the selection of indicators, the problem of summarizing a set of socio-economic variables raises several important problems. The researcher needs to fnd the best suitable method to construct a composite index that depends, among others, on the type of indicator, the type of aggregation, and the type of weights used for constructing the indicator (Maggino and Zumbo 2012; OECD 2008). Therefore, this process is associated with subjective judgments and reveals a high degree of arbitrariness.

In this Section we carry out a sensitivity analysis to assess the impact of the methodology used to construct our base well-being indicator by focusing on (a) how the selected variables are treated with respect to the normalization procedure, the weighting, and aggregation schemes; (b) on the dimensionality issue, that is, how RWI indicator results are sensitive to the inclusion/exclusion of one of its components (Saltelli et al. 2008).

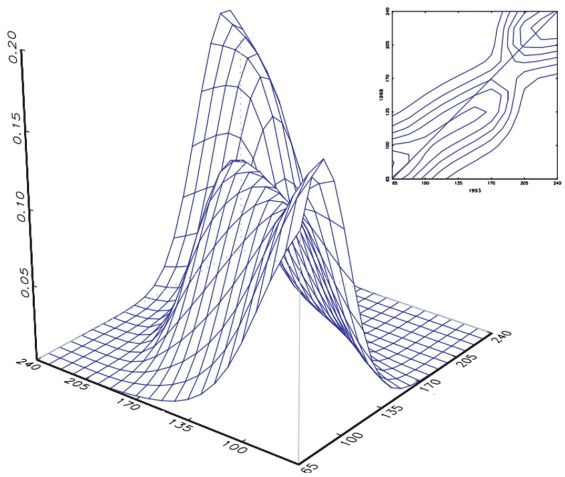

Figure 2. : Stochastic kernel and contour plot of RWI

We also test the impact of outliers on our well-being indicator. Variables with one or more observations with unusually large or small values were trimmed to partially correct for extreme values (we identify outliers as those values of the distribution outside the 2.5 and 97.5 percentile scores (OECD 2008)). The outlier-adjusted well-being indicator shows a large Spearman's rank correlation coefcient (0.90) with the base indicator, which suggests that outliers play only a marginal role in explaining diferences in provincial ranks. Therefore, our analysis retains all observations, outliers included.

A. *Dimentionality*

Finally, we focus on the dimensionality issue, that is, we assess how the fnal RWI is sensitive to the inclusion/exclusion of a single dimension. To this purpose, given that our well-being overall indicator is the aggregation of k dimensions (k=21), we construct k RWI by excluding one dimension at a time.

In Fig. 2 we show the box plots of the k RWI. Again, changes in regional ranking across the k indicators are relatively small. Apart from few provinces, most of them shift only a limited number of positions in the ranking, less than$\pm$20 positions in any of the k indicators, which suggests that our RWI indicator is sensitive to the exclusion of a single dimension only to a very limited extent.

The analysis also shows that, for instance, when we exclude the "Human Rights" dimension, the average absolute mean diferences of ranks is 5.3, and the Spearman's rank correlation with the original RWI is around 0.98. Additionally, the provinces that are shifting more than 5 positions in the new ranking is around 42% of the total number of provinces, which is a percentage considered not too large. Excluding other dimensions leads to a smaller relative number of ranking changes.

V. Discussion

Useful measures of progress and well-being have been proposed over the past few years as alternatives and complements to GDP. However, much of the existing literature on welfare indicators lacked the general consensus on what well-being and progress are and how they are measured. In this work, we constructed constructing a synthetic measure of welfare for European Regions. We followed Melios, Tzivanakis and Papadimitriou (2022) synthetic approach for the dimensions of welfare.

Despite the multidimensionality aspect of the phenomenon and the difficulty of summarizing heterogeneous information in a synthetic indicator, the analysis shows that welfare disparities are still persistent across European Regions, within and across the same country, and that this result is robust towards variations in indicators and in aggregation methodologies.

Results also show that focusing at a more disaggregated territorial level, welfare variability may be large across adjacent territories, a feature that is only marginally accounted for when the analysis is carried out at national level. As such, our study contributes to the existing literature, which is rather limited, as it provides additional information on sub-national welfare endowments and socio-economic disparities.

