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JRC Statistical Audit of the 2019 Global Attractiveness Index

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Abstract

Attractiveness is a crucial factor in the global scramble for prosperity as it implies a nation's ability to 'charm' talented people, investments and know-how – a prerequisite for competitiveness. Attractiveness has become even more important with globalisation as it has eased the movement of capitals and the inclusion of new areas of the world in the international circuits of consumption and production. In this context, it has become all the more relevant to have comparable information available to benchmark national performance across the world with a view to support the identification of areas of intervention for public policies as a means to improve a country's attractiveness power. In line with this view, the European House - Ambrosetti has developed an international monitoring framework – the Global Attractiveness Index (GAI) – that measures a country's attractiveness as determining element of its ability to be competitive and grow. The GAI builds on four attributes of attractiveness: Openness, Innovation, Efficiency, and Endowment. These pillars are used to organise and aggregate 21 Key Performance Indicators (KPIs) into a single summary measure for 144 countries that altogether cover approximately 93% of the world's population and 99% of Gross Domestic Product (in US$) worldwide. This framework inevitably entails both conceptual and practical challenges ([1]). The statistical audit discussed in this note was conducted by the European Commission's Joint Research Centre, and it aims at maximising the reliability and transparency of the Global Attractiveness Index ([2]). It should enable policy analysts and researchers alike to draw more relevant, meaningful and useful conclusions on good practices and challenges that countries face in today's competitive game to business and job creation.

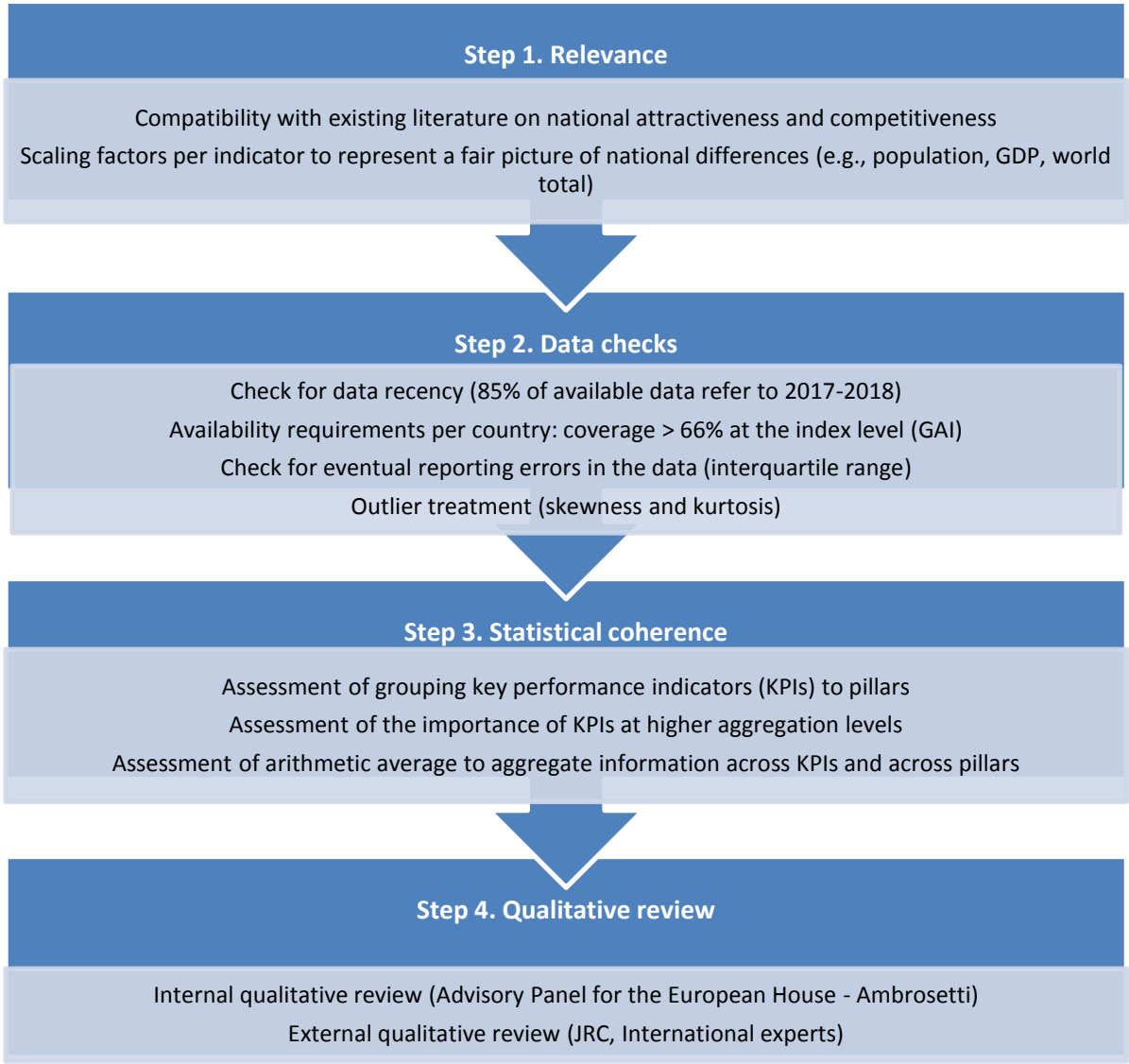
([1]) The Positioning Index of the Global Attractiveness Index (GAI) measures the current level of a country's attractiveness in relation to other countries. Two more indices complement the conceptual framework of a country's attractiveness. A Dynamism Index that measures the short-to-medium term change in the preceding three-year period of the attractiveness level of the 21 KPIs. A Sustainability Index that attempts to show how the position achieved in the Positioning Index can be maintained over time. This latter builds on two pillars that are antithetic and complementary: resilience and vulnerability. The Dynamism index and Sustainability Index results are only communicated in qualitative terms (traffic light approach). The present JRC audit focuses on the GAI index (the Positioning Index). Upon request of the European House Ambrosetti, the Dynamism and Sustainability indices will be discussed in next year's audit.

