Fuzzy Measures and Experts' Opinion Elicitation

An Application to the FEEM Sustainable Composite Indicator

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Abstract. To over pass the limits inherent in liner models, suitable aggregation operators are required, taking into account interactions among the criteria. This becomes more and more crucial in Decision Theory, where all the information can be inferred by one or more Experts, using an *ad hoc* questionnaire. This is the case of the FEEM SI sustainability index, a composite geo-referenced index which aggregates several economic, social and environmental dimensions-structured in a decision tree- into a single number between zero (the worst sustainable country) and one (the best one). Fuzzy measure (*non additive measures*) are here proposed for the aggregation phase. To this purpose, each intermediate node of the structure combines the values of the sub-nodes using a model based on *second-order* non additive measure. To infer the value of the measure for each node, a suitable questionnaire has been fulfilled by a set of Experts, and the obtained answers were processed using an optimization algorithm. To guarantee the strict convexity of the algorithm, the questionnaire needs to be carefully designed. The individual measures are subsequently aggregated and the numerical results permitted to compare the sustainability of all the considered territorial units.

Keywords: Fuzzy measures, non-additive measures, Choquet integral, preference structure, sustainability, aggregation operators.

1 Introduction

In Multi Attribute problems the Weighted Averaging operator (WA) is widely used to aggregate the normalized values of the criteria. Anywise, the linear WA method is unable to include interactions (synergies or redundancies) among the criteria. For this reason, more specialized algorithms need to be considered. One of the most commonly used is based on fuzzy measures (or capacity, or non-additive measures, NAMs for brevity), which assigns a weight to every possible coalition of criteria, and not to a singleton only. A suitable aggregation operator, the Choquet integral [Beliakov, 2009], extends the Weighted Averaging (WA) to the computation of an aggregated results using NAM. The interested reader can refer to [Grabisch, 2000], [Marichal, 2000-2] for a methodological analysis of fuzzy measures. In the case of WA only n

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parameters need to be elicited, if n is the number of the criteria to be aggregated. But in NAM the number of the required parameters – the value of the fuzzy measures - exponentially increases with n, and the numerical complexity becomes crucial, especially in the case of Decision Theory, where the information can be inferred only by one or more Experts. The *reduced order* model, which considers interactions only between subset of limited cardinality, can be applied to reduce the numerical complexity. In particular, the second order model admits interactions only between couple of criteria. In this paper we propose an elicitation method based on a suitable questionnaire. The questionnaire is formed by a set of alternatives, i.e. *what ... if...* questions, and the answers can be used to elicit the non-additive measure by means of the *Least Square* optimization algorithm that minimizes the sum of squared distances between the answers of the Expert(s) and the solutions of the problem. The procedure was applied to a real world case study, the project FEEM SI, a composite Sustainability Index including 23 indicators grouped in a tree structure. A team of Experts were asked to fulfil a questionnaire, by which the NAMs were implicitly elicited, one for each node of the tree. To avoid a too strong mental effort, the number of the questions needs to be limited, then a second order model was selected as aggregation operator. The paper is organized as follows. Section 2 introduces the concept of fuzzy measures, included the reduced order model, and the Choquet integral as aggregation operator. Section 3 describes the proposed elicitation approach, while Section 4 reports its application to the FEEM SI sustainability indicator. Some conclusive comments and suggestions are reported in Section 5; technical results are briefly reported in the Appendix.

2 Fuzzy Measures and the Choquet Integral

A fuzzy measures or NAM, defined over the set of criteria $N = \{1,2,\dots,n\}$, is a set function $\mu: 2^N \to [0,1]$ satisfying the following boundary and monotonicity conditions:

$$\begin{cases} \mu(\emptyset) = 0 \\ \mu(N) = 1 \\ S \subseteq T \subseteq N \;\Rightarrow\; \mu(S) \le \mu(T) \le 1 \;\; \forall\, S,T \subseteq N \end{cases} \tag{1}$$