Moreover, our results show the potential and the need measuring well-being at the regional level that better describes the social and economic context where individuals live. As such, a particularly important issue is that a measure of well-being at regional level has huge implications for the policy-making process. For the European case, as local authorities are the main responsible for implementing decentralized policies in sectors such as education, healthcare, transport and culture, our measure provide an effective tool for governments and local authorities when designing and delivering specific policy responses to economic, environmental and social needs ((Botta and Koźluk, 2014); Taralli, Capogrossi and Perri (2015)).

We believe that, despite our attempt to measure well-being at regional level across countries, there is still room for future research. A great limitation of the well-being indicator constructed in this paper concerns the regularity and the reliability of the data at regional level. Some of the data are "non-conventional", as the indicators built required an ad hoc research, or data from subjective indicators (i.e. Eurobarometer perception questions). Therefore, inferences suggested by such indicators should be considered with care for policy suggestions.

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Appendix

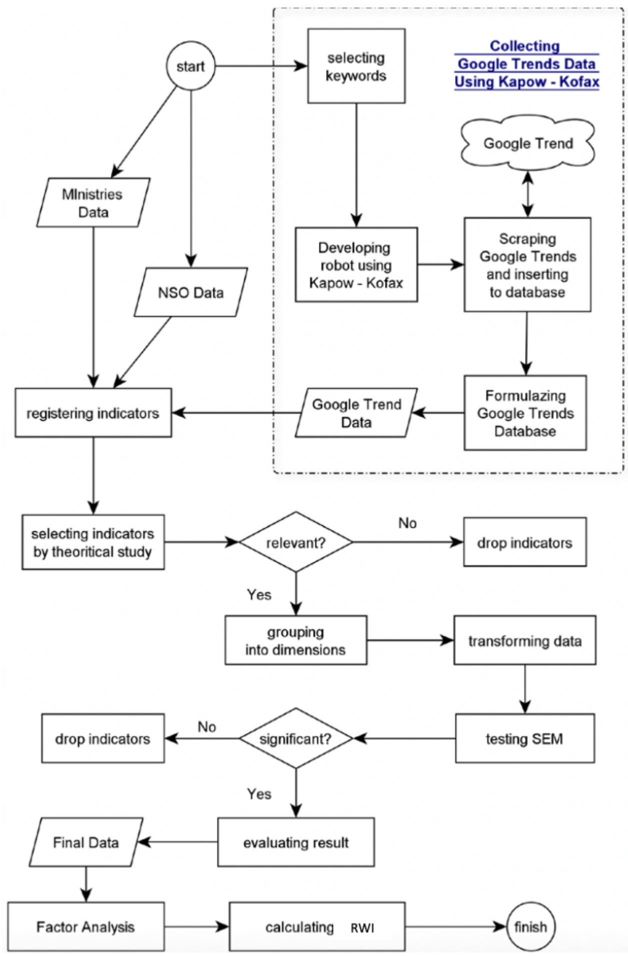

Figure 3. : Process of Estimating RWI

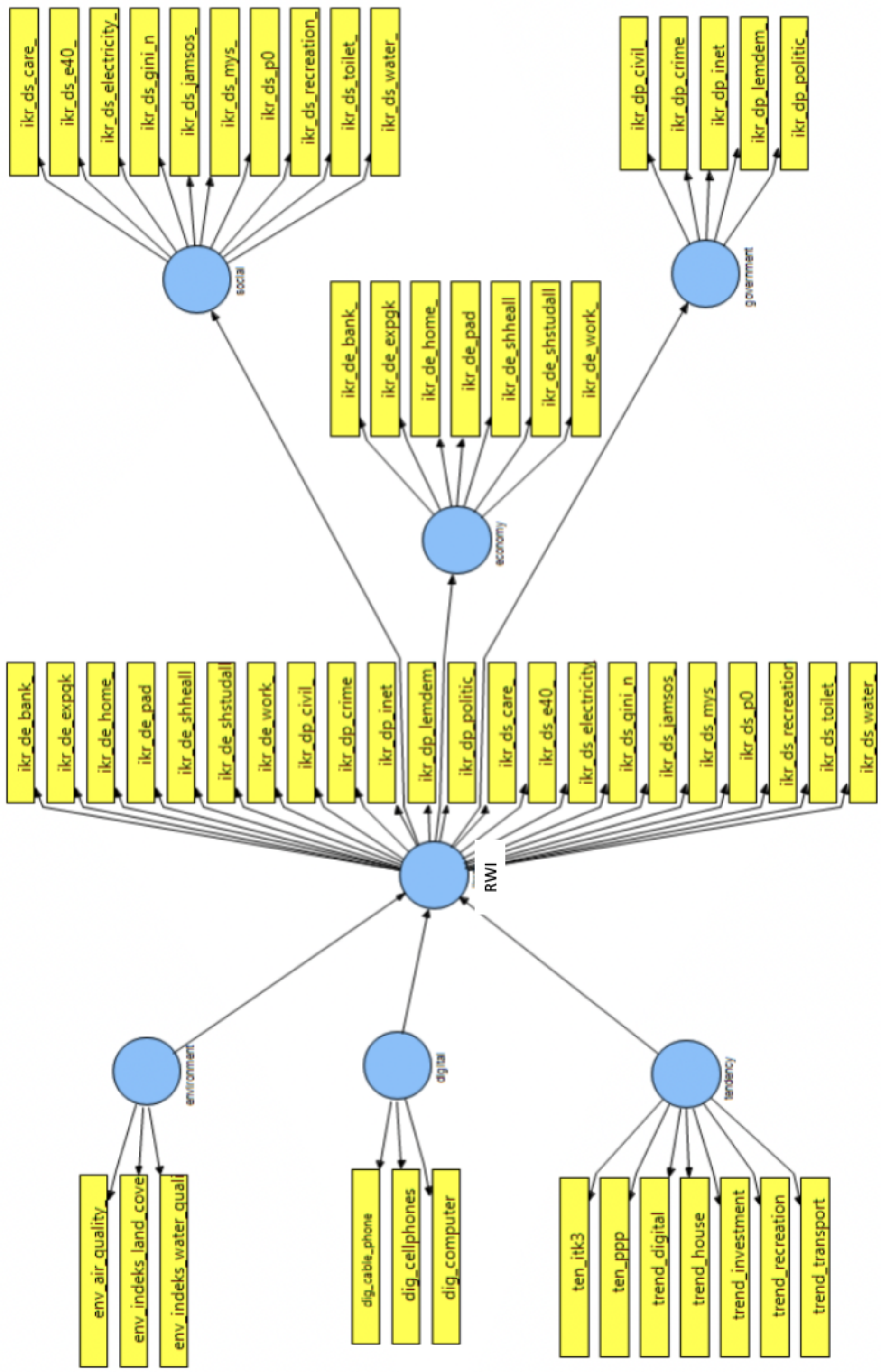

Figure 4. : Simultaneous equations modeling