([2]) The JRC statistical audit is based on the recommendations of the OECD & JRC (2008) Handbook on Composite Indicators, and on more recent research from the JRC. In principle, JRC audits of composite indicators and scoreboards are conducted upon request of their developers, see https://ec.europa.eu/jrc/en/coin and https://composite-indicators.jrc.ec.europa.eu/

1 Conceptual and statistical coherence in the GAI framework

Earlier versions of the Global Attractiveness Index were assessed by the JRC in May-June 2016, in May-June 2017 and June-July 2018. Fine-tuning suggestions made by the JRC were taken into account by the European House – Ambrosetti in the final computation of the rankings, with a view to setting the foundation for a balanced indicator framework. The entire process followed four steps (Figure 1).

Figure 1. Conceptual and statistical coherence in the GAI 2019 Framework



Source: European Commission, Joint Research Centre, 2019.

Step 1: Relevance

Almost 200 variables were initially considered by the European House – Ambrosetti for their relevance to the four attractiveness attributes – Openness, Innovation, Efficiency, and Endowment - on the basis of a literature review and expert consultation in 2016. *Openness* captures a country's efforts to promoting the circulation of economic, human and business resources both internally and externally. *Innovation* synthesizes how a country's ecosystem (research network, public institutions, businesses, financial system) promote scientific and technological progress. *Efficiency* monitors the ability of organisational and function-related structures to guarantee proper functioning (and quality) of capital markets, the labour market, services and government. Finally, *Endowment* captures high-quality assets that are capable of being sources of competitive advantage.

After screening for data coverage and subsequently testing for statistical coherence, twenty-one key performance indicators (KPIs) were selected. To represent a fair picture of country differences, two types of denominators for the indicators were used. External factors: for those KPIs that express magnitudes related to the attractiveness of a country in relation to others, raw data values were divided by the world total (e.g., KPI 7 Exports of high-technology goods, compared with world total) ([3]). Internal factors: for those KPIs that capture aspects of internal attractiveness, raw data values were divided by relevant national factors (e.g., KPI 4 Foreign university students, compared with youth population).

Step 2: Data checks

The most recently released data within the period 2014–18 were used for each country (total 144 countries): 85% of available data for the GAI refer to 2017 or 2018. Countries are included in the GAI if data availability is at least 66% (i.e., 14 out of 21 KPIs). Exceptionally, nine countries with lower data coverage have been included in the GAI: Syrian Arab Republic, Puerto Rico and Venezuela (with 45% up to 60% data available) and Chad, Gabon, Haiti, Libya, Swaziland and Yemen (with 62% data availability, i.e. 13/21 KPIs available).

In practice, data availability in the GAI is overall very good: at least 80% data available for 121 (out of 144) countries, compared to 100 last year. Also, for some countries data coverage has improved at pillar level. For instance, while last year Libya had only one value available out of the six KPI values under the Endowment pillar, this year it has three (i.e. 50%). That said, for a few countries data coverage is not satisfactory yet. For example, for Venezuela no KPI values are available under the Endowment pillar for the year 2018. However, data coverage is considerably better (67%, i.e. 4 out of 6) if taking data from 2015. Also, for the Syrian Arab Republic, only one KPI value is available under the Endowment pillar. This is in general undesirable because the single KPI value available will dictate the pillar score for those countries. The impact of missing values on the GAI results is discussed in Section 2.

Potentially problematic indicators that could bias the overall results were identified on the basis of two measures related to the shape of the indicators' distribution: skewness and kurtosis. Values were treated if the indicators had absolute skewness greater than 3.0 and kurtosis greater than 3.5.[4] These criteria were proposed by the JRC back in 2016 for the specific dataset underpinning the GAI model. These indicators were treated by

([3]) See Giampietro (2014) for a discussion on scaling factors for indicators (intensive versus extensive properties).
([4]) Groeneveld and Meeden (1984) set the criteria for absolute skewness above 1 and kurtosis above 3.5. The skewness criterion was relaxed in the GAI case after having conducted ad-hoc tests in the 2014-2018 timeseries.

winsorization (four or less outliers per indicator) in order to avoid that few very high/low values result in polarised indicators and scores, and introduce distortion in the correlation coefficients that are subsequently used for the analysis of the statistical coherence in the GAI framework.

Step 3: Statistical Coherence

The reliability of the Global Attractiveness Index depends, *inter alia*, on the degree of coherence between the conceptual framework – 21 KPIs grouped into 4 pillars and finally into an index – and the statistical structure of the data. The more the statistical structure of the data is compatible with the GAI conceptual framework, the higher the reliability of the GAI will be. The coherence of the GAI framework was assessed by analysing whether the 21 KPIs explain a sufficient amount of variation in the aggregate scores (either in the four pillars or the overall index) by means of correlation, cross-correlation, and principal component analysis.

Given that the analysis of statistical coherence of the Global Attractiveness Index is based on correlations, the correspondence of the GAI to a real-world phenomenon needs to be critically addressed by experts in the field because 'correlations need not necessarily represent the real influence of the individual indicators on the phenomenon being measured' ([5]). The point made here is that the validity of the GAI framework relies on the combination of both statistical and conceptual soundness. In this respect, the GAI framework has been developed following an iterative process that went back and forth between the theoretical understandings of national competitiveness and attractiveness on the one hand, and data observations on the other.

Principal component analysis was used to assess the extent to which the conceptual framework underpinning the GAI – 21 indicators grouped in 4 pillars and finally into an index – is compatible with the data statistical properties. Results suggest that the expectation of a single statistical dimension (i.e., no more than one principal component with eigenvalue greater than 1.0) is confirmed for two of the four pillars, namely for the Openness and Innovation pillars. Instead there are two statistical dimensions within each of the other two pillars: Efficiency and Endowment. The presence of more than one statistical dimension in the Efficiency and Endowment pillars suggests that some of the information content of some KPIs does not arrive at the pillar level. This point is discussed in more detail in the concluding remarks in this section.

A more detailed analysis of the correlation structure within and across the four GAI pillars confirms the expectation that the indicators are generally more correlated to their own pillar than to any other (see Table 1). This result suggests that the allocation of the 21 KPIs to a specific attribute of a country's attractiveness is consistent both from conceptual and statistical perspectives. Furthermore, all associations between indicators and the respective pillar are statistically significant, and most correlation coefficients within a GAI pillar are close to or greater than 0.70, which suggests that at least half of the variance in the GAI pillar scores can be explained by an underlying indicator.

