AN ECO-SYSTEMS APPROACH TO CONSTRUCTING ECONOMIC COMPLEXITY MEASURES: ENDOGENIZATION OF THE TECHNOLOGICAL DIMENSION USING LOTKA–VOLTERRA EQUATIONS

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Economic complexity measures have been constructed on the basis of bipartite country-product network data, but without paying attention to the technological dimension or manufacturing capabilities. In this study, we submit a Ternary Complexity Index (TCI), which explicitly incorporates technological knowledge as a third dimension, measured in terms of patents. Different from a complexity indicator based on the Triple Helix model (THCI) or a measure based on patents and countries (PatCI), TCI — products, countries, and patents — can be modeled in terms of Lotka–Volterra equations and thus the further evolution of an innovation eco-system can be specified. We test the model using empirical data. The results of a regression analysis show that TCI improves on Hidalgo and Hausmann's [The building blocks of economic complexity, *Proc. Natl. Acad. Sci.* 106 (26) (2009) 10570–10575] and Tacchella *et al.*'s [A new metrics for countries fitness and products complexity, *Sci. Rep.* 2 (2012)] complexity measures with respect to both the ranking of countries in terms of their complexity and in terms of the correlation with GDP per capita.

Keywords: Economic complexity; metrics; triple helix; eco-system; simulation.

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1. Introduction

The quantitative assessment of the competitive advantages of nations in terms of complexity measures has hitherto not focused on the knowledge intensity of the economy. Assuming that the products in the export portfolio of a country are related to the capabilities needed for manufacturing these products, Hidalgo and Haussmann [24] developed an iterative procedure — the Method of Reflections (MR) — for measuring the complexity of a country's economy. The technological capabilities drive the iteration, but this dimension is otherwise not specified. According to these authors (HH), the merit of the method is that the value of the Economic Complexity Index (ECI) is correlated with a country's GDP per capita [24, Fig. 3, p. 10573]. As a consequence, the deviation of the indicator's value from a country's level of income might be useful for predicting future growth.

Considering that HH's index did not account for empirically observed correlations between a country's competitive advantages and the diversity of its exports, Tacchella *et al.* [46, 47] proposed an alternative — nonlinear — iterative approach: the so-called "Fitness and Product Complexity index" (FCI). These authors noted that their approach resembles models of biological systems in which diversification provides an evolutionary advantage over specialization.

Both FCI and ECI organize the data in terms of bipartite networks of countries versus products. HH noted that they "interpret data connecting countries to the products they export as a bipartite network and assume that this network is the result of a larger, tripartite network, connecting countries to the capabilities they have and products to the capabilities they require" [24, p. 10570]. However, neither HH nor Tacchella *et al.* [46] provide an explicit definition of these intermediating capabilities. Consequently, the capabilities have remained implicit. Cristelli *et al.* [12] submitted that from the perspective of a data-driven approach capabilities can be modeled as a hidden layer of "intangibles" between countries and products.

The endowments of a nation can be considered as one of the factors of manufacturing capabilities. However, these endowments are relatively stable over time. Yet, economic theory has pointed to the importance of technology for explaining economic growth [41]. Long-run economic growth is largely based on the primacy of technological progress [43, 44]. Consequently technological knowledge is the cause of economic growth provided by improvements in manufacturing capabilities.

The capabilities can be considered as the ability to manufacture certain products. HH mention that empirical research "emphasized the accumulation of a few highly aggregated factors of production, such as physical and human capital or general institutional measures" [24, p. 10575]. These factors may also refer to geography, climate, and other regional/national production possibilities and competitive advantages which cannot be exported, or easily acquired from another nation. Furthermore, HH emphasized the importance of new capabilities including the ones originating from technological progress. Considering the present state of technological and economic development, technological knowledge can be expected to play a major role in creating additional value.

Another reason for introducing the technological dimension is that countries exporting the same products do not necessarily have the same capabilities. Some sectors in the economy of developed countries can be offshored to emerging economies. For example, China is the manufacturer and exporter of computers though it does not have the capabilities to produce some key computer components, such as processors. In other words, the degree of localization of offshored technology is also important. One way to account for this problem is to develop and make use of value-added trade data. However, this data are subject to different factors, such as labor costs, taxes, etc.

The major input to the added value is made by technology. Hausmann and Hidalgo [23] provided a more accurate definition of capabilities by accounting the structure of output in the countries-products network. Utkovski *et al.* [51] implemented clustering methods in order to reveal capabilities. Boschma *et al.* [5] used patent classes instead of product groups to measure the complexity in the technology base of US cities, and Balland and Rigby [3] used this method for mapping the diffusion and evolution of knowledge complexity in US cities. However, in terms of the complexity approach, these further studies did not combine the three dimensions of products, countries, and technologies into a single model.

