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ECONOMIC COMPLEXITY AND INFORMATION SOCIETY PARADIGMS: A HYBRID CONTRIBUTION TO EXPLAIN ECONOMIC GROWTH

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Abstract. In the last decades, the *Information Society* (IS) paradigm has brought together various research lines related to the diffusion and adoption of Information and Communication Technologies (ICTs) and their contribution to economic, social and human development. On the other hand, other research lines have recently explored the phenomenon of *Economic Complexity* (EC), providing new metrics to quantify this decisive factor for the prediction of economic growth and other human relevant variables. This article explores these two trends with the construction of two composite indexes. Then, it evaluates their explanatory power to predict economic growth, first separately, and afterwards together. The results show they can predict economic growth and improve their predictive capacity by working combined. In the conclusions, some difficulties and challenges for the development of these metrics are analyzed.

Keywords: Information Society, Economic Complexity, information technologies, metrics.

JEL Classification: D83, F43, O33, O57.

Introduction

The Information Society (IS) is a concept that is increasingly present in the economic, sociological, technological and philosophical literature of the last half century. For decades we have declared that we are in the "information age" although we have not yet been able to fully specify what we mean by it. The truth is that the growing role of information in our lives is redefining our forms of economic, social and political organization.

However, the IS phenomenon is not so novel if it is observed from the perspective that *information* is associated with the development of *complex* structures; and that this *complex*-

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ity is an inherent tendency in the development of life. Biological structures exposed to a changing environment evolve by natural selection prioritizing versatility, that is, the ability to offer different adaptive responses. Although in certain circumstances simpler forms have performed better towards surviving, the general trend observed in nature is that this versatility is provided by more complex structures, which means, structures able to embody, retain and process higher levels of information to keep their own stability (Rosen, 1986). Therefore, information and complexity are quantities that can be measured in similar terms, as happens in dynamic systems (Grassberger, 1991), since the structural complexity of a system is closely related to the amount of information with which it can be described (Vigo, 2011; Lui et al., 2015). In fact, there have been proposals of enormous practical application that have measured the complexity of systems as information fluctuation (Bates & Shepard, 1993). Thus, the growth of information, of complexity, is the distinguishing characteristic of life forms, from cells and tissues, through individuals and populations, to species and ecosystems. This has happened with the human species, capable of imposing itself and dominating nature thanks to its ability to generate and exchange information (language, writing, printing and now information and communication technologies). It is a truism to say that the dissemination of information, and the consequent acquisition of knowledge applied to technological development, is the crucial factor in our history as a species. The IS, therefore, would be one more stage in that history of progressive complexity, with the difference being that it has been socially accepted that the increasing availability of information is at the base of progress.

For this reason, it is extremely interesting to explore the nexus running through two apparently different research lines. On the one hand, there are the studies that show that the massive exchange of information associated with the diffusion and adoption of Information and Communication Technologies (ICT) plays a central role in explaining economic and human development. On the other hand, there are the investigations developed around the idea of Economic Complexity (EC) which, in the last decade, have been able to make useful predictions on economic growth, income inequality and environmental performance.

Both research lines go hand in hand in this article, interacting and intertwining to empirically observe how their autonomous explanatory capacity for economic growth is improved when linking both of them. For this purpose, the article proposes:

- The independent construction of two composite indexes for the evaluation of the IS and the EC progress: the so-called respectively IGR and ECI+.
- The exploration of multiple linear regression models that first incorporate each of these two indexes and then both, in order to assess first their capacity to predict economic growth, in terms of per capita income, and second, the improvement of this ability when they work together.

The results of this study confirm, first, that IS and EC composite indexes, each one taken separately, can predict economic growth in a 5 year timeframe; second, they confirm that IS and EC concepts can be combined successfully through these composite indexes in order to improve their autonomous ability to predict this growth. Although there are some very recent works that explore nearby paths, such as trying to unite ICT exports, human capital and EC (Moreno-Hurtado et al., 2020), or carrying out an empirical analysis on the effect of Internet in the sophistication of the economy (Lapatinas, 2019), this is the first time, to the best of our knowledge, that two metrics of this type have been combined, resulting in a very satisfactory joint explanatory capacity.

The article is organized as follows. After this introduction, Section 1 presents a brief review of the literature on the notions of the IS and the EC, and their relationship with economic development. Section 2 explains the construction of the respective IS and EC indexes. In Section 3, an evaluation of the behavior of both indexes and their explanatory capacity for the economic growth of a wide group of countries is carried out. In Section 4 the results obtained are discussed. We present our conclusions to close the article.

1. Information and complexity foundations

1.1. Information Society

The concept of the IS flourished in the 1960s and the 1970s of the twentieth century, together with other twinned concepts that tried to characterize and quantify a new paradigm of social and economic organization. The pioneer works on the *knowledge industry* in the US (Machlup, 1962), or the growing *knowledge economy* (Drucker, 1968), were followed by several studies on the advent of a *postindustrial society* (Bell, 1973) or the *information age* (Porat, 1977) under different quantitative approaches. In the eighties, building a more refined notion of the *Information Society* (Masuda, 1980) soon made the concept popular (Naisbitt, 1982).

Unlike fuzzier concepts, useful for the qualitative discussion, but imprecise for the quantitative one, these aforementioned works tried to measure the role of information and knowledge in economic growth, focusing on patents, R&D investment, capitalization of technology companies, or analyzing the workforce identified as "*knowledge workers*". However, researchers found much more empirical potential in the analysis of ICT diffusion and direct adoption, as these technologies are specifically dedicated to the information process and communication (Gómez-Barroso & Marbán-Flores, 2020a).

Some criticisms, however, questioned the excessively technology-centered approach of these studies. The real contribution of the IS to economic growth in the least developed countries has been discussed (Oliner & Sichel, 2000; Lee et al., 2005). The most optimistic promises that linked IS progress with enhancement of democracies have not been totally fulfilled (underlining ICTs capacity to promote greater concentrations of economic power (Dawson & Foster, 1998)). Moreover, the anticipated reduction of environmental impact has received significant objections (excessive electricity consumption, technological waste and sustainability (Rodríguez Casal et al., 2005; Mantz, 2008; Teppayayon et al., 2009; Magazzino et al., 2021)). These and other criticisms helped to refine the IS concept as an elusive and complex reality, understanding that the IS virtues do not lie *only* in ICTs diffusion and adoption, but other requirements are needed: basic economic infrastructures, investment in human capital (Seo et al., 2009), social reliability to facilitate links and exchanges (Rodríguez & Wilson III, 2000) and, ultimately, an adaptation to social reality (especially in developing countries (Audenhove et al., 1999; Heeks, 2002; Sahay & Avgeroum, 2002; Wilson, 2003; Beck et al., 2004; Courtright, 2004; Gómez Barroso & Feijóo, 2006; Kuriyan et al., 2008)).