Finally, the four GAI pillars also share a single statistical dimension. The GAI captures 75% of the total variance in the four pillars, and the four correlation coefficients (between the index and each pillar) are high, 0.80 or greater. This result supports the aggregation of four GAI pillars into one number and suggests that all four pillars of a country's attractiveness can explain more than half of the variation of the GAI scores, as envisaged by the index developers. The reliability of the GAI, measured by the Cronbach-alpha value, is very good at 0.88—well above the 0.7 threshold for a reliable aggregate of the four pillars ([6]).

([5]) See (OECD-JRC, 2008).
([6]) See Nunnally (1978).

Concluding, the statistical coherence tests corroborate the two-level structure in the GAI framework, and confirm the desired unidimensionality of two out of the four pillars (Openness and Innovation), and the overall index. Furthermore, all 21 indicators are found to be influential at least at the first aggregation level (pillars) and for 17 out of the 21 indicators, this influence arrives up to the overall index. This is a highly desirable outcome as it suggests that the information content in the majority of the underlying indicators is maintained at all levels of aggregation in the GAI framework.

At the same time, the analysis (see Table 1) has also helped to evidence several issues that are worth of further reflection either because they indicate avenues for refining the index or for further policy analysis.

First, there are four indicators that do not have statistically significant correlation to the overall index: Total productivity of factors (KPI13) and Total tax rate (KPI15) within Efficiency, and Gross fixed investment (KPI18) and Natural Endowment Index (KPI19) within Endowment. Although conceptually enriching the overall GAI framework, these KPIs are found not to co-vary with the overall index. This means that countries may achieve high GAI scores irrespective of high or low values in KPIs 13, 15, 18 and 19, and the same holds for low GAI scores. In particular the Natural Endowment Index (KPI19) has been updated at source: data now come from the World Bank thanks to the availability of data from more recent years and an expected yearly update of this composite indicator. However, the new KPI behaves differently from the one used in the previous releases of the GAI. It maintains a statistically significant correlation coefficient with the Endowment pillar (yet much lower compared to last year: 0.29 vs. 0.57), and it does not correlate with the overall Index (unlike last year where the correlation to the overall index was significant yet low at 0.29). One option for the developers would be to check whether some of underlying components of the World Bank's Natural Endowment Index would better relate to the GAI. Overall, the JRC recommendation to the GAI development team is to carefully monitor how these four indicators (KPIs 13, 15, 18, 19) behave in the coming releases of the index and eventually to fine-tune the framework by considering a different formulation or different data source for these indicators. This refinement can be inspired by the positive impact to the coherence of the GAI of the new data source on migrants (next point).

First, the new data source selected last year by the developing team for capturing the Net number of migrants (KPI5 within Openness, which is now based on United Nations Population Division data) maintains a high statistical coherence of 0.65 with the Openness pillar in this year's GAI.

Second, this year the indicator Employed in high-technology sectors (KPI6) has a statistically significant correlation with the GAI, which represents an improvement from the 2018 edition. However, as its correlation coefficient considerably deviates from the values of nearly all the other GAI's indicators (i.e. 0.32 vs. 0.6 or more in most cases), it is worth monitoring the behaviour of this KPI as well in the future editions of the GAI.

Third, unlike what one may expect, a country's unemployment level (KPI11) is not strongly related to the overall index (correlation merely at 0.26). This outcome merits further analysis as it suggests that countries can achieve high levels of attractiveness despite high unemployment levels (as it is the case for Spain, which ranks 19th in the GAI 2019 despite having one of the highest unemployment levels worldwide).

Fourth, differently from last year, the Logistics Performance Index (KPI12) now correlates more with its assigned pillar: Efficiency. Still, it remains highly correlated with two other pillars of a country's attractiveness as well, namely with Openness and Innovation. Similarly, although Gross National Product (KPI17) belongs to the Endowment pillar, it is found to have much stronger statistical association to the Openness and Innovation pillars. Export + Import (KPI2) is also slightly more correlated to the Innovation pillar than to its assigned Openness pillar. This transversal impact of

KPI2, KPI12 and KPI17 across various pillars may be worth of further reflection and analysis.

Fifth, although the PISA Test score (KPI21) belongs to the Endowment pillar (correlation 0.29), it again presents a much stronger correlation to the other three pillars (correlations at about 0.60). The stronger links between PISA test scores and a country's Openness, Innovation and Efficiency and the weaker link to Endowment call for further reflection.

Finally, while most of the 21 KPIs are influential at the index level, two of them – Export + Import (KPI2) and the Logistics Performance Index (KPI12) – remain the best single predictors for a country's attractiveness level (i.e. correlation coefficients with the GAI at 0.84 and 0.90, respectively).