Country	**Region**	**RWI Region Score**
Austria	Burgenland	7.18
Austria	Lower Austria	7.16
Austria	Vienna	6.31
Austria	Carinthia	7.26
Austria	Styria	7.33
Austria	Upper Austria	7.41
Austria	Salzburg	7.52
Austria	Tyrol	7.60
Austria	Vorarlberg	7.26
Belgium	Brussels-Capital Region	6.31
Belgium	Flemish Region (Vlaams Gewest)	7.56
Belgium	Wallonia (Région wallonne)	6.41
Croatia	Panonska	5.47
Croatia	Jadranska	5.18
Croatia	Grad Zagreb	5.96
Croatia	Sjeverna	5.24
Czech Republic	Prague	6.36
Czech Republic	Central Bohemian Region	5.48
Czech Republic	Southwest	5.79
Czech Republic	Northwest	5.19
Czech Republic	Northeast	5.76
Czech Republic	Southeast	5.79
Czech Republic	Central Moravia	5.89
Czech Republic	Moravia-Silesia	4.83
Cyprus	Cyprus	6.26
Denmark	Copenhagen Region	7.60
Denmark	Zealand	7.16
Denmark	Southern Denmark	7.39
Denmark	Central Jutland	7.61
Denmark	Northern Jutland	7.53
Estonia	North Estonia	6.32
Estonia	West Estonia	5.27
Estonia	Central Estonia	5.95
Estonia	Northeast Estonia	4.53
Estonia	South Estonia	5.66
Finland	Western Finland	7.35
Finland	Helsinki-Uusimaa	7.52
Finland	Southern Finland	7.22
Finland	Eastern and Northern Finland	7.14
Finland	Åland	6.75
France	Île-de-France	6.55
France	Centre - Val de Loire	6.46
France	Bourgogne-Franche-Comté	6.51
France	Normandy	6.21
France	Hauts-de-France	5.79
France	Grand Est	6.35
France	Pays de la Loire	6.93
France	Brittany	6.98
France	Nouvelle-Aquitaine	6.74
France	Occitanie	6.67
France	Auvergne-Rhône-Alpes	6.80
France	Provence-Alpes-Côte d'Azur	6.28
France	Corsica	5.94

Table 1: RWI by region (cont.)