Despite these criticisms and nuances, there are countless studies that have supported the contribution of the IS notion to economic and human growth. After the *dotcom crisis* disappointment in 2001, further research confirmed the systematic correlation between ICT investment and economic growth (Jalava & Pohjola, 2002; Bakhshi & Larsen, 2005; Jalava &

Pohjola, 2007; Goldfarb et al., 2007; Jalava & Pohjola, 2008), and continued to do so after the 2008 recession (Venturini, 2009; UNCTAD, 2009; Hosseini & Aghaei, 2009; Prochniak, 2011) supporting its positive impact even on general human development indexes (Alfaro Cortés & Alfaro Navarro, 2011). In recent years, the literature continues to confirm that ICTs can be considered a determining factor in terms of productivity and, by extension, of economic growth (Rincon et al., 2012; Cardona et al., 2013; Erumban & Das, 2016; Corrado et al., 2017; Niebel, 2018; Toader et al., 2018; Bahrini & Qaffas, 2019; Sepehrdoust & Ghorbanseresht, 2019; Pradhan et al., 2019; Tripathi & Inani, 2020; Bulturbayevich & Jurayevich, 2020; Vu & Bohlin, 2020; Pradhan et al., 2022; Soomro et al., 2022). Some even see an economic singularity of superabundance associated with ICT, despite the multiple challenges that threaten to cause economic stagnation (Nordhaus, 2021).

Defining the IS as "*an elusive and complex reality*", as previously done, highlights one of the main problems, if not the main one, for the studies that analyze its impact: the absence of a precise definition of the IS. Several indicators have been promoted from different international organizations to measure the more tangible part of the abstract IS. These statistics are gradually being completed and improved, although some of the criticisms initially made (Albright, 2005; James, 2006; Menou & Taylor, 2006) are still valid. The importance of these measurements cannot be underestimated, as long as they are useful for policy makers. However, with some exceptions (Gómez-Barroso et al., 2008), they have not been used in academic work. Indeed, there are no IS quantitative representations in the literature that have managed to consolidate measurements. Although the methodology follows lines of work that are regularly repeated (Gómez-Barroso & Marbán-Flores, 2020b), practically each piece of work creates its own index or uses a different set of variables.

1.2. Economic complexity

Complexity as a fundamental notion to understand the constitution and development of economic systems has been studied throughout history from different points of view. The economy behaves as a *complex adaptive system* capable of explaining the origin of wealth (Krugman, 1994; Beinhocker, 2006). The notion of complexity is already found in that of *catallactics*, a spontaneous order that emerges in the complex system of the market (Hayek, 1978). Complexity has been associated with economic development, attempting to validate the hypothesis through evolutionary models (Nelson & Winter, 1982; Hodgson, 1998), considering the size of companies (Axtell, 2001), or modeling financial markets (Follmer, 2005).

Those previous approaches have not been able to quantify complexity. Indeed, the mechanisms for quantifying are still under debate. A heterodox but interesting way of trying to solve this problem has been provided by *econophysics* (Durlauf, 2005; Rosser, 2008). However, as nonlinear dynamic systems out-of-equilibrium offer enormous difficulties to be modeled, this approach has not found much acceptance, unlike other models (Jakimowicz, 2020). An alternative research establishes links with quantum physics, in what has come to be called *quantum economics* (Orrell, 2018).

Far from the econophysic area, the method based on the *Economic Complexity Index* (ECI) has been demonstrated to be much easier and simpler, as it simplifies the quantification process analyzing easily characterizable properties. Mathematically formalized by

Hidalgo and Hausmann (Hidalgo & Hausmann, 2009), the ECI is able to estimate the availability, diversity and sophistication of the factors or inputs in an economy. The main idea is that complex products (those which require higher skills, knowledge and technology to be produced) would be geographically located. This research line has taken shape in just one decade. It began with the discovery of their ability to predict future economic growth using international trade data (Hidalgo & Hausmann, 2009; Hausmann et al., 2014). This finding was soon replicated in different studies reinforcing the idea that complexity explains a great part of economic growth and competitiveness (Ourens, 2012; Poncet & de Waldemar, 2013; Erkan & Yildirimci, 2015; Stojkoski et al., 2016; Chávez et al., 2017; Tacchella et al., 2018; Domini, 2019). The ECI mathematical framework has also provided the tool to explain other social variables as technology development levels or employment distribution (Petralia et al., 2017; Wohl, 2020).

The original ECI metric has been improved in different ways. For instance, a third dimension to the country-product bipartite network (i.e., products' patents) has been added, thereby building a triangular-shaped matrix or considering equations provided from the biological ecosystems' studies. Other authors have quantitatively enhanced some ECI features in order to differentiate countries' capacities to create products in terms of their complexity. Among all these suggested improvements, the so-called *Improved Economic Complexity Index*, or ECI+, has succeeded in improving some statistical aspects, but keeping the original simplifying spirit that maintains its independence from other variables different from trade exports (Albeaik et al., 2017).

Overall, new metrics have improved ECI's capacity to explain different social variables of relevance (to cite some of them: (Tacchella et al., 2012, 2013; Cristelli et al., 2013; Ivanova et al., 2017, 2019, 2020; Gala et al., 2018)). ECI variants continue to show their capacity to make useful predictions on economic growth (Hidalgo, 2015; Hausmann et al., 2014; Ourens, 2012; Poncet & de Waldemar, 2013; Chávez et al., 2017; Tacchella et al., 2018; Domini, 2019; Stojkoski et al., 2016), income inequality (Hartmann et al., 2017; Zhu et al., 2020; Sbardella et al., 2017; Fawaz & Rahnama-Moghadamm, 2019) and even environmental performance (Neagu & Teodoru, 2019; Can & Gozgor, 2017; Mealy & Teytelboym, 2020; Romero & Gramkow, 2021; Boleti et al., 2021).

2. Economic complexity and Information Society indexes

The assessment of the impact on economic growth of the IS and the EC concepts should start with the construction of composite indexes that characterize them. For reasons that will be explained in detail in the next section (time-delayed impact on growth), both indexes are constructed for the year 2014.

2.1. Information Society Level of Development to Gross Domestic Product Ratio (IGR) index

The level of IS development is determined in this article using the *Information Society Level of Development to Gross Domestic Product Ratio* (IGR) index (Jurado-González & Gómez-Barroso, 2016). Instead of creating a new *ad hoc* index, this IGR index has been chosen from the existing literature, considering that its definition and methodology address the statistical shortcomings and weaknesses of other metrics: IGR theoretically justifies the selection of variables, not only focusing on technology, and then applies a principal component analysis (PCA) that ensures the correct weighting of these variables, avoiding problems of bias or overrepresentation.