We argue in this study that technological capabilities can be explicitly endogenized into the model of complexity as a third dimension in addition to geographical positions and economic relations. The advancement of technological knowledge can be expected to change the system or, in other words, to disturb the tendencies toward equilibrium Nelson and Winter [35] and Schumpeter [42]. We bring together the ideas of product and knowledge complexity by extending HH's MR to the technological domain and present a nonlinear generalization of ECI. Our model is based on the tripartite network of countries, technologies, and products.

2. Operationalization

We follow Boschma *et al.* [5] and Balland and Rigby [3] in considering patent portfolios as indicators of technological complexity. Patents are analytically independent from products since they are indicators of invention and not innovation. One can consider patents to be a proxy of technological knowledge and the technological knowledge base can hence be measured in terms of patent portfolios [1, 51]. The manufacturing capabilities of a country can be expected to largely overlap with its technological knowledge base [14, 19, 20, 36].

The three interacting dimensions provide a reference to the Triple Helix (TH) model of innovations [16] in which the constituent actors — university, industry, and government — interact among themselves and drive a process of self-organization within the system. In this context, Ivanova *et al.* [28] proposed the Triple-Helix Complexity Index (THCI). In this study, we elaborate the THCI to its nonlinear version, which we designate as TCI. TCI can be evaluated, in terms of Lotka–Voltera (L–V) equations.

L–V equations can be used to model the evolutionary dynamics of eco-systems and thus we can bring the complexity model into the mainstream of evolutionary theorizing (Hodgson & Knudsen [25]). Eco-system approaches have also been used for modeling manufacturing systems [21], business systems [34], from the platform-management perspective [22], and from a multi-actor network perspective [48]. In most of these studies, an eco-system is understood as a number of actors and their relationships [8, 40] (Storper [45]; Mazzucato and Robinson [33]) with an emphasis on relationships. However, there is no precise and agreed definition of an "innovation eco-system" in the innovation-studies literature (Ritala & Almpanopoulon, in press).

Using generalized L–V equations, we are able to show that the complexity measure TCI follows general mechanisms for modeling dynamically evolving ecosystem [7]. As noted, we build on Ivanova *et al.*'s [28] THCI — which remained a linear model — and extend Hidalgo and Hausmann's (HH) Method of Reflections (MR) from two to three dimensions in order to elaborate this Ternary Complexity Index (TCI). We perform model calculations on the basis of empirical data in order to compare the results obtained with HH's MR, Tacchella *et al.*'s [46] FCI, and TCI. The results show that the correlation between TCI and ln(GDP per capita) is improved when compared with ECI. Using this criterion, the complexity ranking of the countries is modified. Since ECI, Fitness, and TCI demonstrate approximately similar results with respect to the prediction of economic growth, this question needs further investigation with extended sets of data.

3. Method

3.1. *HH's method of reflections*

HH's Method of Reflections begins with a country-product export matrix $\{X_{c,p}\}$, where $X_{c,p}$ is the value of product p manufactured by country c. Product p represents a product class. A matrix $M_{c,p}$ is constructed in which the index c refers to a country and p refers to a product group measured as an amount of output. The corresponding matrix elements are set to one if Balassa's [2] RCA is larger than or equal to unity; otherwise the element is equal to zero (Eq. (1)):

$$\mathrm{RCA}_{c,p} = \frac{X_{c,p}/\sum_p X_{c,p}}{\sum_c X_{c,p}/\sum_{c,p} X_{c,p}}. \tag{1}$$

In other words, a country is assumed to export a product if it produces this product proportionally more than the average of the group of countries under consideration.

Summing the elements of matrix $M_{c,p}$ by rows (countries), one obtains a vector with components referring to the corresponding products and indicating a measure of product ubiquity relative to the world market. The sum of matrix elements over the columns (products) provides another vector defining the diversity of a country's exports.

$$\begin{aligned} k_{p,0} &= \sum_{c=1}^{N_c} M_{c,p}, \\ k_{c,0} &= \sum_{p=1}^{N_p} M_{c,p}, \end{aligned} \tag{2}$$

where N_c is the number of countries and N_p is the number of product groups.