Country	**Region**	**RWI Region Score**
Germany	Baden-Württemberg	7.17
Germany	Bavaria	7.09
Germany	Berlin	6.66
Germany	Brandenburg	6.52
Germany	Bremen	6.71
Germany	Hamburg	7.22
Germany	Hesse	6.88
Germany	Mecklenburg-Vorpommern	6.68
Germany	Lower Saxony	6.95
Germany	North Rhine-Westphalia	6.88
Germany	Rhineland-Palatinate	7.06
Germany	Saarland	6.65
Germany	Saxony	6.79
Germany	Saxony-Anhalt	6.51
Germany	Schleswig-Holstein	7.14
Germany	Thuringia	6.83
Greece	East Macedonia - Thrace	3.59
Greece	Central Macedonia	4.06
Greece	West Macedonia	3.53
Greece	Thessaly	3.92
Greece	Epirus	3.82
Greece	Ionian Islands	3.84
Greece	West Greece	3.91
Greece	Central Greece	3.78
Greece	Peloponnese	4.04
Greece	Attica	4.02
Greece	North Aegean	3.51
Greece	South Aegean	4.13
Greece	Crete	4.41
Hungary	Central Hungary	4.55
Hungary	Central Transdanubia	4.45
Hungary	Western Transdanubia	4.51
Hungary	Southern Transdanubia	4.17
Hungary	Northern Hungary	3.81
Hungary	Northern Great Plain	3.72
Hungary	Southern Great Plain	4.24
Ireland	Northern and Western Region	6.30
Ireland	Southern and Eastern	6.57
Italy	Piedmont	5.74
Italy	Aosta Valley	5.44
Italy	Liguria	5.74
Italy	Lombardy	5.72
Italy	Abruzzo	5.65
Italy	Molise	4.87
Italy	Campania	4.21
Italy	Apulia	4.71
Italy	Basilicata	5.48
Italy	Calabria	4.32
Italy	Sicily	3.80
Italy	Sardinia	5.69
Italy	Bolzano-Bozen	6.36
Italy	Trento	6.57
Italy	Veneto	5.81
Italy	Friuli-Venezia Giulia	6.13
Italy	Emilia-Romagna	5.84
Italy	Tuscany	5.76
Italy	Umbria	5.53
Italy	Marche	5.55
Italy	Lazio	5.76
Latvia	Kurzeme	4.44
Latvia	Latgale	3.17
Latvia	Riga	4.93
Latvia	Pieriga	5.12
Latvia	Vidzeme	3.86
Latvia	Zemgale	4.05

Table 2: RWI by region (cont.)

Country	**Region**	**RWI Region Score**
Lithuania	Alytus	3.96
Lithuania	Kaunas	4.52
Lithuania	Klaipeda	4.48
Lithuania	Marijampole	3.35
Lithuania	Panevežys	4.19
Lithuania	Šiauliai	3.51
Lithuania	Taurage	4.08
Lithuania	Telšiai	4.03
Lithuania	Utena	3.95
Lithuania	Vilnius	4.94
Luxembourg	Luxembourg	7.70
Malta	Malta	6.51
Netherlands	Groningen	7.73
Netherlands	Friesland	7.70
Netherlands	Drenthe	7.83
Netherlands	Overijssel	7.72
Netherlands	Gelderland	7.59
Netherlands	Flevoland	7.44
Netherlands	Utrecht	7.89
Netherlands	North Holland	7.77
Netherlands	South Holland	7.64
Netherlands	Zeeland	7.67
Netherlands	North Brabant	7.76
Netherlands	Limburg	7.44
Norway	Oslo Region	8.42
Norway	Hedmark and Oppland	8.06
Norway	South-Eastern Norway	8.18
Norway	Agder and Rogaland	8.14
Norway	Western Norway	8.35
Norway	Trøndelag	8.47
Norway	Northern Norway	7.96
Poland	Lódzkie	4.14
Poland	Mazowieckie	4.80
Poland	Malopolskie	4.62
Poland	Slaskie	4.21
Poland	Lubelskie	4.26
Poland	Podkarpackie	4.45
Poland	Swietokrzyskie	3.84
Poland	Podlaskie	4.50
Poland	Wielkopolskie	4.74
Poland	Zachodniopomorskie	4.74
Poland	Lubuskie	4.09
Poland	Dolnoslaskie	4.33
Poland	Opolskie	4.10
Poland	Kujawsko-Pomorskie	4.26
Poland	Warminsko-Mazurskie	4.02
Poland	Pomorskie	4.82
Portugal	North	4.78
Portugal	Algarve	4.64
Portugal	Central Portugal	4.86
Portugal	Lisbon	5.51
Portugal	Alentejo	4.52
Portugal	Azores	4.46
Portugal	Madeira	4.07