To get IGR, the process starts with the construction of the *Information Society Level of Development* (ISLD) index. IGR is defined as the ISLD value for a given GDP (Gross Domestic Product). In this way, the impact of economic development itself on the progress of the IS is softened, minimizing the problems of cause-and-effect relationship by simple correlation. ISLD was conceived as an attempt to deal with a complex reality that needs to be analyzed considering several heterogeneous dimensions. The basic ISLD core is composed of different variables that cover the following features: availability of accessible, affordable and reliable ICT infrastructures; knowledge prevalence and diffusion; real adoption of ICTs through social use; ICTs real weight in the economy. In this article, the list of single indicators initially selected to build ISLD has been updated, always bearing in mind analytical soundness, country coverage, relevance to the measured phenomenon and relationship between variables. The list of updated single indicators is shown in Table 1.

ISLD, and later IGR, have been built for the 2014 year with data obtained from the ITU World Telecommunication/ICT Indicators Database (https://www.itu.int/pub/D-IND-WTID.OL-2020) and the World Bank Database (https://data.worldbank.org); human capital data were collected from the Penn World Tables (PWT 10.0) (https://doi.org/10.15141/S5Q94M).

Table 1. ISLD single indicators. In comparison with the original list, A2 and A5 have been added and HC replaces OT2 (Gross enrolment ratio in tertiary education)

Code	Indicator description
A1	Fixed telephone lines per 100 inhabitants
A2	Mobile cellular telephone subscriptions per 100 inhabitants
A3	Fixed Internet subscribers per 100 inhabitants
A4	Fixed broadband Internet subscribers per 100 inhabitants
A5	Active mobile-broadband subscriptions per 100 inhabitants
A6	International Internet bandwidth per inhabitant (bits/second/inhabitant)
A7	Percentage of the population covered by a mobile cellular telephone network
A8	Fixed broadband Internet access tariffs per month in US dollars as a percentage of monthly per capita income
A9	Mobile cellular telephone prepaid tariffs per month in US dollars as a percentage of monthly per capita income
HH7	Proportion of individuals who used the Internet in the past 12 months
ICT3	ICT goods imports as a percentage of total imports
ICT4	ICT goods exports as a percentage of total exports
OT1	Gross enrolment ratio secondary education
HC	Human capital index, based on years of schooling and returns to education

Following the process defined by IGR's creators, imputation of missing data was applied, despite a strong data availability. The Markov Chain Monte Carlo (MCMC) method was used, assuming that data are drawn from a multivariate normal distribution using a Bayesian approach. A missing at random (MAR) assumption was considered according to an EM convergence test. The iterations for this process were M = 100, in N = 10 different imputations. The results have provided a complete data set of 14 indicators for 180 countries. Normalization was then applied to the indicators to render them comparable. The method employed was the standardization (or z-scores) which converts indicators to a common scale with a mean of zero and standard deviation of one. Previously, A8 and A9 were reoriented by multiplying them by factor −1, as desirable affordability is inversely proportional to access tariffs. As this normalization method makes indicators with extreme values have a greater effect on the composite indicator, values whose $|Z| > 4$ were considered as outliers (Younger, 1979). This left at the end a dataset of 14 indicators for 125 countries. This dataset is reasonable for a multivariate analysis, addressing usual requirements as maintaining a cases-to-variables proportion higher than 5 (Bryant & Yarnold, 1995).

Factor analysis suitability to reduce the dimension of the dataset was then explored considering two tests: the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's Test of sphericity. The results showed 0.849 in the KMO and 0 significance in the Bartlett's, which confirms the fitness of a factor analysis. As originally defined for ISLD, PCA was then performed. According to the Kaiser criterion, all factors with eigenvalues below 1.0 were dropped, leaving three main underlying factors explaining more than 71.88% of the total variance: (1) ICTs & knowledge structures diffusion and adoption (A1–A5, A7, HH7, OT1, HC); (2) ICTs affordability (A8, A9) and effective International Internet bandwidth per inhabitant (A6); and (3) ICTs economy weight in the trade balance (ICT3, ICT4). Factors were then weighted and aggregated. ISLD is a more robust index than other composite indexes that rely on equal weighting, or weighting based on "experts" subjective opinions. ISLD index was finally normalized into values between zero and one.

As identified when originally defined, ISLD shows a strong correlation with economic and human development variables, such as Gross Domestic Product per capita based on power parity purchase (GDPpcPPP). To minimize this effect, an operation was performed over ISLD to obtain the proportion of ISLD in relation to GDPpcPPP. This is IGR, whose definition transforms the strong logarithmic shape relationship between ISLD and GDP into a linear one:

$$IGR_c^n = \left[\frac{ISLD_c^n}{\log GDP_c^{pcPPP}} \right]_n ,$$

where GDP_c^{pcPPP} is the GDP per capita PPP for the cth country, and where the $\log GDP_c^{pcPPP}$ has been normalized (n) as well as the final IGR value. In the Appendix A, IGR and ISLD values are shown for the reference year of 2014.

2.2. Improved Economic Complexity Index

The Improved Economic Complexity Index known as ECI+ is built upon the previous ECI, which uses the so-called *Method of Reflections* developed by Hidalgo and Hausmann (Hidalgo & Hausmann, 2009). The method begins with a country-product export matrix in which main exported products are identified depending on the specific weight that they represent in comparison with the total exports of that country, and the total exports of that product. Afterwards, an iterative calculus is performed over the average value of the previous-level properties of a node's neighbors. This method of reflections finally converges into the mentioned ECI.

ECI is based on the convention of a revealed comparative advantage (RCA). This criterion establishes a hard threshold that introduces noise around the boundary, as it was soon observed by some authors (Tacchella et al., 2012). The main criticism focuses on the attempt to characterize the complexity of a product from the simple observation that the product is made by a developed country. In fact, this gives limited information on the complexity of the product itself because rich countries export a great variety of, either complex or not, products. On the other hand, when an underdeveloped country can export a given product, very likely this product requires a low level of sophistication. Thus, it is reasonable to measure the competitiveness and adaptability of a country through the sum of quality and complexity of its products, but it is not possible to adopt the same approach to measure the quality and complexity of products.

As previously mentioned, some attempts to improve ECI were proposed, such as the Fitness and product Complexity Index (FCI) (Tacchella et al., 2012), the *Patent Complexity Index* (PatCI) (Ivanova et al., 2017) or the Modified Economic Complexity Index (Ivanova et al., 2020). However, these multivariable approaches might be potentially subject to the typical problems of missing data, bias, weighting, or underlying factors identification. Considering these observations, some authors proposed the ECI+ (Albeaik et al., 2017). This new version tries to avoid the original ECI's limitations while keeping its original simplifying approach. ECI+ defines the complexity of an economy as the total exports of a country corrected by how difficult it is to export each product and by the size of that country's export economy.