A NAM assigns to every subset (coalition) of criteria a measure that is not necessarily the sum of the measures of their singletons. Namely, if the measure of a coalition is greater (smaller) than the sum of the measures of their singletons, that measure represents a synergic (redundant) interaction among the criteria belonging to the coalition. Instead when the measure of a coalition equals the sum of the measures of the singletons belonging to it, the NAM collapses to the linear aggregation (WA) and no interaction exists among the criteria. Given a NAM μ, its Möbius representation is the following set function, see [Marichal, 2000-2]:

$$m(S) = \sum_{T \subseteq S} (-1)^{s-t} \mu(T) \,, \forall\, S,T \subseteq N \tag{2}$$

where $s = card(S)$, $t = card(T)$. Moreover the following boundary and the monotonicity conditions are required, see [Marichal, 2000-2]:

$$\begin{cases} m(\emptyset) = 0 \\ \sum_{T \subseteq N} m(T) = 1 \\ \sum_{\substack{T \subseteq S \\ T \ni i}} m(T) \geq 0, \ \forall\, S \subseteq N, \ \ \forall\, i \in S \end{cases} \tag{3}$$

Let μ be a NAM defined on N and $X = \{x_1, x_2, \dots, x_n\}$ the normalized values of the criteria belonging to N; the (discrete) Choquet integral with respect to μ is given by [Grabisch, 2000]:

$$C_\mu(x_1, \dots, x_n) = \sum_{i=1}^{n} (x_{(i)} - x_{(i-1)}) \mu(A_{(i)}) \tag{4}$$

where (i) means that the indices have been permutated in such a way that $x_{(1)} \leq \dots \leq x_{(n)}$, while $A_{(i)} = \{x_{(1)}, \dots, x_{(n)}\}$ and $x_{(0)} = 0$. Using the Möbius representation the Choquet integral can be written as:

$$C_m(x_1, \dots, x_n) = \sum_{T \subseteq N} m(T) \bigwedge_{i \in T} x_i \tag{5}$$

being $\wedge$ the minimum operator. To define a capacity μ on N, 2^{N-1} parameters are required. If the capacity represents the preference structure of an Expert, it needs to be directly or implicitly elicited using a suitable questionnaire. In the case of a complete model, the number of parameters exponentially increases with n, usually a prohibitive task, thus a reduced order model is proposed [Grabisch, 1997], satisfying the compromise between criteria interaction and numerical complexity. A capacity μ on N is said to be k-additive if its Möbius representation satisfies $m(T) = 0 \ \forall T \subseteq N$ such that $t > k$, and there exists at least one subset T with $card(T) = k$ such that $m(T) \neq 0$. In this way a k-additive capacity with $k \in \{1,2, \dots, n\}$ is completely defined by the identification of $\sum_{j=1}^{k} \binom{n}{j}$ parameters. If $k = 2$ we have a *second order* model (2-order model for brevity) and only $\frac{n(n+1)}{2}$ parameters are required.

2.1 Behavioural Analysis

We limit to mention the two most popular indices developed in order to have a direct interpretation of non additive measures: the *Shapley* value [Shapley, 1953] and the *Interaction* index [Grabisch, 1997].

The Shapley value is a measure of the relative importance of a criterion, computed averaging all the marginal gains between any coalition not including the criterion, and the one which includes it. In terms of Möbius representation the Shapley value of criterion *i* is defined as following:

$$\varphi(m; i) = \sum_{T \ni i} \frac{1}{t} m(T) \ \forall \ T \subseteq N \tag{6}$$

When fuzzy measures are not additive, interaction among criteria exists; in terms of Möbius representation the Interaction index among a combination S of criteria, can be formulated as:

$$I_S(m;S) = \sum_{T \supseteq S} \frac{1}{t-s+1} m(T) \quad \forall \ S \subseteq N \tag{7}$$

In a 2-order model the interaction index of a coalition coincides with its Möbius representation.

