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# MEASURING ECO-INNOVATION: TOWARDS BETTER POLICIES TO SUPPORT GREEN GROWTH

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## Abstract

Green growth strategies thus need to be robust, what requires carefully designed tools. One of the prerequisites is the appropriate green growth measurement framework. It should allow discerning the effectiveness of policies in delivering green growth. This is where this paper tries to offer a new angle by searching for appropriate indicators that can capture different aspects of eco-innovation. Eco-innovation can be defined as innovation that results in a reduction of environmental impact. Country data from the 2008 Community Innovation Survey is used in the analysis. Dataset consist of 14 variables on environmental benefits and motivations. The aim of the presented study is to reduce the number of variables into factors to discover which of available variables form coherent subsets. It is argued here that such approach can help to construct appropriate indicators, that can capture different aspects of eco-innovation, that are crucial from the point of view of policy-making and policy evaluation.

**Keywords:** eco-innovation, community innovation survey, green growth.

**JEL classification:** O3.

## Introduction

In the times of major economic challenges at a global scale innovation has been perceived as a way of overcoming difficulties, ensuring and preserving economic growth and, in consequence, addressing social problems more effectively. Global social challenges such as climate change, food security, availability of drinking water and health protection should not be forgotten. In this respect, innovation has been and still can be a principal factor in the improvement of living standards and moving manufacturing industries towards sustainable production. In 2009, 34 countries signed a Green Growth Declaration, to step up efforts to pursue green growth strategies for achieving economic growth while at the same time combating climate change[1]. Green growth means economic growth and development, while ensuring that natural assets continue to provide the resources. This actually means a significant change to established ways of doing things and naturally may have profound impacts on consumer habits, technology, and infrastructure.

Green growth can open up new sources of growth through innovation, increase of productivity, creation of new markets of green technologies and products. All of these may lead to new job opportunities. Greater efficiency of the use of natural resources is of special importance, not only for its positive environmental impact, but also due to its potential to increase of productivity. This cannot be achieved without innovation, and it does not limit to technological innovation only, but expands over non-technological changes, as new business models or city planning. However, no rose without thorn: no government has all the resources needed to implement green growth, as for example, resource scarcity makes infrastructure more capital-intensive. Indeed, inadequate infrastructure is one among many green growth constraints, together with low returns to R&D in particular and low overall economic returns in general, regulatory uncertainty, lack of innovation capability, technological barriers, insufficient demand, underpricing of environmental externalities.

Green growth strategies thus need to be robust, what requires carefully designed tools. Among the most basic is the appropriate green growth measurement framework. The indicators must cover the crucial areas of environmental and resource productivity, economic and environmental assets, environmental quality of life, economic opportunities and policy response[2]. The measurement framework should allow capturing the need for efficient use of natural capital, the direct impacts of the environment on people's lives, and most importantly help discern the effectiveness of policy in delivering green growth. This is where this paper tries to offer a new angle by searching for appropriate indicators that can capture different aspects of eco-innovation.

As innovation plays an important role in shaping the growth and competitiveness of firms, it is also crucial in moving industries towards sustainable production. In that it can be regarded as contribution of business to sustainable development. Eco-innovation can be defined as innovation that results in a reduction of environmental impact. In other words, it is a new or significantly improved product, process, organizational method or marketing method that creates environmental benefits compared to alternatives. The environmental benefits of an innovation can occur during the production, or during the after sales use of a good or service by the end user.

The data from the 2008 Community Innovation Survey is used in the analysis[3]. The Community Innovation Survey (CIS) is a survey conducted every two years by EU Member States to monitor progress on innovation, based on the Oslo Manual framework[4]. CIS 2008, in contrast to previous surveys, introduced questions about also on organizational and marketing innovation. CIS 2008 questionnaire included also a voluntary one-page module on ECO-innovation. The aim of the presented study is to reduce the number of variables into different factors (concepts) which different patterns of eco-innovation among countries, and to discover which of available variables form a coherent subsets. It is argued here that such approach can help to construct appropriate indicators, that can capture different aspects of eco-innovation, that are crucial from the point of view of policy-making and policy evaluation.