Table 1. Statistical coherence: correlations between GAI components

DIMENSION	ATTRIBUTE		Key Performance Indicators (KPIs)					
				Openness	Innovation	Efficiency	Endowment	GAI
Attractiveness	Openness	KPI1	(Foreign Direct Investment flows into the country IN + the country's investment abroad OUT), % of world total	0.79	0.74	0.54	0.68	0.80
		KPI2	(Export + Import), % of world total	0.78	0.80	0.62	0.73	0.84
		KPI3	(No. foreign tourists IN + No. national tourists abroad OUT), compared with national population	0.61	0.46	0.35		0.47
		KPI4	Foreign university students, compared with youth population	0.74	0.52	0.51	0.38	0.62
		KPI5	Net number of migrants, compared with population	0.65	0.43		0.36	0.49
	Innovation	KPI6	Employed in high-technology sectors, compared with employed		0.56	0.35		0.32
		KPI7	Exports of high-technology goods, compared with world total	0.69	0.71	0.51	0.57	0.72
		KPI8	ICT Development Index	0.77	0.88	0.62	0.51	0.82
		KPI9	Number of scientific publications, compared with world total	0.60	0.71	0.52	0.72	0.73
		KPI10	Internet users, % of population	0.71	0.85	0.56	0.48	0.77
	Efficiency	KPI11	Unemployment level (-1)			0.52		0.26
		KPI12	Logistics Performance Index	0.82	0.84	0.83	0.66	0.90
		KPI13	Total productivity of factors			0.39		0.14
		KPI14	Rule of Law Index	0.73	0.71	0.75	0.51	0.76
		KPI15	Total tax rate (% commercial profits)			0.26		0.02
	Endowment	KPI16	Gross Domestic Product (GDP), compared with world total	0.58	0.69	0.50	0.72	0.71
		KPI17	Gross National Product, (GNP), per capita	0.83	0.73	0.55	0.61	0.79
		KPI18	Gross Fixed Investment, compared with GDP				0.31	0.01
		KPI19	Natural Endowment Index				0.29	-0.14
		KPI20	College graduates, compared with world total		0.39		0.61	0.40
		KPI21	PISA Test Score	0.57	0.51	0.76	0.29	0.61
	Attributes of Attractiveness							
				Openness	Innovation	Efficiency	Endowment	GAI
			Openness	1.00	0.84	0.62	0.65	0.91
			Innovation	0.84	1.00	0.67	0.69	0.94
			Efficiency	0.62	0.67	1.00	0.54	0.80
			Endowment	0.65	0.69	0.54	1.00	0.81

Notes: Numbers represent the Pearson correlations coefficients between the GAI components (pillars or index) and the underlying indicators (for 144 countries) for last year only (2018). Values greater than 0.7 are desirable because they imply that the pillar captures at least 50% (≈ 0.7×0.7) of the variation in the underlying KPIs. Instead, values lower than 0.21 are not presented because they are not statistically significant. Grey boxes show the conceptual grouping of the indicators. KPIs for which lower values are desirable are marked with (-1); this is the case for the Unemployment level (KPI 11) for which lower values are desirable.

Source: European Commission, Joint Research Centre, 2019.

Step 4: Qualitative Review

Finally, the GAI results were evaluated by an ad-hoc Advisory Panel and by international experts invited by the European House – Ambrosetti to verify that they are, to a great extent, consistent with current evidence, existing research and prevailing theory.

To complement this qualitative evaluation, the GAI results are compared herein vis-à-vis other similar indices. The expectation is that the GAI correlates strongly to other international indices on competitiveness and innovation. Table 2 compares the GAI 2019 with the World Economic Forum's 2018 Global Competitiveness Index with Cornell University, INSEAD, and WIPO's 2020 Global Innovation Index and with INSEAD's 2019 Global Talent Competitiveness Index. The rank correlation between GAI 2019 with all three international indices is substantially high (correlation ≈ 0.9), which suggests that the GAI framework has many elements in common with other international frameworks that monitor innovation and competitiveness at national level worldwide.

Table 2. Statistical consistency between the GAI and other relevant international indices

	Global Innovation Index (Cornell, INSEAD,	Global Competitiveness Index (WEF)	Global Talent Competitiveness Index (INSEAD)
More than 30 positions	6%	5%	10%
20 to 29 positions	17%	6%	10%
10 to 19 positions	32%	34%	33%
More than 10 positions (*)	**55%**	**45%**	**53%**
5 to 9 positions	27%	25%	22%
Less than 5 positions	14%	27%	22%
0 positions	4%	3%	3%
Total	100%	100%	100%
Pearson correlation coefficient with the GAI	0.89	0.92	0.87
Spearman rank correlation coefficient with the GAI	0.89	0.94	0.89
Common countries with the GAI	119	131	115

Notes: The comparison between the GAI and the other indices was based on the common set of countries.
(*) This row is the sum of the prior three rows.

Source: European Commission, Joint Research Centre, 2019.

At the same time, looking at the shifts in rankings, one finds that 45% up to 55% of the countries differ in ranking by more than 10 positions when comparing the GAI 2019 with the recent releases of the Global Competitiveness Index, the Global Competitiveness Index and the Global Talent Competitiveness Index. This result suggests that the GAI 2019 receives validity when compared to other relevant international indices, and that the GAI offers additional insights into nations' attractiveness and competitiveness that go beyond the findings of other international indices.

Notwithstanding these statistical tests and the positive outcomes on the statistical coherence together with the suggestions for refinement made above, the GAI model, in its fourth edition now, has been and should remain open for future improvements as better data, more comprehensive surveys and assessments, and new relevant research studies on national attractiveness and competitiveness become available.

2 Impact of modelling assumptions in the GAI

Assessing the effect of varying modelling assumptions in the GAI inside plausible ranges is an important part of the statistical audit. The rationale for the choices made by the GAI development team is manifold. For instance, literature review and expert opinion on national attractiveness and competitiveness, coupled with statistical analysis, is behind the selection of the 21 individual indicators and their grouping in four pillars and into an overall index; common practice and easy of interpretation suggests the use of a min-max normalization approach in the [0–100] range for the indicators; statistical analysis guides the choice on the treatment of outliers; and simplicity seems to advocate for not estimating missing data, assigning equal weights at all levels and adopting an arithmetic average formula.

Despite the well-substantiated rationale for the choices made during the GAI development, there is an unavoidable subjectivity (or uncertainty), which is accounted for in the robustness assessment carried out by the JRC. More precisely, the uncertainly analysis is conducted herein in order to allow for the **joint** analysis of the impact of the modelling choices on the GAI results, resulting in error estimates and confidence intervals calculated for the 144 countries included in the GAI.

As suggested in the relevant literature on composite indicators ([7]), the robustness assessment of the GAI model was based on Monte Carlo simulation and multi-modelling approaches, applied to 'error-free' data where eventual errors and typos have already been corrected in a preliminary stage. In particular, the three key modelling issues considered in the assessment of the GAI were the treatment of missing data, the aggregation formula at the pillar level and finally the pillar weights.