Table 3: RWI by region (cont.)

Country	**Region**	**RWI Region Score**
Romania	Nord-Vest	6.12
Romania	Centru	5.69
Romania	Nord-Est	5.20
Romania	Sud-Est	5.81
Romania	Sud-Muntenia	5.09
Romania	București-Ilfov	5.69
Romania	Sud-Vest Oltenia	6.00
Romania	Vest	6.23
Slovak Republic	Bratislava Region	5.39
Slovak Republic	West Slovakia	4.59
Slovak Republic	Central Slovakia	4.62
Slovak Republic	East Slovakia	4.39
Slovenia	Eastern Slovenia	5.00
Slovenia	Western Slovenia	5.50
Spain	Galicia	5.73
Spain	Asturias	6.01
Spain	Cantabria	6.34
Spain	Basque Country	6.73
Spain	Navarra	6.81
Spain	La Rioja	5.78
Spain	Aragon	6.35
Spain	Madrid	6.39
Spain	Castile and León	6.13
Spain	Castile-La Mancha	5.64
Spain	Extremadura	5.44
Spain	Catalonia	5.84
Spain	Valencia	5.62
Spain	Balearic Islands	5.87
Spain	Andalusia	5.03
Spain	Murcia	5.70
Spain	Ceuta	4.08
Spain	Melilla	3.96
Spain	Canary Islands	4.96
Sweden	Stockholm	7.35
Sweden	East Middle Sweden	7.11
Sweden	Småland with Islands	7.41
Sweden	South Sweden	7.03
Sweden	West Sweden	7.38
Sweden	North Middle Sweden	7.25
Sweden	Central Norrland	7.40
Sweden	Upper Norrland	7.42
Switzerland	Lake Geneva Region	6.99
Switzerland	Espace Mittelland	7.42
Switzerland	Northwestern Switzerland	7.45
Switzerland	Zurich	7.53
Switzerland	Eastern Switzerland	7.63
Switzerland	Central Switzerland	7.86
Switzerland	Ticino	6.78
United Kingdom	North East England	6.99
United Kingdom	North West England	7.19
United Kingdom	Yorkshire and The Humber	7.12
United Kingdom	East Midlands	7.54
United Kingdom	West Midlands	7.33
United Kingdom	East of England	7.61
United Kingdom	Greater London	7.55
United Kingdom	South East England	7.84
United Kingdom	South West England	7.82
United Kingdom	Wales	7.24
United Kingdom	Scotland	7.51
United Kingdom	Northern Ireland	7.03

Table 4: RWI by region (cont.)

Country	Region	RWI	Formal Institutions	Human Rights	Informal Institutions	Freedom	Social Capital
Norway	Trøndelag	8.47	8.13	9.04	9.46	8.13	10.04
Norway	Oslo Region	8.42	8.08	8.99	9.40	8.08	9.98
Norway	Western Norway	8.35	8.01	8.91	9.32	8.01	9.89
Norway	South-Eastern Norway	8.18	7.85	8.73	9.13	7.85	9.70
Norway	Agder and Rogaland	8.14	7.81	8.70	9.09	7.81	9.65
Norway	Hedmark and Oppland	8.06	7.73	8.61	9.00	7.73	9.55
Norway	Northern Norway	7.96	7.64	8.50	8.89	7.64	9.43
Netherlands	Utrecht	7.89	7.57	8.42	8.81	7.57	9.35
Switzerland	Central Switzerland	7.86	7.54	8.39	8.78	7.54	9.32
United Kingdom	South East England	7.84	7.52	8.37	8.76	7.52	9.29
Netherlands	Drenthe	7.83	7.51	8.36	8.74	7.51	9.28
United Kingdom	South West England	7.82	7.50	8.35	8.73	7.50	9.27
Netherlands	North Holland	7.77	7.46	8.30	8.68	7.46	9.21
Netherlands	North Brabant	7.76	7.45	8.29	8.67	7.45	9.20
Netherlands	Groningen	7.73	7.41	8.25	8.63	7.41	9.16
Netherlands	Overijssel	7.72	7.40	8.24	8.61	7.40	9.14
Netherlands	Friesland	7.70	7.39	8.23	8.60	7.39	9.13
Luxembourg	Luxembourg	7.70	7.39	8.22	8.59	7.39	9.12
Netherlands	Zeeland	7.67	7.36	8.19	8.57	7.36	9.09
Netherlands	South Holland	7.64	7.33	8.16	8.53	7.33	9.06