3 The Least Square Elicitation Approach

The specialized literature reports several approaches to elicit fuzzy measures. Among them, we limit to recall the Least Square (LS) and the Heuristic Least Square (HLS) [Grabisch, 1995], the approach of Marichal and Roubens (MR) [Marichal, 2000-1], the Minimum Variance (MV) [Kojadinovic, 2007] and Minimum Distance (MD) [Kojadinovic, 2000]. Such methods differ together by the required information (for instance, cardinal or ordinal type), the objective function, and the applied algorithm. The LS and the HLS require cardinal information about the alternatives, that is, a global evaluation (sometimes defined as *utility*), assigned by an Expert. For this reason, we define these methods as *cardinal-based* models. Conversely, the MR, MV and MD method require only a preference order of the alternatives; they can be defined *ordinal-based* models. In this contribution we applied the LS, after having designed carefully the questionnaire, in such a way that the optimization problem is strictly convex and thus the LS can return a unique solution[1].
To this purpose, let be:

1. $B = \{c_1, c_2, \dots, c_n\}$ the set of the criteria;
2. $A = \{a_1, a_2, \dots, a_v\}$ a scenario, that is a set of v alternatives;
3. $\mathbf{X} = \begin{pmatrix} x_1(1), \dots, x_n(1) \\ \dots\dots\dots\dots\dots\dots \\ x_1(v), \dots, x_n(v) \end{pmatrix}$ the normalized values of the criteria for each alternative (or the criteria utility for each alternative);
4. $y(a)$: the utility assigned by the Expert to alternative a
5. $C_m(j),\ j = 1,,.v$: the value of the j-th alternative computed through the 2-order model, with the elicited parameters, $C_m(a) \equiv C_m\big(x_1(a), \dots, x_1(a)\big)$;

We now briefly formalize the LS optimization algorithm which minimizes the sum squared differences between the evaluation of the Expert and the ones computed by the *k*-order model.

[1] If the optimization problem is not strictly convex, the solution is not unique [P. Miranda, M. Grabisch, 1999]. Nerveless the strict convexity depends on the questionnaire structure, see Subsection 3.1.

$$\mathbf{LS}: MIN_{m(T)} \sum_{a=1}^{v} \left(C_m(a) - y(a)\right)^2$$

$$s.t. \quad (8)$$

$$\left.\begin{cases} \sum_{\substack{T \subseteq S \\ T \ni i}} m(T) \geq 0 \ \forall\, S \subseteq N, \forall\, i \in S \\ \sum_{T \subseteq N} m(T\,) = 1 \end{cases}\right\} \quad Boundary\ and\ monotonicity\ conditions$$

If an algebraic condition is satisfied about the scenario's values proposed in the questionnaire -see Subsection 3.1- the solution to problem (8) is unique.

3.1 Optimization Issue

We underline that the LS approach returns a unique vector of Möbius representations *iff* the number of alternatives to be judged and the utilities associated to the criteria satisfy the mathematical condition stated in the Property below.

The property needs the following preliminary definition: let define the *full* scenario matrix $\mathbf{A}$ whose elements in the first v rows are partitioned by the matrix $\mathbf{X}$ of utilities associated to each criteria for each alternative, and the matrix $\boldsymbol{\Lambda}$ containing the minimum utilities values of each coalition and for each alternative; all the elements in the last row are equal to one (representing the boundary condition):

$$\mathbf{A} = \begin{bmatrix} \mathbf{X} & \boldsymbol{\Lambda} \\ \mathbf{1}' & \mathbf{1}' \end{bmatrix} = \begin{bmatrix} x_1(1) & \dots & x_n(1) & \bigwedge_{i \in T} x_i(1) \\ x_1(2) & \dots & x_n(2) & \bigwedge_{i \in T} x_i(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_1(v) & \dots & x_n(v) & \bigwedge_{i \in T} x_i(v) \\ 1 & \dots & 1 & \mathbf{1}' \end{bmatrix} \quad (9)$$

with $card(T) \leq k$.

Property 1

The LS approach returns a unique vector of Möbius representations *iff* the questionnaire is designed in such a way that the *full* scenario matrix has rank equal to the number of Möbius representations to be elicited in a *k*-order model.

Consider for instance a *2*-additive model with two criteria and two alternatives; following the formulation in Section 3, the *full* scenario matrix has the following structure:

$$\mathbf{A} = \begin{bmatrix} x_1(1) & x_2(1) & Min(x_1(1), x_2(1)) \\ x_1(2) & x_2(2) & Min(x_1(2), x_2(2)) \\ 1 & 1 & 1 \end{bmatrix}$$

A necessary and sufficient condition to have $rank(\mathbf{A}) = 3$ is $x_i(1) > x_j(1)\ and\ x_i(2) < x_j(2)$.