The building of ECI+ starts by defining

$$X_c^0 = \sum_p X_{cp}$$

as the total exports of a country and

$$\frac{1}{\sum_c X_{c,p} / X_c^0}$$

as a measure of how difficult it is to export a product (one over the average share that a product represents in the average country). This simply assumes that products that are hard to export will represent a small share of exports for most countries (even when their export volumes are large). Then, the corrected total exports of a country are defined as:

$$X_c^1 = \sum_p \frac{X_{c,p}}{\sum_c \frac{X_{c,p}}{X_c^0}}.$$

This correction makes X_c^1 a measure of the total exports of a country corrected by how difficult it is to export each product. This corrected value of total exports can be used to again calculate the share that a product represents of the average country $\left(X_c^1 \to X_c^2\right)$. This provides a second order correction:

$$X_c^2 = \sum_p \frac{X_{c,p}}{\sum_c \frac{X_{c,p}}{X_c^1}}.$$

The limit of this iterative approach is intuitive:

$$X_c^N = \sum_p \frac{X_{c,p}}{\sum_c \frac{X_{c,p}}{X_c^{N-1}}}.$$

Finally, using this definition, ECI+ is defined as the total exports of a country corrected by how difficult it is to export each product, minus the average share that the country represents in the export of a product (which accounts for the size of a country's export economy):

$$ECI_c^+ = \log(X_c^\infty) - \log\left(\sum_p \frac{X_{c,p}}{X_p}\right).$$

To guarantee the numerical convergence of the mapping Xc is normalized at each step (including X_c^0) by its geometric mean:

$$X_c^N = \frac{X_c^N}{\left(\prod_{c'} X_{c'}^N\right)^{\frac{1}{\{C\}}}},$$

where {C} is the number of countries in the sample.

Following this process, ECI+ has been built for 2014. Data for the products exported by countries have been harvested from UN data (https://comtrade.un.org/data/), classified by the format of the Standard International Trade Classification (SITC) revision 3 at the 2-digit level. Some outliers were discarded to reduce noise, such as city-sized national economies, or economies for which no reliable data were available. Certain countries were also excluded because levels of exports were too low or they were under a state of conflict (i.e., civil war). Non-representative products (too low exports value) were also excluded from ECI+ construction. This finally allowed us to build ECI+ based on the exports of 63 products by 125 countries, which represents more than 95% of global GDP and 82% of global trade.

ECI+ values are shown in Appendix B.

3. Model

As an initial step, the relationship of IGR and ECI+ with economic growth is explored. The behavior of both indicators against GDPpcPPP seems to indicate a significant relationship. Taking the data from 2014, the usual logarithmic relationship shows strong positive correlations (see Figure 1), with a higher value of coefficient of determination (R^2) for IGR values (0.586) than for those of ECI+ (0.497).

To confirm and formalize this apparent impact of IGR and ECI+ on economic growth, different models were developed. In all of them, economic growth was considered as the independent variable, and calculated as the percentage rate of variation of GDPpcPPP between different years, specifically in a five-year window:

$$\Delta GDPpcPPP_{t-5}^{t} = \frac{GDPpcPPP_t - GDPpcPPP_{t-5}}{GDPpcPPP_{t-5}}.$$

Annual economic growth, due to many different factors, usually shows a volatility that can be avoided using this kind of time window. In fact, the practice of using lagged variables is relatively frequent in studies that relate ICT development to economic growth (Gómez-Barroso & Marbán-Flores, 2020b). It should also be noted that other studies have already verified that IGR and ECI+ indexes monitor long-term growth flows, which can mitigate the effect of the most turbulent periods (Jurado-González & Gómez-Barroso, 2016; Albeaik

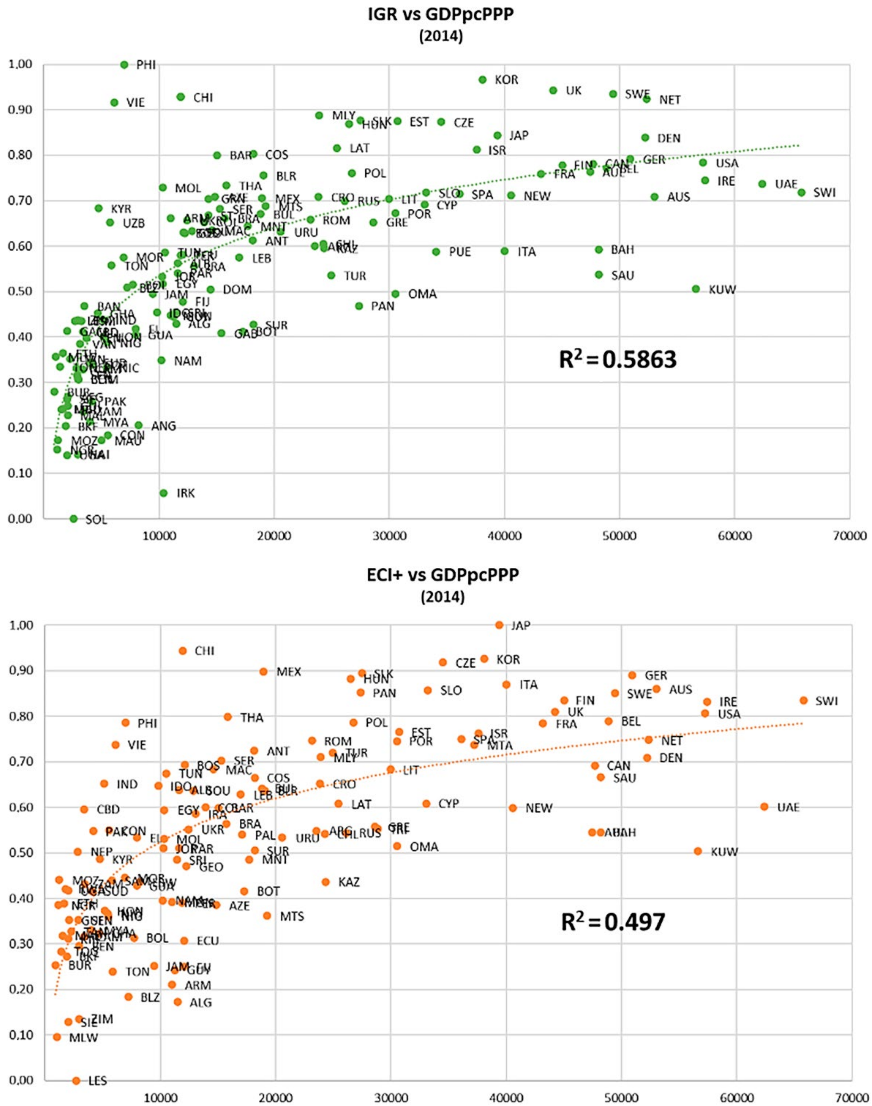

Figure 1. IGR vs GDPpcPPP 2014 & ECI+ vs GDPpcPPP 2014

et al., 2017). At the time of our analysis, the last complete available series for GDP covered the year 2019, so the values of the rest of the variables were dated back to 2014. This is the reason why, as mentioned in the previous section, IGR and ECI+ values were calculated for 2014. The 2014–2019 period is particularly suitable for the study, as it offers generalized global growth (2.8% on average, oscillating each year between 2.3% and 3.2% year-on-year, according to World Bank data). Beyond theoretical arguments, a simple exercise can help to support this approach: when repeating the operation presented at the beginning of the section (correlation of both ECI+ and IGR with GDPpcPPP) for the year 2019, Table 2 indicates that the explanatory power seems to improve over time.