Table 5: Top 20 Regions for Just Societies

Country	Region	RWI	Poverty	Education	Health	Access	Wealth	Security
Norway	Trøndelag	8.47	7.10	9.91	8.08	9.07	6.64	10.88
Norway	Oslo Region	8.42	7.06	9.85	8.03	9.01	6.60	10.81
Norway	Western Norway	8.35	6.99	9.77	7.96	8.93	6.54	10.72
Norway	South-Eastern Norway	8.18	6.85	9.57	7.80	8.76	6.41	10.50
Norway	Agder and Rogaland	8.14	6.82	9.53	7.77	8.72	6.38	10.46
Norway	Hedmark and Oppland	8.06	6.75	9.43	7.69	8.63	6.32	10.35
Norway	Northern Norway	7.96	6.67	9.31	7.59	8.52	6.24	10.22
Netherlands	Utrecht	7.89	6.61	9.23	7.52	8.44	6.18	10.13
Switzerland	Central Switzerland	7.86	6.59	9.20	7.50	8.42	6.16	10.10
United Kingdom	South East England	7.84	6.57	9.18	7.48	8.39	6.15	10.07
Netherlands	Drenthe	7.83	6.56	9.16	7.47	8.38	6.14	10.05
United Kingdom	South West England	7.82	6.55	9.15	7.46	8.37	6.13	10.04
Netherlands	North Holland	7.77	6.51	9.10	7.41	8.32	6.09	9.98
Netherlands	North Brabant	7.76	6.50	9.08	7.40	8.31	6.08	9.96
Netherlands	Groningen	7.73	6.47	9.04	7.37	8.27	6.06	9.92
Netherlands	Overijssel	7.72	6.46	9.03	7.36	8.26	6.05	9.91
Netherlands	Friesland	7.70	6.46	9.01	7.35	8.25	6.04	9.89
Luxembourg	Luxembourg	7.70	6.45	9.01	7.34	8.24	6.03	9.88
Netherlands	Zeeland	7.67	6.43	8.98	7.32	8.21	6.01	9.85
Netherlands	South Holland	7.64	6.40	8.94	7.29	8.18	5.99	9.81

Table 6: Top 20 regions for Secured Livelihoods

Country	Region	RWI	Output	Employment	Business Environment	Investment Environment	Innovation
Norway	Trøndelag	8.47	6.11	9.09	8.24	7.21	9.27
Norway	Oslo Region	8.42	6.07	9.04	8.19	7.17	9.22
Norway	Western Norway	8.35	6.02	8.96	8.12	7.11	9.14
Norway	South-Eastern Norway	8.18	5.90	8.78	7.96	6.97	8.96
Norway	Agder and Rogaland	8.14	5.87	8.74	7.92	6.93	8.92
Norway	Hedmark and Oppland	8.06	5.81	8.65	7.84	6.86	8.82
Norway	Northern Norway	7.96	5.74	8.55	7.74	6.78	8.71
Netherlands	Utrecht	7.89	5.69	8.47	7.68	6.72	8.64
Switzerland	Central Switzerland	7.86	5.67	8.44	7.65	6.69	8.61
United Kingdom	South East England	7.84	5.66	8.42	7.63	6.68	8.58
Netherlands	Drenthe	7.83	5.65	8.41	7.62	6.67	8.57
United Kingdom	South West England	7.82	5.64	8.39	7.61	6.66	8.56
Netherlands	North Holland	7.77	5.61	8.35	7.56	6.62	8.51
Netherlands	North Brabant	7.76	5.60	8.33	7.55	6.61	8.50
Netherlands	Groningen	7.73	5.57	8.30	7.52	6.58	8.46
Netherlands	Overijssel	7.72	5.56	8.28	7.51	6.57	8.45
Netherlands	Friesland	7.70	5.56	8.27	7.50	6.56	8.43
Luxembourg	Luxembourg	7.70	5.55	8.26	7.49	6.55	8.43
Netherlands	Zeeland	7.67	5.53	8.24	7.46	6.53	8.40
Netherlands	South Holland	7.64	5.51	8.20	7.43	6.51	8.36