## 1. Methodology

Application of multidimensional exploratory techniques like factor analysis used here raise the potential of revealing hidden patterns of eco-innovation. Specifically, this is done by examination which of variables measuring eco-innovation characteristics in some sense stick together, leading to formation of summary joint indicators of eco-innovation, which add to the traditional measures of based on single indicators. To reveal these patterns, factor analysis and k-means clustering are used, supported by biplot and dendrogram visualization techniques.

The aim of factor analysis is to reduce the number of variables and to detect structure in the relationships between variables that is to classify variables. In the sense of exploratory analysis, it is a technique for data reduction, It reduces the number of variables in an analysis by creation of linear combinations of the variables that contain most of the information and that admit meaningful interpretations. The variables of a subset are correlated with one another and the strength of their correlation is summarized in factor loadings. Generally, variables, which score high in one factor, are largely independent of other factors. Factor analysis is used here to derive different practices of eco-innovation. An advantage is that the factor analysis provides actual indicators in the form of a set of factor scores for each firm, which can be used in further analysis, as it is done in this case (i.e. k-means clustering). We expect to be able to identify factors linked to different patterns of eco-innovation, which will then be interpreted. An advantage of the factor analysis is that it provides indicators that are uncorrelated with one another.

After the factor analysis the resulting factor scores are fed into biplot, dendrogram and non-hierarchical k-means cluster analyses with the aim of classifying countries by different modes of eco-innovation[5]. Clustering techniques allow for grouping objects of similar kind into respective categories thus discovering structures in data. In general, the k-means method produce *k* different clusters of greatest possible distinction. Usually, as the result of a k-means clustering analysis, the means for each cluster on each variable are examined to assess how distinct the clusters are[6]. Cluster analysis based on the factor scores is done in order to analyze if the eco-innovation characteristics of countries follow a specific pattern.

To get the initial insight underlying patterns, visual inspection of biplot and dendrogram is proposed. Biplots[7] are a typo of exploratory graphs simultaneously displaying the relative positions of observations and variables. Observations are projected to two or three dimensions in way that preserves the approximately distance between the observations[8]. The angle between arrows representing variables approximates the correlation between them. Dendrogram is a standard output from hierarchical clustering. It presents a hierarchy of clusters obtained based on some similarity measure. Each node in a dendrogram, where a new cluster is formed, is placed over the distance at which the elements were linked together forming a new cluster[9]. Dendrogram is formed based on the choice of distance measure and linkage rule to determine the distances between clusters.

## 2. Results

The presented methods were used to analyze the data for the European Union countries from the results of Community Innovation Survey (2008). The survey covered the period of 2006–2008. The whole set of available indicators was used for the total of 22 countries. The exact list is presented here, with short names of variables used later on (codes in parentheses). First is the group are the indicators of environmental benefits from the production of goods or services within the enterprise: reduced material use per unit of output (*peb_rmu*), reduced energy use per unit of output (*peb_reu*), reduced $CO^2$ 'footprint' (*peb_rco2*), replaced materials with less polluting or hazardous substitutes (*peb_lps*), reduced air, water, soil or noise pollution (*peb_rp*), recycled waste, water, or materials (*peb_rec*). Second is the list of environmental benefits indicators from the after sales use of a good or service by the end-user: reduced energy use (*eueb_reu*), reduced air, water, soil or noise pollution (*eueb_rp*), improved recycling of product after use (*eueb_rec*). Then follow motivation indicators: existing environmental regulations or taxes on pollution (*m_exreg*), environmental regulations or taxes expected to be introduced in the future (*m_expreg*), government grants, subsidies or other financial incentives for environmental innovation (*m_govaid*), current or expected market demand from customers for environmental innovations (*m_mardem*) and voluntary codes or agreements for environmental good practice within sector (*m_goodpr*).