Table 2. ECI+ and IGR vs GDPpcPPP – R^2 improvement (2014–2019)

	ECI+ 2014	**IGR 2014**
vs GDPpcPPP 2019	0.5297	0.6222
vs GDPpcPPP 2014	0.497	0.5863
	6.6%	6.1%

As dependent variables, very different social and economic indicators were introduced into multiple models. Obviously, the three models showing the best fit (and, therefore, the greatest explanatory capacity for economic growth) were selected. The first two models evaluate the impact of ECI+ and IGR on economic growth separately, and the third model includes both indexes to assess their joint impact:

$$\Delta GDPpcPPP_{t-5}^{t} = \beta_0 + \beta_1 GDPpcPPP_{t-5} + \beta_2 Upop_{t-5}^{4} + \beta_3 PMt_{t-5} + \beta_4 FdI_{t-5} + \beta_5 Exp_{t-5} + \beta_6 Gcf_{t-5} + \beta_7 ECI_{t-5}^{+} + \varepsilon; \quad (1)$$

$$\Delta GDPpcPPP_{t-5}^{t} = \beta_0 + \beta_1 GDPpcPPP_{t-5} + \beta_2 Upop_{t-5}^{4} + \beta_3 PMt_{t-5} + \beta_4 FdI_{t-5} + \beta_5 Exp_{t-5} + \beta_6 Gcf_{t-5} + \beta_7 IGR_{t-5} + \varepsilon\,; \quad (2)$$

$$\Delta GDPpcPPP_{t-5}^{t} = \beta_0 + \beta_1 GDPpcPPP_{t-5} + \beta_2 Upop_{t-5}^{4} + \beta_3 PMt_{t-5} + \beta_4 FdI_{t-5} + \beta_5 Exp_{t-5} + \beta_6 Gcf_{t-5} + \beta_7 ECI_{t-5}^{+} + \beta_8 IGR_{t-5} + \varepsilon. \quad (3)$$

As shown in Eqs (1), (2) and (3), the variables introduced in the model are the following:

- *Upop* is the percentage of the population living in urban areas. It is raised to the fourth power after verifying that this is how it shows the best behavior. Both *Upop* and *GDPpcPPP* serve as complementary variables to negatively predict the effect of the previous level of development, because the most developed countries (with higher per capita income and, generally, higher level of urban concentration) usually experience a more moderate growth.
- *PMt* is the estimated value of the network emerged from the interactions between the individuals of each country. To estimate this value, the classic Metcalfe approach (Metcalfe, 2013), based on information exchange nodes structure, was used; this approach had been empirically tested (Gonçalves, 2011; Madureira et al., 2013; Zhang et al., 2015), assimilating in this case individuals to nodes, and therefore, using population as an input. Population has also been used in other ways as a predictor of

economic growth (Becker et al., 1999; Peterson, 2017). This variable is thus aligned with ECI+ and IGR to assess the emerging complexity of human interactions and their contribution to economic development.

– *FdI* (*Foreign direct investment*), *Exp* (*Exports*) and *Gcf* (*Gross Capital Formation*) are all measured as a percentage of GDP, and are variables that have been extensively used in the literature to predict economic growth (Balassa, 1978; Feder, 1983; Li & Liu, 2005; Kanu & Ozurumba, 2014). In a globalized and hyperconnected world, they can also be closely related to EC and IS.

The results of models (1), (2) and (3) are summarized in Tables 3 and 4. In the subsections that follow, these results are analyzed in detail.

Table 3. Linear regression model analysis

	(1)	(2)	(3)
GDPpcPPP	−0.115	−0.162	−0.207
Upop	−0.435***	−0.496***	−0.480***
PMt	0.160**	0.167**	0.138*
FdI	0.068	0.067	0.070
Exp	0.158*	0.086	0.097
Gcf	0.053	0.119	0.091
ECI+	0.417***		0.271***
IGR		0.506***	0.267***
N	125	125	125
$\overline{R}^2$ adjusted	0.330	0.331	0.363
F	9.721	9.780	9.842
Durbin-Watson	2.112	2.222	2.187

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Tolerance and Variance Inflation Factors

	(1)		(2)		(3)	
	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
GDPpcPPP	0.363	2.754	0.341	2.929	0.335	2.986
Upop	0.496	2.015	0.485	2.064	0.483	2.071
PMt	0.862	1.161	0.869	1.150	0.852	1.174
FdI	0.969	1.032	0.969	1.032	0.969	1.032
Exp	0.741	1.350	0.691	1.447	0.690	1.450
Gcf	0.892	1.121	0.878	1.139	0.861	1.161
ECI+	0.668	1.497			0.480	2.082
IGR			0.459	2.178	0.330	3.029

3.1. ECI+ effect

The first model (Eq. (1)) assesses the impact of ECI+ on economic growth. The model shows the complementary variables *GDPpcPPP* and *Upop*^{4} present a negative coefficient as expected; the latter being significantly more relevant when predicting economic growth and showing an acceptable level of significance (<0.01), while the former does not reach the standard levels of significance.

Furthermore, *PMt* presents a positive coefficient, as expected, and is statistically significant (<0.05). This is also the case for *Exp*, although its relevance is slightly lower. Contrarily, *FdI* and *GcF* do not show significance in this model.

Finally, ECI+ presents a positive coefficient and is more relevant than the rest of the positive predictors that have been included in the model (*PMt*, *FdI*, *Exp*, *Gcf*). Its coefficient practically triples the weight of the closest one (*PMt*). Its level of significance is high (≤0.01).

The model meets the usual adequacy criteria: independence of errors, with a Durbin-Watson value very close to 2; homoscedasticity, without patterns detected in the variation of the residuals; noncollinearity, with tolerance values that are appreciably above 0.1 and VIF values below 10; and normality, as the Kolmogorov-Smirnov test has offered values of bilateral asymptotic significance for ECI+ > 0.05 (0.2).

3.2. IGR effect

The second model (Eq. (2)) evaluates the impact of IGR in economic growth. The coefficients for all the variables are like the values obtained in model (1), but with IGR taking the place of ECI+ as the most relevant variable. *PMt* slightly improves its relevance and significance. *Exp*, however, falls at the level of the rest of the remaining comparative variables (*FdI*, *GcF*), worsening its coefficient weight and losing significance.

As in the previous case, is the results confirmed that this model fulfills the usual adequacy criteria: independence of errors, homocedasticity and noncollinearity, as shown in the corresponding tests. Only in the case of the normality criterion, the Kolmogorov-Smirnov test for IGR has offered bilateral asymptotic significance values of 0.008 that do not meet the usual criterion (> 0.05). However, the number of samples can justify this deviation from the normal distribution and, nevertheless, its closeness to normality is substantiated when drawing the histogram and the normal plot of regression standardized residuals.