Missing data. The GAI developers, for transparency and replicability and following common practice on composite indicator development, opted not to estimate missing data. Technically, the 'no imputation' choice is equivalent to replacing an indicator's missing value for a given country with the respective pillar score. Hence, the available data (indicators) in the incomplete pillar may dominate the results, sometimes biasing the ranks up or down. Furthermore, the 'no imputation' choice might encourage countries not to report low data values. To test the impact of the 'no imputation' choice, the JRC estimated missing values in the GAI dataset using the Expectation Maximization (EM) algorithm that was applied in the entire set of 21 indicators. ([8])

Aggregation. Regarding the aggregation formula, decision-theory practitioners challenge the use of simple arithmetic averages because of their fully compensatory nature, in which a comparative high advantage on a few indicators can compensate a comparative disadvantage on many indicators.([9]) To assess the impact of this compensability issue, the strong perfect substitutability assumption inherent in the arithmetic average was relaxed in this analysis; instead the geometric average across the four GAI pillars was considered as an alternative. Nevertheless, the arithmetic average has been maintained at the KPIs level, where full compensability may be justifiable. The geometric average is a partially compensatory approach that rewards countries with balanced profiles and

([7]) Saisana et al., 2005; Saisana et al., 2011 ; Vértesy 2016; Vértesy and Deiss, 2016

([8]) The Expectation-Maximization (EM) algorithm (Little and Rubin, 2002; Schneider, 2001) is an iterative procedure that finds the maximum likelihood estimates of the parameter vector by repeating two steps. Step 1: The expectation E-step: Given a set of parameter estimates, such as a mean vector and covariance matrix for a multivariate normal distribution, the E-step calculates the conditional expectation of the complete-data log likelihood given the observed data and the parameter estimates. Step 2: The maximization M-step: Given a complete-data log likelihood, the M-step finds the parameter estimates to maximize the complete-data log likelihood from the E-step. The two steps are iterated until the iterations converge.

([9]) Munda, 2008.

motivates countries to improve in the GAI pillars in which they perform poorly, and not just in *any* GAI pillar.([10])

Weights. While the term *multi-modelling* refers to testing alternative assumptions—that is, an alternative aggregation method, and missing data estimation method—the Monte Carlo simulation explored the issue of weighting and comprised 1,000 runs, each corresponding to a different set of weights for the four pillars, randomly sampled from uniform continuous distributions centred in the reference values (equal weighting; pillar weights are 25%). The choice of the range for the weights' variation was driven by two opposite needs: to ensure a wide enough interval to have meaningful robustness checks, and to respect the rationale of GAI that places equal importance on all four pillars – Openness, Innovation, Efficiency, Endowment. Given these considerations, limit values of uncertainty intervals for the pillar weights are 15% to 35% for the four pillars (see Table 3). In all simulations, sampled weights are then rescaled so that they always sum to 1.

Four models were tested based on the combination of no imputation versus EM imputation at the indicator level, arithmetic versus geometric average at the pillar level. Combined with 1,000 simulations per model (random weights versus fixed weights), a total of 4,000 simulations for the Global Attractiveness Index were run.

Table 3. Uncertainty parameters in the GAI: missing values, weights, aggregation

	Reference	Alternative
I. **Uncertainty in the treatment of missing values**	No estimation of missing data	Expectation Maximization (EM)
II. **Uncertainty in the aggregation formula at pillar level**	Arithmetic average	Geometric average
III. **Uncertainty intervals for the weights of the four GAI pillars**	Reference value for the weight	Distribution assigned for robustness analysis
Openness	0.25	U[0.15,0.35]
Innovation	0.25	U[0.15,0.35]
Efficiency	0.25	U[0.15,0.35]
Endowment	0.25	U[0.15,0.35]

Source: European Commission, Joint Research Centre, 2019.

The main results of the robustness analysis are shown in Figure 2 with median ranks and the 90% confidence intervals computed across the 4,000 Monte Carlo simulations for the Global Attractiveness Index. Countries are ordered from high to low performance according to their reference GAI rank (black line), the dot being the median rank over the simulations.

All published GAI 2019 ranks lay within the simulated 90% confidence intervals, and for the vast majority of the countries these ranks can be considered as representative of the plurality of scenarios simulated herein. Taking the median rank as the yardstick for an economy's expected rank in the realm of the GAI's unavoidable methodological uncertainties, 75% of the economies are found to shift fewer than five positions with respect to the median rank in the GAI.

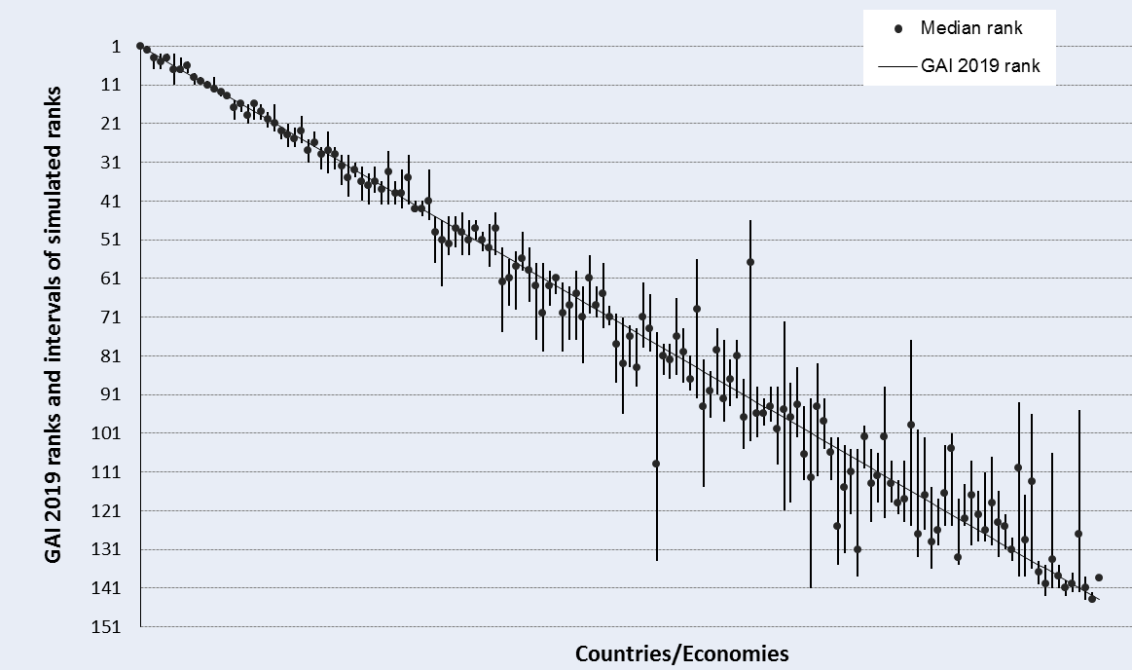
Furthermore, for most economies the simulated rank intervals are narrow enough for meaningful inferences to be drawn: there are fewer than 10 positions for 64 of the 144 economies. Nevertheless, several country ranks vary significantly with changes in the