Table 1. Summary statistics of eco-innovation indicators ($n$ = 22)

| | Mean | Median | Min | Max | Lower quartile | Upper quartile | Standard deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|
| peb_rmu | 24.923 | 25.70 | 10.8 | 38.8 | 20.2 | 29.3 | 7.635 | –0.196 | –0.334 |
| peb_reu | 27.564 | 28.40 | 11.7 | 46.4 | 23.5 | 32.9 | 8.826 | –0.025 | –0.027 |
| peb_rco2 | 19.595 | 17.70 | 6.0 | 38.5 | 13.4 | 25.9 | 8.414 | 0.503 | –0.219 |
| peb_lps | 23.332 | 24.10 | 8.2 | 41.3 | 19.8 | 26.5 | 7.023 | 0.056 | 1.744 |
| peb_rp | 25.050 | 24.25 | 10.0 | 46.2 | 21.3 | 28.2 | 9.300 | 0.456 | 0.413 |
| peb_rec | 29.668 | 28.55 | 8.6 | 58.5 | 21.5 | 38.8 | 13.202 | 0.402 | –0.121 |
| eueb_reu | 25.405 | 25.50 | 5.4 | 44.0 | 19.8 | 30.7 | 8.996 | –0.268 | 0.564 |
| eueb_rp | 21.532 | 20.90 | 6.1 | 38.8 | 16.9 | 27.5 | 9.048 | 0.069 | –0.332 |
| eueb_rec | 20.868 | 18.85 | 5.6 | 41.8 | 13.8 | 29.2 | 9.416 | 0.464 | –0.107 |
| m_exreg | 24.082 | 23.90 | 7.2 | 41.3 | 15.8 | 35.7 | 11.178 | 0.052 | –1.143 |
| m_expreg | 18.432 | 18.05 | 5.3 | 34.5 | 12.3 | 23.8 | 7.884 | 0.276 | –0.339 |
| m_govaid | 6.841 | 6.85 | 2.4 | 12.8 | 4.4 | 8.4 | 2.869 | 0.378 | –0.248 |
| m_mardem | 16.700 | 14.85 | 3.9 | 31.9 | 13.0 | 19.6 | 7.188 | 0.451 | 0.306 |
| m_goodpr | 23.086 | 24.10 | 5.2 | 43.2 | 14.8 | 29.1 | 9.840 | 0.376 | –0.287 |

Source: own calculations.

First correlation matrices are computed, and after that the factor analysis is performed. The general rule suggesting to retain factors which have eigenvalues greater than 1 was applied, and the decision was made to include three factors. Principal component analysis and varimax rotation were used to generate the factors. The factor loadings are correlation coefficients between the initial variables and factors, squared factor loadings is a percentage of variance in a variable, explained by a factor. Analysis of factor loadings enables to interpret the factors. Table 2 present factor loadings obtained for the dataset, based on the Pearson correlation.

Table 2. Factor loadings (pattern matrix) after rotation*

| | Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|
| Environmental benefits from the production of goods or services: | | | |
| – reduced material use per unit of output (*peb_rmu*) | | | 0.6147 |
| – reduced energy use per unit of output (*peb_reu*) | 0.7412 | | |
| – reduced $CO^2$ 'footprint' (*peb_rco2*) | 0.7874 | | |
| – replaced materials with less polluting or hazardous substitutes (*peb_lps*) | | | 0.6736 |
| – reduced air, water, soil or noise pollution (*peb_rp*) | 0.8674 | | |
| – recycled waste, water, or materials (*peb_rec*) | 0.8259 | | |
| Environmental benefits indicators from the after sales use of a good or service by the end-user: | | | |
| – reduced energy use (*eueb_reu*) | 0.9083 | | |
| – reduced air, water, soil or noise pollution (*eueb_rp*) | 0.8633 | | |
| – recycled waste, water, or materials (*peb_rec*) | 0.8925 | | |
| Motivation: | | | |
| – existing environmental regulations or taxes on pollution (*m_exreg*) | | 0.9235 | |
| – environmental regulations or taxes expected in the future (*m_expreg*) | | 0.8987 | |
| – government grants, subsidies or other financial incentives (*m_govaid*) | | 0.6374 | |
| – current or expected market demand from customers (*m_mardem*) | | | 0.7380 |
| – voluntary codes, agreements for good practice (*m_goodpr*) | | | 0.6660 |

*) values below 0,3 are suppressed.