4 The FEEM SI Composite Index

The project FEEM Sustainability Index (FEEM SI) started some years ago [FEEM Sustainability Index Methodological Report, 2011] with the aim to construct a global sustainability index on a national scale. The data generating model is based on a Computable General Equilibrium (CGE) dynamic economic model which is able to forecast macro-economic variables of interest over a time window of about 20 years. The CGE furnishes for each nation and for each year inside the time window, the forecasted values of the macro variable. We do not discuss here the CGE methodology, see the quoted references for a detailed explanation, but focus the attention on the aggregation methodology that, year by year and for every nation, computes a single Sustainability Index for any considered nation in the world. Doing so, it permits an immediate ranking and comparison of nations putting in evidence possible variation of nation sustainability, strength and weakness points. Figure 1 shows the FEEM SI composite index, which is split into the three main pillars of sustainability (*economic*, *social* and *environmental*). Each pillar is split again into sub-dimension, and so on until the 23 leaves that are the sampled indicators. For each node and sub-node, the aggregation follows a bottom-up procedure using the 2-order model, from the leaves up to the root, the FEEM SI composite index.

4.1 Methodology

FEEM SI is based on two main and complementary blocks of operations: the CGE model, which processes the macro variables used as input data, and the criteria weighting scheme which aggregates the normalized data for each block of criteria used. Data input have been normalized by means of suitable functions that transform the input criteria data on a scale between zero and one, given suitable thresholds imposed by Experts specialized in that field. This is hence a data-insensitive normalization approach, necessary to neutralize the risk of potential *rank reversal* problem, as can appear, for example, in the *min-max* normalization approach.

The criteria weighting scheme is based on Experts' opinion elicitation by means of an *ad-hoc* questionnaire satisfying the solution uniqueness condition as explained in Subsection 3.1. Subsections below explain how the questionnaire has been developed, together with the methodology used to aggregate Experts' preferences into a single "representative" one.

4.1.1 Ad-Hoc Questionnaire for Fuzzy Experts 'Opinion Elicitation'

Each Expert has been asked to evaluate some hypothetical nations on the base of the joint performance of some criteria considered. Given the structure of the decision tree whose nodes are formed by different set of criteria, this process has been performed for all nodes. Table 1. shows the discrete qualitative scale used in the questionnaire to describe the criteria performance (first column) and the Expert choices to evaluate alternatives (second column); the third column describes the equivalent numerical scale used in the elicitation algorithm.

Table 1. Evaluation scheme

Qualitative Scale		Numerical Scale
Criteria Performance	*Expert Evaluation*	
Very bad	Very Dissatisfied	0
Bad	Dissatisfied	0.25
Fair	Nor Diss./ Sat.	0.5
Good	Satisfied	0.75
Excellent	Very Satisfied	1

The criteria performance of each alternative has been set according to **Property 1** (see Subsection 3.1). Table 2 is an example of the FEEM SI main node, where 5 hypothetical nations with different performances in the economic, social and environmental dimension have to been evaluated by each interviewed Expert.

Table 2. FEEM SI (main node) questionnaire example

	Criteria			Expert
Nation	*Economic*	*Social*	*Environment*	*Overall Evaluation*
1	Excellent	Good	Bad	-
2	Excellent	Bad	Good	-
3	Good	Excellent	Bad	-
4	Bad	Excellent	Good	-
5	Bad	Good	Excellent	-

4.1.2 Experts' Opinion Elicitation and Their Aggregation

Given that NAM approach is sufficiently general to cover many preference structures, Expert's preference has been weighted according to his/her overall consistency in judging the alternatives proposed. This is indeed an important step, especially when a survey is conducted without having a direct and immediate control on Expert's evaluation. We measure Expert's consistency as a function of the sum of squared distances in problem 8), in such a way that the greater (smaller) this sum, the smaller (greater) the contribution from the relative Expert. The above conditions can be formalized as following. Given v alternatives to be judged, let define the vector $\boldsymbol{\varepsilon}_j$ $(1 \times v)$ whose elements represent the differences between the overall utilities values set by the j-th Expert and the respective Choquet values (solution of the problem 8)).