([10]) In the geometric average, pillars are multiplied as opposed to summed in the arithmetic average. Pillar weights appear as exponents in the multiplication. A constant of 0.001 was added to the pillar scores to avoid zero values that would have led to zero geometric averages.

four pillar weights, the aggregation formula across the four pillars or the estimation of missing data (where applicable): confidence interval widths are 30 or greater for the following 16 countries that are placed between the 78th (Timor-Leste) and the 141st (Swaziland) position: Timor-Leste, Montenegro, Bolivia, Seychelles, Gabon, Cabo Verde, Guinea, Tanzania, Chad, Bosnia and Herzegovina, Venezuela, Rwanda, Libya, Namibia, Gambia, and Swaziland. For these countries the GAI ranks are highly sensitive to the modelling choices when building the GAI and should hence not be taken at face value.

For full transparency and information, Table 4 reports the GAI 2019 country ranks together with the simulated 90% confidence intervals in order to better appreciate the robustness of the results to the estimation of missing data, the choice of the four pillar weights and of the aggregation formula at pillar level.

Figure 2. Robustness analysis (GAI rank vs. median rank, 90% confidence intervals)



Notes: Median ranks and intervals are calculated over 4,000 simulated scenarios based on imputing (or not) missing values, random weights plus/minus 25% around the reference weights for the four pillars on Openness, Innovation, Efficiency, Endowment, and aggregation formula at pillar level (as shown in Table 3). The Spearman rank correlation between the median rank of the simulations and the GAI 2019 rank is 0.985.

Source: European Commission, Joint Research Centre, 2019.

Table 4. GAI 2019: Index ranks and simulated 90% intervals

Germany	1 [1, 2]	Thailand	51 [46, 51]	Guinea	101 [92, 141]
United States	2 [1, 2]	Kazakhstan	52 [49, 54]	Macedonia, FYR	102 [83, 112]
Singapore	3 [3, 7]	Greece	53 [47, 58]	Jamaica	103 [92, 105]
Japan	4 [3, 7]	Cyprus	54 [44, 55]	Nicaragua	104 [102, 113]
United Kingdom	5 [3, 5]	Azerbaijan	55 [53, 75]	Tanzania	105 [102, 135]
Hong Kong SAR, China	6 [3, 11]	Puerto Rico	56 [56, 68]	Zambia	106 [104, 132]
China	7 [4, 8]	Lithuania	57 [54, 69]	Sri Lanka	107 [105, 122]
France	8 [5, 8]	Croatia	58 [49, 59]	Chad	108 [105, 138]
Australia	9 [8, 11]	Indonesia	59 [53, 67]	Lao PDR	109 [99, 110]
Netherlands	10 [9, 11]	Iran, Islamic Rep.	60 [57, 77]	Mauritania	110 [105, 124]
Canada	11 [10, 12]	Suriname	61 [57, 80]	Bangladesh	111 [106, 119]
Switzerland	12 [9, 13]	Vietnam	62 [59, 68]	Bosnia and Herzegovina	112 [89, 123]
Korea, Rep.	13 [12, 14]	Bulgaria	63 [60, 65]	Senegal	113 [108, 119]
Austria	14 [13, 14]	Colombia	64 [62, 80]	Guatemala	114 [113, 122]
Sweden	15 [15, 20]	Philippines	65 [63, 77]	Nigeria	115 [108, 124]
Italy	16 [15, 18]	Uruguay	66 [59, 77]	Venezuela, RB	116 [77, 125]
Belgium	17 [16, 21]	Costa Rica	67 [63, 83]	Rwanda	117 [100, 133]
Ireland	18 [15, 20]	Lebanon	68 [55, 70]	Benin	118 [102, 126]
Spain	19 [16, 20]	Panama	69 [63, 71]	Mali	119 [115, 136]
Denmark	20 [18, 22]	Jordan	70 [57, 74]	Cameroon	120 [118, 130]
United Arab Emirates	21 [16, 23]	Ukraine	71 [68, 73]	Nepal	121 [104, 125]
New Zealand	22 [22, 25]	Algeria	72 [70, 88]	Botswana	122 [101, 125]
Norway	23 [21, 27]	Moldova	73 [71, 96]	Mozambique	123 [118, 135]
India	24 [22, 27]	Serbia	74 [73, 84]	Myanmar	124 [114, 125]
Qatar	25 [19, 26]	Peru	75 [74, 89]	Cambodia	125 [108, 130]
Finland	26 [25, 31]	Georgia	76 [62, 79]	Pakistan	126 [116, 129]
Luxembourg	27 [23, 27]	Albania	77 [65, 80]	Honduras	127 [111, 129]
Russian Federation	28 [27, 33]	Timor-Leste	78 [75, 134]	El Salvador	128 [107, 130]
Bahrain	29 [23, 34]	Dominican Republic	79 [78, 86]	Syrian Arab Republic	129 [116, 133]
Iceland	30 [27, 33]	Trinidad and Tobago	80 [78, 87]	Uganda	130 [122, 131]
Poland	31 [29, 37]	Kyrgyz Republic	81 [66, 86]	Kenya	131 [128, 134]
Czech Republic	32 [29, 40]	Armenia	82 [74, 88]	Libya	132 [93, 138]
Estonia	33 [31, 35]	Morocco	83 [81, 90]	Zimbabwe	133 [117, 138]
Slovenia	34 [32, 41]	Montenegro	84 [56, 92]	Namibia	134 [96, 136]
Hungary	35 [34, 42]	Bolivia	85 [82, 115]	Malawi	135 [134, 140]
Israel	36 [32, 39]	Ecuador	86 [85, 97]	Madagascar	136 [135, 143]
Brazil	37 [36, 42]	South Africa	87 [74, 91]	Gambia, The	137 [106, 141]
Kuwait	38 [28, 42]	Cote d'Ivoire	88 [77, 98]	Liberia	138 [135, 141]
Malaysia	39 [36, 42]	Bhutan	89 [82, 94]	Burundi	139 [139, 143]
Oman	40 [33, 43]	Mauritius	90 [77, 92]	Sierra Leone	140 [137, 142]
Saudi Arabia	41 [29, 42]	Ghana	91 [87, 105]	Swaziland	141 [95, 142]
Mexico	42 [41, 44]	Seychelles	92 [46, 103]	Yemen, Rep.	142 [138, 144]
Portugal	43 [41, 45]	Mongolia	93 [89, 102]	Haiti	143 [142, 144]
Malta	44 [33, 46]	Tunisia	94 [92, 99]	Lesotho	144 [129, 144]
Slovak Republic	45 [45, 57]	Egypt, Arab Rep.	95 [89, 98]		
Chile	46 [46, 63]	Guyana	96 [89, 109]		
Argentina	47 [45, 55]	Gabon	97 [72, 121]		
Latvia	48 [45, 53]	Cabo Verde	98 [88, 119]		
Turkey	49 [44, 55]	Paraguay	99 [84, 102]		
Romania	50 [46, 55]	Tajikistan	100 [94, 113]		