Source: `own calculations.

The results presented in the table show that factor 1 is strongly related to environmental benefits from the after sales use of a good or service by the end-user (*eueb_reu*, *eueb_rp*, *eueb_rec*) and most of the environmental benefits from the production of goods or services within the enterprise (*peb_reu*, *peb_rco2*, *peb_rp*, *peb_rec*), except reduced material use per unit of output and replacement of materials with less polluting or hazardous substitutes. Interestingly, variables related to existing environmental regulations or taxes on pollution (*m_exreg*), expected environmental regulations or taxes in the future and government grants (*m_expreg*) and subsidies or other financial incentives for environmental innovation (*m_govaid*) load up strongly on factor 2. Factor 3 represents variables related to current or expected market demand from customers for environmental innovations (*m_mardem*), voluntary codes or agreements for environmental good practice within sector and materials (*m_goodpr*), reduced material use per unit of output (*peb_rmu*) and replaced materials with less polluting or hazardous substitutes (*peb_lps*). It is thus reasonable to interpret the second factor as one representing strong motivations in reaction or related to public policy measures, the third representing good will and basic eco-innovations in terms of reduced or replaced materials. The first factor integrates all the remaining indicators of environmental benefits, both internal and external. Therefore it seems, at least from the point of view of the factor analysis, that the major differentiating factors among countries are those related to motivations. This is further confirmed by the analysis of biplot.

Figure 1 presents the biplot based on factor scores. The plot is constructed such that it tries to visualize the maximum possible amount of information in the data. We naturally observe similar angles between the arrows representing variables as factor analysis leads to produce uncorrelated factors. The plot shows some of the main characteristics of the countries. Lithuania is, for example, strong on factor 2. Interestingly Finland, Estonia and to some degree Hungary are all strong on the third factor. Seven countries, however, are placed along the first factor.

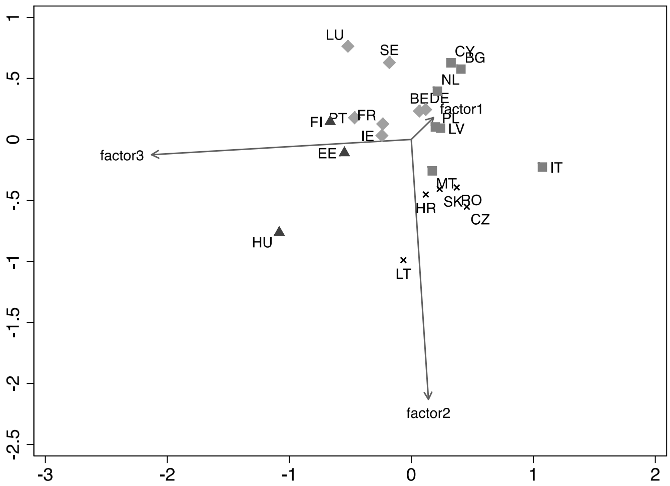


Fig. 1. Biplot based on factor scores

Source: own calculations.

Clustering techniques can be broadly divided into overlapping, partitional, and hierarchical. The advantage of the last one is its ability to produce meaningful visual representations of the similarity structure of objects by means of dendrogram. Figure 2 presents results of hierarchical clustering based on the same factor scores used before in biplot. Euclidean distance and Ward's amalgamation method were chosen to construct the tree diagram.

Biplot illustrates the strengths of countries in terms of factors, dendrogram stresses the similarities among countries. Obviously, the choice of the similarity measure and linkage rule impacts the result, nevertheless it is very useful in a sense that it provides clear and detailed visualization of the underlying similarities. However, caution should be used when defining groups based on cluster analysis, as different approaches may yield different results.