More accurate measures of diversity and ubiquity can be obtained by adding the following iterations:

$$\begin{aligned} k_{p,n} &= \frac{1}{k_{p,0}} \sum_{c=1}^{N_c} M_{c,p} k_{c,n-1}, \\ k_{c,n} &= \frac{1}{k_{c,0}} \sum_{p=1}^{N_p} M_{c,p} k_{p,n-1}, \end{aligned} \tag{3}$$

that is, each product is weighted proportionally to its ubiquity on the market, and each country is weighted proportionally to the country's diversity. Substituting the first equation of the system (3) into the second, one obtains

$$k_{c,n} = \frac{1}{k_{c,0}} \sum_{c'=1}^{N_c} \sum_{p=1}^{N_p} M_{c,p} \frac{1}{k_{p,0}} M_{c',p} k_{c',n-2}. \tag{4}$$

Equation (4) can be formulated as a matrix equation

$$\vec{k} = W \cdot \vec{k}, \tag{5}$$

where the vector $\vec{k}$ is a limit of iterations, as follows:

$$\vec{k} = \lim_{n \to \infty} k_{c,n}. \tag{6}$$

HH use the eigenvector $\vec{k}$ of the matrix $W_{c,c'}$

$$W_{c,c'} = \sum_{p} \frac{M_{c,p} M_{c',p}}{k_{c,0} k_{p,0}} \tag{7}$$

associated with the second largest eigenvalue since this eigenvector captures most of the variation[10] for introducing ECI. ECI is defined according to the formula

$$\mathrm{ECI} = \frac{\vec{k} - \langle \vec{k} \rangle}{\mathrm{stdev}(\vec{k})}. \tag{8}$$

In sum, ECI is a vector of which the components refer to the respective countries.

3.2. *Tacchella' et al.'s FCI*

The methods of HH and Tacchella *et al.* have in common that they begin with a binary country–product matrix which is the result of cross-tabling a country's product diversity and product ubiquity as a first step in the iteration. However, Tacchella *et al.* [46] note that the exports of less developed countries require lower levels of sophistication. In their opinion and based on empirical observations, countries produce and export the whole specter of products for which they have production capabilities. Due to uneven development stages of the economies, however, there are a few developed countries producing all products and many less developed ones which produce and export only a limited number of products. Therefore, the binary matrix connecting countries to products has a triangular shape.

In order to more correctly measure a country's manufacturing sophistication, the initial diversity measure is consequently modified in a nonlinear iterative sequence. The newly obtained variable — Fitness — is assumed to measure the level of sophistication of manufacturing capabilities in the respective countries. Tacchella *et al.* [46] augment the weight to different products proportionally to the ubiquity of products when iterating the diversity score.

Since the value of $k_{c,n}$, used to calculate ECI, would deviate with each iteration increasingly from the initial diversity of a country's export $k_{c,0}$, as defined in Eq. (2), these authors propose to iterate a country's product diversity *inversely* proportional to the ubiquity of the products, so that the correlation between initial diversity and Fitness is preserved at each step of the iterations. This modification changes the method from a linear into a nonlinear one. The authors introduce the fitness of countries $F_c^{(n)}$ and the complexity of products $Q_p^{(n)}$, connected by the following iterative sequences:

$$\begin{aligned} \tilde{F}_c^{(n)} &= \sum_p M_{cp} Q_p^{(n-1)}, \\ \tilde{Q}_p^{(n)} &= \frac{1}{\sum_c M_{cp}\left(1/F_c^{(n-1)}\right)}. \end{aligned} \tag{9}$$

At each step of the iteration intermediate values are first computed and are then normalized as follows:

$$\begin{aligned} F_c^{(n)} &= \frac{\tilde{F}_c^{(n)}}{\langle \tilde{F}_c^{(n)} \rangle_c}, \\ Q_p^{(n)} &= \frac{\tilde{Q}_p^{(n)}}{\langle \tilde{Q}_p^{(n)} \rangle_p}. \end{aligned} \tag{10}$$

The initial conditions are: $\tilde{F}_c^{(0)} = 1$ and $\tilde{Q}_p^{(0)} = 1$; the denominators in the system of equation (10) correspond to the average values for each country and product. The following correspondence between first-order values of Tacchella's Fitness and

Product Complexity and HH's diversity/ubiquity holds

$$\tilde{F}_c^{(1)} = k_{c,0},$$
$$\tilde{Q}_p^{(1)} = \frac{1}{k_{p,0}}. \tag{11}$$

The authors note furthermore that in their model the initial meaning of the variables does not change during the iterations.

Although Tacchella *et al.*'s level of development of manufacturing capabilities and HH's level of competitiveness are constructed in similar terms, they are not identical measures. The models are different: the Fitness measure preserves and enhances initial zero-order diversity in Tacchella's models, while the Complexity Index is orthogonally developed to the initial diversity in HH's models. Moreover, ECI is correlated with ln(GDP per capita) and can, according to the claim of the authors, be used as a predictive indicator of long-term growth [24, Fig. 3, p. 10573], whereas as it will be shown below empirically FCI does not correlate with ln(GDP per capita).