Let g_j be the sum of squared distances for the j-th Expert:

$$g_j = \boldsymbol{\varepsilon}_j{}'\boldsymbol{\varepsilon}_j. \tag{10}$$

The sum of squared distances for the j-th Expert is filtered using an exponential model:

$$h_j = e^{-\rho g_j} \quad \text{with } \rho > 0, \tag{11}$$

In such a way that $h_j \in (0,1]$, being ρ a suitable positive constant.

The relative contribution from the j-th Expert (on a total of D interviewed) is defined as the following *importance* weight:

$$w_j = \frac{h_j}{\sum_{j=1}^{D} h_j}. \tag{12}$$

The final Möbius representation as the result of the weighted average of each Expert's preference, can be defined in the following:

$$m^*\{T\} = \sum_{j=1}^{D} w_j m_j\{T\} \quad \forall\, T \subseteq N \; and \; t \leq k \tag{13}$$

4.2 Some Results

We limit to show the results of the elicitation process in the main node of the FEEM Si index where the three pillars of sustainability have been jointly considered. Figure 2 illustrates the results of the weighting scheme with $\rho = 3$; from the left to the right are shown in decreasing order the weights to be associated to each of the 23 Expert interviewed in accordance to their overall coherence in this node. The data row of Figure 2 represent the numerical values of equations 10), 11) and 12) respectively. Figure 3 illustrates the Shapley values derived by the elicited Möbius representation for each Expert. Figure 4 illustrates the Interaction indices derived by the elicited Möbius representation. Table 3 shows the results of Experts' preferences aggregation in terms of Shapley values, from which the social dimension appears to be the most important pillar (38.6%), followed by the environmental pillar (35.70%), while the economic pillar is the least (25.70%). Table 4 shows the relative importance of the criteria belonging to the second level of the decision tree; *wellbeing* is considered the most important factor of sustainability and *GDP p.c.* the least one.

5 Conclusions

In this paper we proposed a multi-criteria approach based on the second order Choquet Integral, with the aim to take interaction among the criteria into account and, at the same time, to maintain the numerical complexity as low as possible. The fuzzy measures are elicited using an *ad hoc* questionnaire to be fulfilled by a panel of Experts, and a suitable optimization algorithm based on Least Square approach. In particular we showed that, when the questionnaire is structured in a particular way, the solution of the optimization problem is unique. The method was applied to the FEEM SI project, which is a computable geo-referenced sustainability index, organized into an hierarchical tree. For each node of the tree, the second order Choquet algorithm aggregates the values of the sub-node referring to it, bottom-up moving from the leaves up to the root. The aggregated sustainability index is computed for every considered territorial unit, permitting an immediate comparison. We are going to develop other optimization techniques based on alternative algorithms, like Goal Programming, testing the efficiency in comparison with the Least Square method.

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Appendix

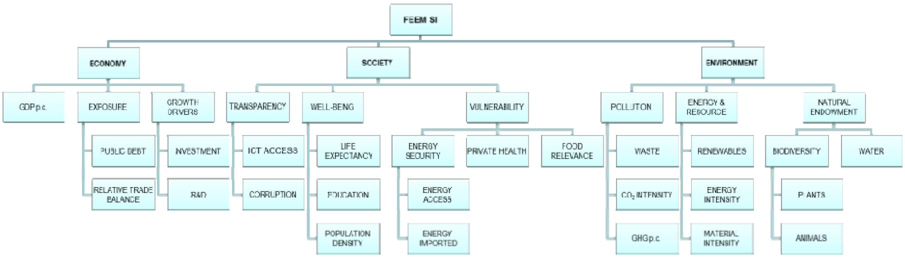
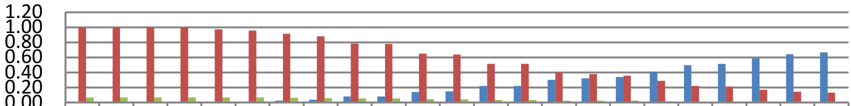
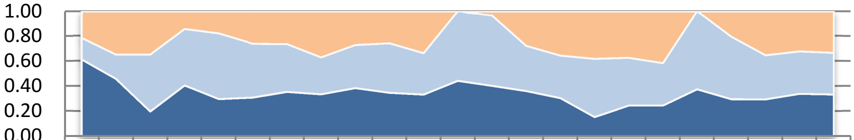