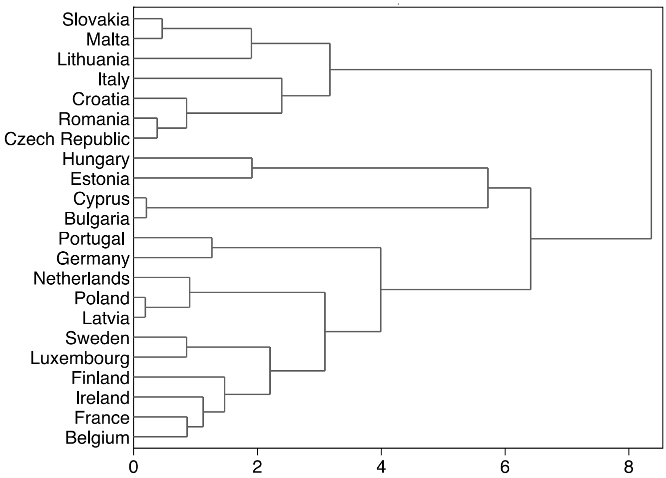


Fig. 2. Dendrogram of countries based on factor scores

Source: own calculations.

Table 3. Factor loadings (pattern matrices) after rotation for countrywide and regional data (based on the Pearson correlation, innovation active firms only)*

| Group 1 | Group 2 | Group 3 | Group 4 |
|---|---|---|---|
| Luxembourg | Italy | Hungary | Lithuania |
| Ireland | Poland | Finland | Czech Republic |
| France | Bulgaria | Estonia | Croatia |
| Germany | Netherlands | | Romania |
| Sweden | Malta | | Slovakia |
| Belgium | Latvia | | |
| Portugal | Cyprus | | |

Source: own calculations.

Hierarchical clustering is a very efficient method to visualize the similarities among objects, giving a quick insight into the dataset. However, as it tends to create clusters of small size, k-means clustering was used to obtain specified number of separate groups. There are different methods to choose the number of clusters. One of the quite efficient is the index of Caliński and Harabasz[10]. To confirm the choice based on the index, the analysis was further complemented by the inspection of clustergram. Both methods suggested grouping into four clusters. Table 3 presents obtained groups. It's interesting to relate these results to the biplot. To facilitate this the observations on the plot were marked according to cluster membership.

This comparison shows that both methods lead to coherent results, as the cluster members are apparently fairly close to each other. It is also interesting to note that the clusters quite well correspond to the dendrogram.

Summary of factor scores in resulting clusters are presented by means of box plot (for quartiles, Figure 3). Profiles of the groups based on the factor scores are recognizably different. First group consist of members strong on the first factor, weak on the second and average on the third. Second group is low on all factors. Third cluster is composed of three countries, with low values of the first, average values of the second factor and high values of the third one. The forth group shows low variation of the second and third factor among its members.

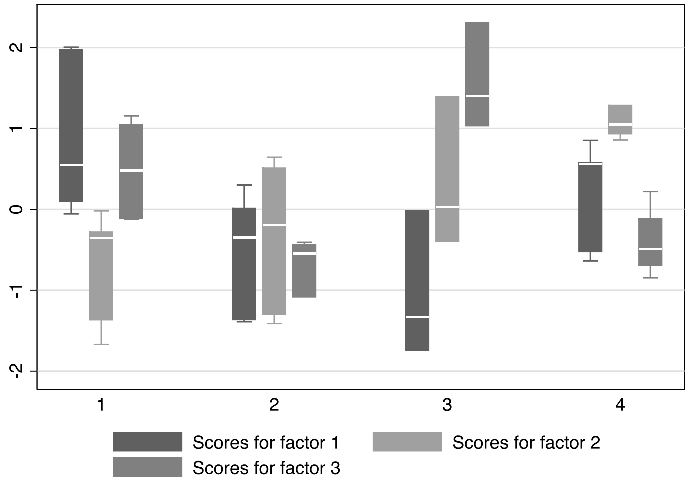


Fig. 3. Summary of factor scores for the clusters

Source: own calculations.