Table 7: Top 20 regions for Open Economies

Country	Region	RWI	Land	Water	Air	Sustainable Productions	Green Transformation
Norway	Trøndelag	8.47	3.55	6.18	3.77	6.98	7.10
Norway	Oslo Region	8.42	3.53	6.15	3.75	6.94	7.06
Norway	Western Norway	8.35	3.50	6.09	3.71	6.88	6.99
Norway	South-Eastern Norway	8.18	3.43	5.97	3.64	6.74	6.85
Norway	Agder and Rogaland	8.14	3.41	5.94	3.62	6.71	6.82
Norway	Hedmark and Oppland	8.06	3.38	5.88	3.58	6.64	6.75
Norway	Northern Norway	7.96	3.33	5.81	3.54	6.56	6.67
Netherlands	Utrecht	7.89	3.30	5.76	3.51	6.50	6.61
Switzerland	Central Switzerland	7.86	3.29	5.74	3.50	6.48	6.59
United Kingdom	South East England	7.84	3.29	5.72	3.49	6.46	6.57
Netherlands	Drenthe	7.83	3.28	5.71	3.48	6.45	6.56
United Kingdom	South West England	7.82	3.27	5.70	3.48	6.44	6.55
Netherlands	North Holland	7.77	3.26	5.67	3.46	6.41	6.51
Netherlands	North Brabant	7.76	3.25	5.66	3.45	6.40	6.50
Netherlands	Groningen	7.73	3.24	5.64	3.44	6.37	6.47
Netherlands	Overijssel	7.72	3.23	5.63	3.43	6.36	6.46
Netherlands	Friesland	7.70	3.23	5.62	3.43	6.35	6.46
Luxembourg	Luxembourg	7.70	3.22	5.62	3.42	6.35	6.45
Netherlands	Zeeland	7.67	3.21	5.60	3.41	6.32	6.43
Netherlands	South Holland	7.64	3.20	5.58	3.40	6.30	6.40

Table 8: Top 20 regions for Sustainable Environment

Country	**Region**	**RWI**
Norway	Trøndelag	8.47
Norway	Oslo Region	8.42
Norway	Western Norway	8.35
Norway	South-Eastern Norway	8.18
Norway	Agder and Rogaland	8.14
Norway	Hedmark and Oppland	8.06
Norway	Northern Norway	7.96
Netherlands	Utrecht	7.89
Switzerland	Central Switzerland	7.86
United Kingdom	South East England	7.84
Netherlands	Drenthe	7.83
United Kingdom	South West England	7.82
Netherlands	North Holland	7.77
Netherlands	North Brabant	7.76
Netherlands	Groningen	7.73
Netherlands	Overijssel	7.72
Netherlands	Friesland	7.70
Luxembourg	Luxembourg	7.70
Netherlands	Zeeland	7.67
Netherlands	South Holland	7.64
Greece	Attica	4.02
Spain	Melilla	3.96
Lithuania	Alytus	3.96
Lithuania	Utena	3.95
Greece	Thessaly	3.92
Greece	West Greece	3.91
Latvia	Vidzeme	3.86
Poland	Swietokrzyskie	3.84
Greece	Ionian Islands	3.84
Greece	Epirus	3.82
Hungary	Northern Hungary	3.81
Italy	Sicily	3.80
Greece	Central Greece	3.78
Hungary	Northern Great Plain	3.72
Greece	East Macedonia - Thrace	3.59
Greece	West Macedonia	3.53
Greece	North Aegean	3.51
Lithuania	Šiauliai	3.51
Lithuania	Marijampole	3.35
Latvia	Latgale	3.17

Table 9: Top 20 and Worse 20 regions