Notes: Rank intervals are calculated over 4,000 simulated scenarios based on imputing (or not) missing values, random weights plus/minus 25% around the reference weights for the four pillars on Openness, Innovation, Efficiency, Endowment, and aggregation formula at pillar level. Countries with confidence interval widths that are 30 positions or greater are highlighted in grey.

Source: European Commission, Joint Research Centre, 2019.

Next, the impact of not estimating missing values in the GAI is analysed in more detail. The 2018 dataset has a very good coverage: 85% data available across 144 countries and 21 indicators. Out of the 449 missing values, only 28 data gaps in 26 countries are found to have a high impact on the results. Table 5 lists the 26 countries that are strongly affected (moving 20 positions or more in a given GAI pillar) when missing values are estimated via the EM algorithm as opposed to not being estimated at all (reference scenario). Data availability per pillar is reported as well. Most country ranks are particularly sensitive to the missing data estimation in two of the four pillars, namely the Efficiency or the Endowment pillar. Only four countries are sensitive to missing values in the other pillars: Iran, Swaziland, Syria and Venezuela. It is worth noting that the sensitivity of country ranks to the treatment of missing data is not necessarily directly related to the amount of missing data in a given country but rather the result of the missing values in the ensemble of countries. To give an example, in the Endowment pillar, countries with no data at all, namely Venezuela, or countries with 83% data availability, namely Bahrain, Iceland, Malta, Slovak Republic, United Arab Emirates, are equally affected by the estimation of missing data in the GAI dataset. The JRC recommendation to readers and policy analysts is to consider the GAI pillar ranks (and scores) for these 26 countries with a grain of salt when drawing inferences on the countries performance when it comes to national Openness, Innovation, Efficiency or Endowment. The suggestion to the GAI developers is to find reliable estimates for those 28 missing values because of the high impact on the GAI pillar ranks.

Table 5. Impact of missing data estimation on countries with most sensitive pillar ranks

	Country ranks sensitive to the treatment of missing data				Data availability			
	Openness	Innovation	Efficiency	Endowment	Openness	Innovation	Efficiency	Endowment
Azerbaijan			YES		100%	80%	60%	83%
Bahrain				YES	100%	80%	80%	83%
Chad			YES		60%	60%	60%	67%
El Salvador			YES		100%	80%	80%	83%
Honduras			YES		80%	80%	80%	67%
Hong Kong SAR, China				YES	100%	80%	100%	67%
Iceland				YES	100%	100%	80%	83%
Iran, Islamic Rep.	YES				80%	80%	100%	83%
Lebanon			YES		100%	80%	80%	67%
Liberia			YES		80%	40%	80%	67%
Lithuania				YES	100%	100%	80%	50%
Malta				YES	100%	100%	80%	83%
Mauritius			YES		100%	80%	80%	67%
Mozambique			YES		100%	80%	80%	83%
Myanmar				YES	80%	80%	100%	50%
Nepal			YES		80%	80%	80%	67%
Seychelles			YES		80%	80%	20%	83%
Slovak Republic				YES	100%	80%	80%	83%
Swaziland		YES			80%	60%	40%	67%
Syrian Arab Republic	YES			YES	40%	60%	60%	17%
Tajikistan			YES		100%	40%	80%	83%
Tanzania			YES		80%	80%	80%	67%
Timor-Leste			YES		80%	80%	40%	67%
United Arab Emirates				YES	80%	80%	100%	83%
Venezuela, RB		YES		YES	80%	60%	100%	0%

Notes: Countries are listed here if they are strongly affected with shifts of 20 positions or more in a given GAI pillar when missing values are estimated via the EM algorithm as opposed to not being estimated at all (reference scenario).

Source: European Commission, Joint Research Centre, 2019.

Concluding, the published GAI 2019 ranks are reliable and for the vast majority of countries the simulated 90% confidence intervals are narrow enough for meaningful inferences to be drawn. Given the sensitivity of some countries' pillar ranks to the estimation of missing values, the JRC recommendation to the index developers is to find a suitable way for approximating missing values, where possible by contacting national statistical offices or finding additional data sources. For the readers and policy analysts of the GAI 2019 report, the recommendation is to consider country ranks within the 90% confidence intervals in order to better appreciate to what degree a country's rank depends on the three key modelling choices accounted for, namely estimation of missing data, weights and aggregation formula at the pillar level.

3 Added value of GAI - From four pillars to one single number of national attractiveness

This last section aims at touching upon the added value of the Global Attractiveness Index as a summary measure of the four pillars.