Luxembourg, Ireland, France, Germany, Sweden, Belgium and Portugal are active players in the field of eco-innovation, being strong both on environmental benefits and good will. Italy, Malta, Netherlands, Poland, Latvia, Bulgaria and Cyprus constitute the group of countries lagging behind in terms of all three aspects of eco-innovation. Hungary, Finland and Estonia are even stronger on good will indictor, being also motivated by public policies, however performing below the average in terms of actual environmental benefits. Czech Republic, Slovakia, Lithuania, Romania and Croatia react to public policies, with, however, mediocre performance, and rather indifferent attitude to eco-innovation (low values of good will factor).

Table 4. The correlation coefficients between the factors and basic innovation indicators

| | Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|
| Proportion of innovative enterprises | 0.295 | –0.173 | *0.454*[*] |
| Turnover from new or significantly improved products new to the market[*] | –0.164 | 0.372 | –0.216 |

[*] significant at $\alpha = 0,05$.

Source: own calculations.

In the last part of the analysis correlation between factors and two basic innovation indicators were examined. The most striking result to emerge from the data is the significant correlation coefficient between the third factor and the proportion of innovative enterprises. The factor represents good will and basic eco-innovations in terms of reduced or replaced materials. It may suggest that the basic eco-innovation achievements are relatively strongly related to the good will and voluntary codes of practices with the prerequisite of being innovative at all. In other words, those being innovative also tend to be more aware of eco-innovation. Another interesting result is the correlation between second factor and turnover from innovative products. This factor depicts strong motivations in reaction or related to public policy measures, including government grants, subsidies or other financial incentives for environmental innovation. Hence, it could be hypothesized that financial incentives, to some degree, facilitate market success of innovations as measured by turnover from new or significantly improved products.

## Conclusions

In the paper factor analysis and clustering methods are applied, to depict associations between variables, which allows for interesting visual inspection of the underlying patterns, enabling effective interpretation. An advantage is that the factor analysis provides new indicators in the form of a set of factor scores for each country, which can be used in further analysis, as it is done in this case (i.e. k-means clustering). Naturally, the results suggest that further research needs to be done to examine whether depicted patterns are confirmed, using new data from future waves of community innovation survey, if the eco-innovation module would be repeated.

Strong interrelation between good will and codes of practice with actual eco-innovation stresses the voluntary dimension of eco-innovation as very important (see factor 3 in Table 2). It is confirmed by the fact that the strongest relationship was found between good practice and innovation, and that it is mirrored by the relationship between policy tools and turnover from innovative products (Table 4). This study has found that generally the motivations are the main driving force and differentiating factor, with those related to market demand inducing the eco-innovation, and those related to public policy measures impacting the financial market success. It seems that both kind of motivations are equally needed to obtain the ambitious goals of green growth strategies.

This leads to the observation that user-driven innovation can be a very effective transmission belt for green growth policy. One of the possibly most effective policy tools might be effective shaping of consumer awareness. Actually, one can observe a significant trend in that matter, as more and more enterprises tend to stress their environmental responsibility, as a tool to build up a positive image. Another important conclusion is that to ensure successful eco-innovation policy, the carefully designed initiatives need to be directed to innovative enterprises, accompanied by general innovation capacity building. It's hard to pursue an effective eco-innovation policy in non-innovative environment. Those capable of innovating may be better shaped to be eco-friendly.

## Notes

[1] OECD (2011a, 2011b).
[2] *Eco-innovation indicators* (2006).
[3] Eurostat (2012).
[4] OECD, Eurostat... (2005).
[5] See Batóg, Wawrzyniak (2010) and Frenz, Lambert (2008) for discussion on similar cluster analysis applications.
[6] Gatnar (2002); Jajuga, Walesiak, Bąk (2003); Walesiak, Dudek (2007).
[7] Gabriel (1971); Gabriel (2002).
[8] Rozkrut (2006).
[9] Duda, Hart, Stork (2001).
[10] Caliński, Harabasz (1974); Milligan, Cooper (1985).

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