3.3. ECI+ and IGR effect

Finally, the third model (Eq. (3)) combines the effects that ECI+ and IGR produce in economic growth. This model also complies with the usual criteria for adequacy: independence of errors, homoscedasticity, noncollinearity and normality.

The results show that the complementary and comparison variables of the model maintain a profile like what they showed in the previous models. *Upop*^{4} and, to a lesser extent, *PMt* keep exceeding the threshold of significance. Above all, the most relevant result of this model is the shared behavior of ECI+ and IGR that take over and distribute the weight of the explanatory relevance to predict economic growth, both maintaining a level of significance below 0.01.

4. Discussion

First it should be emphasized that the different econometric models used to relate ECI+ and IGR with economic growth have been deployed over a broad set of countries (125) discarding very few outliers, unlike other similar studies. In this sense, this approach has been able to obtain a statistical power higher than 99.999%.

Turning to the substance of the results, the significance of $Upop^4$, and slightly less so of *PMt* are remarkable. As expected, $Upop^4$ presents negative coefficients when predicting economic growth, since the most developed countries (with the highest urban concentration) experience more moderate growth in percentage terms. In contrast, the *PMt* coefficients are positive: the complexity that emerges from the interaction between individuals in most populated countries thanks to the potential for the development of more connections facilitates economic growth over time. In this way, *PMt* models complexity derived from the number of individuals emulating the estimation of the value of ICT-based networks.

The results are different in the case of *FdI*, *Exp* and *Gcf*, which are variables typically used in other economic growth prediction models. A priori, in terms of the EC and the IS, it is intuitive to relate foreign investment flows, exports or capital accumulation with the establishment of large-scale cooperation links that increase global complexity, thanks to intensive information exchanges. However, in the models presented in this article, these variables show poor coefficients to predict economic growth and are not statistically significant, despite their positive contribution to the models' fitness.

Finally, the analysis of ECI+ and IGR results addresses the main objective of this work, which pretended to know their individual significance and their potential improvement when combined. In this regard, we argue that the behavior of both indexes validates the hypotheses raised: ECI+ supposes a differential and positive factor in the prediction of economic growth in the first model (Eq. (1)): the level of EC measured through this index allows predicting a very relevant part of economic growth, only surpassed by that predicted by the complementary variable $Upop^4$; the accumulation of capacities to produce more complex products is the prelude to higher growth rates. In the case of the second model (Eq. (2)), IGR has led the weight in the predictive capacity of the model, even above $Upop^4$: a development of the IS above what would be expected for a country, given its level of economic development, is a good predictor of its future economic growth (the best in the case of this model). Finally, the third model (Eq. (3)), which does not present collinearity problems, shows how ECI + and IGR can complement each other to improve the fitness of the two previous models (improvement of more than 10% for the adjusted $\overline{R}^2$, and improvement as well on the F factor). We suggest a simple explanation of this fact: EC, analyzed in terms of ECI+, rests on the idea that the most complex products that require a greater level of skills, knowledge and technology are geographically located; in order to favor in these places the deployment of higher levels of complexity and an enhancement of the interactions among the different production factors, it is currently necessary to push forward ICT or, more generally, the IS, here modeled by IGR. Therefore, IGR enhances and amplifies the explanatory capacity of ECI+.

Conclusions

This article sought to evaluate the complementarity of the IS and the EC in the explanation of economic growth. The basis for this complementarity lies in the fact that, although EC sprouts from the acquisition, structuring and development of knowledge, the mechanisms that facilitate its exchange, proliferation and consolidation through ICT can accelerate it. In the end, the leading technological development of our last decades related to the promotion and prominence of information allows reducing distances (*tele*-communications), speeding up links, reinforcing their reliability, and boosting cooperation between potential productive areas (individuals, companies, countries, producers-consumers), thereby creating new spaces in which emergent properties can arise at higher levels of complexity.

The results have proved that both ECI+ and IGR are, on their own, reliable tools to predict economic development. In fact, the models developed in this article provide a very satisfactory explanatory power when compared to that obtained by others commonly used in the literature, while including a very large number of countries. Moreover, ECI+ and IGR have shown even better performance when both are combined in the same model. This confirms that was expected: EC and IS paradigms converge in this particular implementation, contributing to the idea of complementarity between information and complexity as global growth trends since life appeared in our planet. On a more practical note, the findings of this work may help to locate the factors that can further enhance and accelerate economic growth.

However, this research suffers from some limitations. The most important ones are derived from the definitions of the indexes used to represent the EC and the IS. On the one hand, IGR, such as any other IS measurement, needs to be updated regularly. This makes impossible the comparison between like-for-like measures and increase the difficulties to perform analysis, for example, through techniques such as panel data. The reason for the need for updating is that these indexes depend on the selection of underlying ICT variables. These variables are adopted and dizzyingly saturated over time. Thus, when the diffusion of certain technologies is still very incipient, their explanatory capacity is limited, and the results do not offer sufficient consistency. However, when their adoption reaches very high rates, their measurement loses the ability to explain other variations as economic growth (i.e., mobile telephony penetration in poor countries is reaching rich countries' rates). In addition, if technologies become obsolete when others replace them, such a replacement must also happen in the construction of IGR (i.e., today it would make no sense to consider the number of fax machines as a relevant variable, and very soon, it will be the case with the fixed telephone lines).

Regarding ECI+, the exports may be significantly affected by the evolution of global international trade. Specifically, the relative growth of the service-based economy (particularly the new service business models that ICT, in turn, are promoting growth) is hardly visible in the export of materials, except for those that behave as intermediate instruments of that service. For instance, the value of the computer exports is significantly higher than that of the raw materials from which they are made, but the value of the services based on the software implemented in a network of computers can be much higher than that of the computers on which they are implemented. However, the value of these services would not be properly represented in the model, as it does not appear among the exports. In addition, the "compass" of metrics such as ECI+ can become disoriented if the level of exports suffers tensions due to causes unrelated to economic activity, such as political conflicts, blocks of a network path for international trade (as happened in 2021 with the Suez Canal) or an unexpected event such as the pandemic caused by the SARS-CoV-2.

On this basis, it is possible to establish some future research lines. First, it would be possible to continue delving into the variants of the EC metrics. One objective could focus on making them more robust and consistent from a purely statistical point of view. Another could seek a better balance between simplicity of elaboration using few data sources (i.e., exports) and sources diversification to increase the resilience of any indicator against fluctuations. Second, EC metrics could gain representativeness through the consideration of not only exported products but also of services. In this regard, different classifications can be used: the *Extended Balance of Payments Services Classification* (EBOPS) carried out by the UN (although it would require further segmentation and data availability), or the classification under the NACE standard of economic activities by sectors at a regional level, carried out since 1970 by the EU. The latter could link the "*gray matter*" inherent to each type of economic activity with the products emerging from those activities, although it would be necessary again to have a greater amount of data and a segmentation in accordance with researchers' needs.