Table 6 shows that the GAI 2019 ranking and any of the four pillar rankings differ by 10 positions or more for at least 40% (up to 73%) of the 144 countries.

This finding suggests that there is an added value in referring to the GAI results in order to identify aspects of countries' attractiveness that do not directly emerge by looking into the four pillars separately. At the same time, this outcome points to the value of examining individual GAI pillars and indicators on their own merit in order to see which components are driving a country's attractiveness.

Table 6. Distribution of differences between pillars and GAI rankings

Shift with respect to the GAI	Openness	Innovation	Efficiency	Endowment
More than 30 positions	11%	9%	26%	24%
20 to 29 positions	15%	5%	16%	14%
10 to 19 positions	31%	26%	31%	31%
More than 10 positions (*)	56%	40%	73%	69%
5 to 9 positions	22%	24%	12%	11%
Less than 5 positions	18%	29%	13%	17%
0 positions	4%	6%	3%	3%
Total	100%	100%	100%	100%
Spearman rank correlation coefficient with the GAI	0.89	0.93	0.80	0.77

Notes: (*) This row is the sum of the prior three rows.

Source: European Commission, Joint Research Centre, 2019.

4 Conclusions

Now in its fourth edition, the Global Attractiveness Index (GAI) developed by The European House - Ambrosetti aims at measuring and benchmarking the attractiveness of 144 countries around the world. With a view to maximise the reliability and transparency of the GAI, The European House – Ambrosetti has asked the JRC to assess the impact of the methodological choices made in the development of the index. More specifically, in the present audit the JRC has analysed the statistical properties of the data and the methodology used in the index construction and provided suggestions for further refinements. Overall the GAI framework is well-constructed, into which a lot of thought has clearly been put and extensive original research into the multiple determinants of a county's attractiveness has been conducted by the developers. The key findings of the statistical assessment conducted herein are the following:

First, the coherence tests suggest that the **conceptual grouping** of the 21 indicators into four pillars and an overall index is corroborated by statistical analysis, and that the GAI scale –average of four key dimensions capturing Openness, Innovation, Efficiency and Endowment – is unidimensional and has high statistical reliability (Cronbach alpha 0.88) well above the recommended threshold (0.7) for a reliable aggregate. Seventeen out of the 21 indicators in the GAI framework are also found to be influential all the way up to the index level. The new data source used in this GAI edition for capturing the Net number of migrants (KPI5) has contributed to increasing the statistical coherence in this year and the past year's GAI. The results of the statistical coherence tests also point to the following issues for further reflection and analysis.

- Four indicators – Total productivity of factors (KPI13) and Total tax rate (KPI15) within Efficiency, and Gross fixed investment (KPI18) and Natural Endowment Index (KPI19) within Endowment – account for a small (almost negligible) amount of variation in the GAI scores. Although these indicators are conceptually enriching the GAI framework and their statistical impact arrives up to the pillar level, it is recommended to carefully monitor how these four indicators behave in the coming releases of the index and eventually to fine-tune the framework in this respect. For example, the new data source used in this year's GAI edition for capturing Natural Endowment Index (KPI19) based on a World Bank study has proven to be sub-optimal in the given context. One option for the index developers would be to check whether some of underlying components of the World Bank's Natural Endowment Index would better relate to the GAI.
- The indicator Employed in high-technology sectors (KPI6) has a statistically significant correlation with the GAI, which represents an improvement from last year's edition. However, the statistical association between KPI6 and the overall index remains particularly low.
- Despite expectations, a country's unemployment level (KPI11) is not strongly related to the overall index (correlation merely at 0.26), which suggests that countries can achieve high levels of attractiveness despite high unemployment levels.
- Although the PISA Test score (KPI21) belongs to the Endowment pillar, it presents a much stronger correlation to the other three pillars on Openness, Innovation and Efficiency.

Second, the GAI dataset has very good **data coverage** and 85% of the data refer to 2017 or 2018. Uncertainty and sensitivity analysis have shown that it is important to find reliable estimates for 28 missing values in 26 countries (i.e. 6% of the missing data) because of the very high impact on the country ranks along specific GAI pillars.

Third, the tests helped to single out 16 countries with GAI ranks that are very **sensitive to the modelling choices** and hence these ranks should be interpreted cautiously. On the other hand and compared to the reference GAI rank, 75% of the economies are found to shift fewer than five positions with respect to the median rank over 4,000

simulations. Thereafter, the GAI framework allows to reliably benchmark national attractiveness in the vast majority of the countries analysed.

Fourth, results show that there is an **added value in referring to the GAI results** in order to identify aspects of countries' attractiveness that do not directly emerge by looking into the four pillars separately. In fact, the GAI ranking and any of the four pillar rankings differ by 10 positions or more for at least 40% up to 73% of the 144 countries.

Fifth, the external validity testing of the GAI confirms the high degree of association (correlation ≈ 0.9) to the latest releases of three relevant international indices: the World Economic Forum's Global Competitiveness Index, the Cornell University, INSEAD, and WIPO's Global Innovation Index, and the INSEAD's Global Talent Competitiveness Index. At the same time, one finds that 45% up to 55% out of the countries included in the GAI 2019 that feature in these three indices differ in ranking by more than 10 positions when comparing the GAI 2019 with the recent releases of these international indices. This latter result suggests that the GAI 2019 offers additional insights into nations' human capital and competitiveness that go beyond the findings of other international indices.

Overall, this year's JRC audit confirms that the Global Attractiveness Index 2019 meets, at large, international quality standards for statistical soundness. Consequently, the GAI framework offers a sound starting point for more informed discussions on the determinants of a country's attractiveness. Readers and policy analysts of the GAI are in particular invited to go beyond the overall index scores (and ranks) and duly take into account the 21 individual indicators and four pillars on their own merit, as they can offer more in-depth insights on the areas of policy attention and intervention to be tackled. Still, the GAI is not intended as the ultimate and definitive measure for monitoring national attractiveness. Instead, the GAI best represents an ongoing attempt by The European House - Ambrosetti to stimulate public interest and help focus policy discussions on the multiple aspects that shape a country's 'charm'. The GAI will continue to be updated as long as new (relevant) data are made available and in line with the theoretical advancement in the field.

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