Fig. 1. FEEM SI decision tree



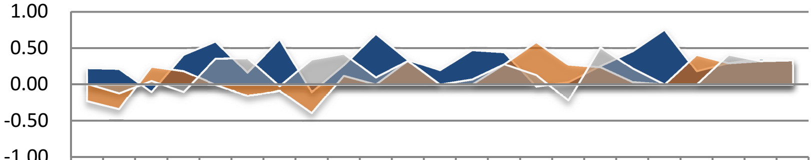
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
g(j)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.2	0.2	0.3	0.3	0.3	0.4	0.5	0.5	0.5	0.6	0.6
h(j)	1.0	1.0	1.0	1.0	0.9	0.9	0.9	0.8	0.7	0.7	0.6	0.6	0.5	0.5	0.4	0.3	0.3	0.2	0.2	0.2	0.1	0.1	0.1
w(j)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Fig. 2. Weighting scheme - FEEM SI node



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Eco	0.2	0.3	0.3	0.1	0.1	0.2	0.2	0.3	0.2	0.2	0.3	0.0	0.0	0.2	0.3	0.3	0.3	0.4	0.0	0.2	0.3	0.3	0.3
Soc	0.1	0.1	0.4	0.4	0.5	0.4	0.3	0.3	0.3	0.4	0.3	0.5	0.5	0.3	0.3	0.4	0.3	0.3	0.6	0.5	0.3	0.3	0.3
Env	0.6	0.4	0.2	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.4	0.4	0.3	0.3	0.1	0.2	0.2	0.3	0.3	0.2	0.3	0.3

Fig. 3. Shapley values for each respondent - FEEM SI node



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Env - Soc	0.2	0.2	-0.	0.4	0.5	0.1	0.6	-0.	0.2	0.6	0.3	0.2	0.4	0.4	-0.	0.0	0.2	0.4	0.7	0.1	0.2	0.3	0.3
Env - Eco	-0.	-0.	0.2	0.1	0.0	-0.	-0.	-0.	0.1	0.0	0.3	0.0	0.0	0.2	0.5	0.2	0.2	0.0	0.0	0.4	0.2	0.3	0.3
Soc - Eco	0.0	-0.	0.0	-0.	0.3	0.3	-0.	0.3	0.4	0.1	0.3	0.0	0.0	0.2	0.1	-0.	0.5	0.2	0.0	0.0	0.4	0.3	0.3

Fig. 4. Interaction indices for each respondent - FEEM SI node

Table 3. Shapley values in each node

Pillar	*Node*	*Criteria*	*Shapley (%)*
	FEEM SI	Environment	35.70
		Society	38.60
		Economy	25.70
Environmental Pillar	*Environment*	Natural Endowment	35.59
		Energy & Resources	30.70
		Pollution	33.71
	Natural Endowment	Water	48.59
		Biodiversity	51.41
	Biodiversity	Animals	51.07
		Plants	48.93
	Energy & Resources	Material Intensity	32.01
		Energy Intensity	31.93
		Renewables	36.06
	Pollution	GHG p.c.	37.33
		CO2 Intensity	33.65
		Waste	29.02
Social Pillar	*Society*	Vulnerability	29.47
		Well-Being	41.19
		Transparency	29.34
	Vulnerability	Food Relevance	33.91
		Private Health	32.28
		Energy Security	33.81
	Energy Security	Energy Imported	29.69
		Energy Access	70.31
	Well-Being	Population Density	21.04
		Education	49.09
		Life Expectancy	29.87
	Transparency	Corruption	70.47
		ICT Access	29.53
Economy Pillar	*Economy*	Growth Drivers	38.34
		Exposure	31.42
		GDP p.c.	30.24
	Growth Drivers	R&D	56.92
		Investment	43.08
	Exposure	Relative Trade Balance	57.69
		Public Debt	42.31

Table 4. Marginal criteria importance in the second level

Pillar	*Criteria*	*Marginal Importance (%)*
Environment	Natural Endowment	12.71
	Energy & Resources	10.96
	Pollution	12.03
Society	Vulnerability	11.38
	Well-Being	15.90
	Transparency	11.32
Economy	Growth Drivers	9.85
	Exposure	8.07
	GDP p.c.	7.77