In turn, IS metrics, such as IGR, should keep the benefits of dimension reduction techniques such as principal component analysis to deal with this complex phenomenon, while trying to mitigate the typical multivariate problems, as ECI+ has achieved. In this sense, a research line might explore a method analogous to the Method of Reflections: this would allow indirect measurement of the increasing complexity that underlies the development of the IS, considering fewer variables and saving efforts on unavailable data estimations, no matter how robust they might be. Thus, simplified complexity measures of the networks in which the exchange of information takes place (in the style of those proposed by Metcalfe, Madureira or Reed) could constitute an alternative way to address the problem. In other words, regardless of the specific ICTs that will emerge over time, special attention should be paid to the structure that these ICTs facilitate and to the behavior and profile of the data that the use of ICTs allows to extract (volumes of traffic, categorization and information patterns, etc.). For example, the population connected to the Internet weighted by the average connection time or the amount per type of information exchanged could be variables of interest. In any case, it will always be necessary to bear in mind that attempts to define new ways of measuring complexity will face the main problem of distinguishing between complexity and disorder.

Whether or not the adopted metrics might be modified, a future research line could focus on clustering countries or regions. This might not only increase the explanatory capacity of the models, but it could also help to identify specific factors that are relevant for each subset. For example, the analysis could yield much more precise results if it were applied to, as is usual in many other studies, developing, emerging and developed countries. In fact, some clustering techniques based on the GDPpcPPP of every country were explored for this study. This approach was not pursued because in order for it to achieve representativeness of the subsets and to avoid cherry-picking effects, outlier identification techniques need to be developed, exceeding the scope and size of this early work. Issues such as the volatility of the

GDP growth rate, which particularly affects those countries with a very low level of GDP, or exogenous factors (national fiscal policies close to tax-havens, internal conflicts or even wars) become particularly critical when it comes to defining homogeneous groups.

Finally, further research could modify or expand the 2014–2019 timeframe. However, note that any additional research effort would require to build ECI+ and IGR indexes for each year considered, which faces the aforementioned problems of definition of the indexes or even of data availability. However, it is clearly tempting for a future research to consider the unfortunate, but at the same time very interesting, scenario that the COVID-19 crisis has created: IS and EC metrics could be updated to check their influence on economic impact mitigation and recovery after such an onslaught.

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APPENDIX

Appendix A

Rank	Country Name	ACRO	IGR	ISLD
1	Korea. Rep.	KOR	1	0.998
2	United Kingdom	UK	0.982	0.994
3	Sweden	SWE	0.978	1
4	Netherlands	NET	0.967	0.995
5	Philippines	PHI	0.961	0.804
6	Iceland	ICE	0.956	0.978
7	China	CHI	0.914	0.812
8	Malaysia	MLY	0.904	0.863
9	Czech Republic	CZE	0.903	0.893
10	Estonia	EST	0.901	0.881
11	Slovak Republic	SLK	0.898	0.868
12	Hungary	HUN	0.889	0.857
13	Denmark	DEN	0.884	0.908
14	Japan	JAP	0.879	0.88
15	Viet nam	VIE	0.871	0.718
16	Israel	ISR	0.845	0.842
17	Germany	GER	0.836	0.857
18	Latvia	LAT	0.835	0.801
19	United States	USA	0.832	0.862
20	Canada	CAN	0.823	0.839
21	Finland	FIN	0.818	0.829
22	Belgium	BEL	0.814	0.832
23	Costa Rica	COS	0.808	0.749
24	Australia	AUL	0.805	0.82
25	Barbados	BAR	0.798	0.726
26	France	FRA	0.798	0.805
27	Norway	NOR	0.796	0.832
28	United Arab Emirates	UAE	0.788	0.824
29	Poland	POL	0.782	0.754
30	Switzerland	SWI	0.771	0.809

Rank	Country Name	ACRO	IGR	ISLD
31	Belarus	BLR	0.763	0.711
32	Austria	AUS	0.755	0.777
33	New Zealand	NEW	0.748	0.751
34	Slovenia	SLO	0.746	0.735
35	Spain	SPA	0.746	0.741
36	Thailand	THA	0.733	0.671
37	Aruba	ARU	0.729	0.723
38	Lithuania	LIT	0.729	0.711
39	Croatia	CRO	0.725	0.691
40	Cyprus	CYP	0.72	0.709
41	Russian Federation	RUS	0.72	0.693
42	Mexico	MEX	0.713	0.664
43	Moldova	MOL	0.709	0.62
44	Azerbaijan	AZE	0.706	0.642
45	Portugal	POR	0.699	0.683
46	Mauritius	MAU	0.696	0.65
47	Serbia	SER	0.68	0.62
48	Bulgaria	BUL	0.678	0.632
49	Greece	GRE	0.677	0.657
50	Romania	ROM	0.673	0.64
51	Brazil	BRA	0.661	0.604
52	Montenegro	MNT	0.649	0.601
53	Colombia	COL	0.647	0.584
54	Armenia	ARM	0.646	0.569
55	Ukraine	UKR	0.646	0.576
56	Uruguay	URU	0.643	0.604
57	Bahrain	BAH	0.636	0.648
58	Macedonia. FYR	MAC	0.631	0.572
59	Italy	ITA	0.625	0.627
60	Kyrgyz Republic	KYR	0.625	0.5

Rank	Country Name	ACRO	IGR	ISLD
61	South Africa	SOU	0.624	0.559
62	Chile	CHL	0.623	0.595
63	Antigua and Barbuda	ANT	0.618	0.573
64	Bosnia and Herzegovina	BOS	0.618	0.55
65	Georgia	GEO	0.618	0.551
66	Argentina	ARG	0.617	0.588
67	Kazakhstan	KAZ	0.613	0.586
68	Saudi Arabia	SAU	0.58	0.591
69	Lebanon	LEB	0.579	0.533
70	Ecuador	ECU	0.57	0.507
71	Tunisia	TUN	0.569	0.499
72	Peru	PER	0.567	0.504
73	Turkey	TUR	0.555	0.532
74	Kuwait	KUW	0.554	0.574
75	Albania	ALB	0.549	0.486
76	Iran. Islamic Rep.	IRA	0.548	0.491
77	Morocco	MOR	0.538	0.45
78	Paraguay	PAR	0.528	0.468
79	Oman	OMA	0.522	0.511
80	Brunei Darussalam	BRU	0.519	0.544
81	Jordan	JOR	0.515	0.45
82	Egypt. Arab Rep.	EGY	0.5	0.437
83	Panama	PAN	0.492	0.475
84	Bolivia	BOL	0.483	0.409
85	Belize	BLZ	0.473	0.398
86	Jamaica	JAM	0.472	0.409
87	Fiji	FIJ	0.467	0.416
88	Sri Lanka	SRI	0.441	0.39
89	Suriname	SUR	0.434	0.403
90	Indonesia	INS	0.433	0.377
91	Mongolia	MON	0.432	0.38

Rank	Country Name	ACRO	IGR	ISLD
92	Guyana	GUY	0.431	0.38
93	Botswana	BOT	0.417	0.385
94	Algeria	ALG	0.416	0.368
95	Ghana	GHA	0.394	0.315
96	El Salvador	ELS	0.388	0.33
97	India	IND	0.385	0.311
98	Guatemala	GUA	0.374	0.318
99	Zimbabwe	ZIM	0.352	0.266
100	Honduras	HON	0.348	0.281
101	Lesotho	LES	0.344	0.257
102	Nigeria	NIG	0.339	0.277
103	Cambodia	CBD	0.334	0.257
104	Namibia	NAM	0.33	0.288
105	Nicaragua	NIC	0.283	0.23
106	Sudan	SUD	0.279	0.219
107	Cameroon	CAM	0.252	0.194
108	Tanzania	TAN	0.25	0.183
109	Nepal	NEP	0.244	0.184
110	Ethiopia	ETH	0.24	0.168
111	Senegal	SEN	0.23	0.173
112	Benin	BEN	0.224	0.169
113	Togo	TOG	0.199	0.136
114	Malawi	MLW	0.195	0.128
115	Pakistan	PAK	0.194	0.153
116	Zambia	ZAM	0.161	0.124
117	Sierra Leone	SIE	0.153	0.11
118	Myanmar	MYA	0.147	0.116
119	Guinea	GUI	0.14	0.101
120	Madagascar	MAD	0.113	0.078
121	Burundi	BUR	0.107	0.068
122	Burkina Faso	BFA	0.091	0.065
123	Uganda	UGA	0.032	0.023
124	Mozambique	MOZ	0.026	0.018
125	Niger	NGR	0	0

Appendix B

Rank	Country Name	ACRO	ECI+
1	Japan	JAP	1.000
2	China	CHI	0.957
3	Korea. Rep.	KOR	0.943
4	Czech Republic	CZE	0.937
5	Mexico	MEX	0.921
6	Slovak Republic	SLK	0.919
7	Germany	GER	0.915
8	Hungary	HUN	0.909
9	Italy	ITA	0.900
10	Austria	AUS	0.892
11	Slovenia	SLO	0.890
12	Panama	PAN	0.886
13	Sweden	SWE	0.884
14	Finland	FIN	0.873
15	Switzerland	SWI	0.872
16	United Kingdom	UK	0.853
17	United States	USA	0.850
18	Thailand	THA	0.844
19	Belgium	BEL	0.837
20	Poland	POL	0.835
21	Philippines	PHI	0.834
22	France	FRA	0.833
23	Estonia	EST	0.819
24	Israel	ISR	0.817
25	Spain	SPA	0.807
26	Netherlands	NET	0.805
27	Romania	ROM	0.804
28	Portugal	POR	0.803
29	Viet nam	VIE	0.797
30	Antigua and Barbuda	ANT	0.787
31	Turkey	TUR	0.784
32	Malaysia	MLY	0.776
33	Denmark	DEN	0.775
34	Serbia	SER	0.770
35	Bosnia and Herzegovina	BOS	0.763
36	Canada	CAN	0.762
37	Macedonia. FYR	MAC	0.755
38	Lithuania	LIT	0.755
39	Tunisia	TUN	0.748
40	Saudi Arabia	SAU	0.742
41	Costa Rica	COS	0.741
42	India	IND	0.731
43	Croatia	CRO	0.731
44	Indonesia	INS	0.727
45	Bulgaria	BUL	0.723

Rank	Country Name	ACRO	ECI+
46	Albania	ALB	0.720
47	Belarus	BLR	0.719
48	South Africa	SOU	0.719
49	Lebanon	LEB	0.713
50	Cyprus	CYP	0.697
51	Latvia	LAT	0.696
52	United Arab Emirates	UAE	0.692
53	Colombia	COL	0.691
54	Barbados	BAR	0.690
55	New Zealand	NEW	0.690
56	Cambodia	CBD	0.688
57	Egypt. Arab Rep.	EGY	0.686
58	Iran. Islamic Rep.	IRA	0.679
59	Brazil	BRA	0.663
60	Greece	GRE	0.658
61	Ukraine	UKR	0.653
62	Argentina	ARG	0.651
63	Pakistan	PAK	0.650
64	Bahrain	BAH	0.648
65	Australia	AUL	0.648
66	Russian Federation	RUS	0.647
67	Chile	CHL	0.645
68	El Salvador	ELS	0.640
69	Uruguay	URU	0.639
70	Moldova	MOL	0.637
71	Oman	OMA	0.625
72	Jordan	JOR	0.621
73	Paraguay	PAR	0.621
74	Suriname	SUR	0.617
75	Kuwait	KUW	0.616
76	Nepal	NEP	0.616
77	Kyrgyz Republic	KYR	0.603
78	Montenegro	MNT	0.602
79	Sri Lanka	SRI	0.602
80	Georgia	GEO	0.590
81	Norway	NOR	0.581
82	Morocco	MOR	0.571
83	Mozambique	MOZ	0.567
84	Kazakhstan	KAZ	0.565
85	Zambia	ZAM	0.561
86	Guatemala	GUA	0.557
87	Uganda	UGA	0.549
88	Botswana	BOT	0.549
89	Sudan	SUD	0.549
90	Namibia	NAM	0.533

Rank	Country Name	ACRO	ECI+
91	Mongolia	MON	0.529
92	Peru	PER	0.528
93	Ethiopia	ETH	0.528
94	Niger	NGR	0.525
95	Azerbaijan	AZE	0.525
96	Honduras	HON	0.515
97	Nicaragua	NIC	0.511
98	Mauritius	MAU	0.507
99	Nigeria	NIG	0.506
100	Guinea	GUI	0.499
101	Senegal	SEN	0.499
102	Iceland	ICE	0.485
103	Myanmar	MYA	0.482
104	Tanzania	TAN	0.480
105	Ghana	GHA	0.477
106	Madagascar	MAD	0.473
107	Cameroon	CAM	0.471
108	Bolivia	BOL	0.469

Rank	Country Name	ACRO	ECI+
109	Ecuador	ECU	0.465
110	Benin	BEN	0.456
111	Togo	TOG	0.446
112	Brunei Darussalam	BRU	0.439
113	Burkina Faso	BFA	0.438
114	Burundi	BUR	0.423
115	Aruba	ARU	0.422
116	Jamaica	JAM	0.421
117	Fiji	FIJ	0.420
118	Guyana	GUY	0.415
119	Armenia	ARM	0.390
120	Belize	BLZ	0.369
121	Algeria	ALG	0.360
122	Zimbabwe	ZIM	0.332
123	Sierra Leone	SIE	0.326
124	Malawi	MLW	0.300
125	Lesotho	LES	0.227