3.3. *The ternary complexity index*

Using HH's MR, a country's diversity score is modified directly proportional to the ubiquity of its products. But using FCI the diversity score is modified inversely proportional to the product's ubiquity, that is, more specialized products contribute more to the countries' capabilities. The inverse proportionality is legitimated by the triangular shape of the binary country–product matrix, i.e., the more diversified capabilities a country possesses, the wider the range of products it can produce.

While exporting simple products, developed countries compete with less-developed ones on the market. Due to the number of parties the competition on simple product markets should be especially intensive. Countries with advanced capabilities can concentrate on the manufacturing of technologically advanced products with higher margin profits and a lower number of competitors. The reason for the developed countries to export simple products is that their advanced level of technology makes the manufacturing and export of such products more profitable than for less-developed countries. For example, the achievements of genetic engineering can be applied in agricultural production, where they allow for increased yields. Similarly, sophisticated technologies of shale oil production make the export of shale oil more profitable. In other words, there is a possible effect of technology influence on the range of manufacturing sectors.

The notion of economic complexity can be extended to the technological domain by substituting product values by patent values in Eq. (1) and introducing a country–patent matrix $M_{c,t}$ instead of a country–product matrix $M_{c,p}$. This way, as with ECI and following HH's method, an indicator for technological complexity or Patent Complexity Index (PatCI) was defined by Boschma *et al.* [6] and Ivanova *et al.* [29]. Taking this a step further, one can envisage an additional product-patent

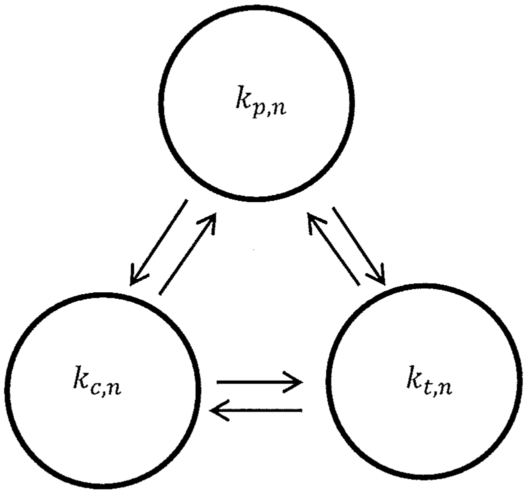


Fig. 1. Interrelations of the complexity measures.

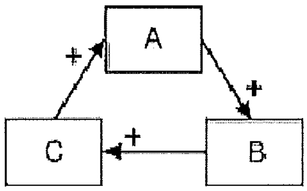
matrix $M_{p,t}$ and a ternary country–product–technology complexity indicator based on the three-dimensional array $M_{p,t,c}$. The latter can be introduced as country–product–patent or patent–product–country cycles with clockwise or counter-clockwise interdependencies [28].

Figure 1 defines these complexity indices in terms of the ecosystems approach which can be extended diachronically.[a]

Instead of the country-product matrix $X_{c,p}$, we use the three-dimensional country–product–technology array $\mathfrak{M}_{c,p,t}$. Initial diversity, product ubiquity and patent ubiquity coefficients are defined as

$$k_{c,0} = \sum_{p=1}^{N_p} \sum_{t=1}^{N_t} \mathfrak{M}_{c,p,t},$$
$$k_{p,0} = \sum_{c=1}^{N_c} \sum_{t=1}^{N_t} \mathfrak{M}_{c,p,t},$$

[a]Ecosystems in biology are defined through the network of interactions among living organisms and the environment. Ecosystems sustain the creation of order against the Second Law of Thermodynamics which is maintained by autocatalysis. Ulanowicz [49, p. 1888] provides the following illustration of the autocatalytic cycle which essentially resembles Fig. 1



$$k_{t,0}=\sum_{c=1}^{N_c}\sum_{p=1}^{N_p}\mathfrak{M}_{c,p,t}. \tag{12}$$

One can consider iterating across these three dimensions simultaneously. That is, country and product complexity create technology complexity, which goes into calculating product complexity, which goes into country complexity, which goes into technology complexity, etc. That is, instead of the system of equation (3) one can write

$$\begin{aligned} k_{c,n} &= \frac{1}{k_{c,0}}\sum_{p=1}^{N_p}\sum_{t=1}^{N_t}\mathfrak{M}_{c,p,t}k_{p,n-1}k_{t,n-1}, \\ k_{p,n} &= \frac{1}{k_{p,0}}\sum_{c=1}^{N_c}\sum_{t=1}^{N_t}\mathfrak{M}_{c,p,t}k_{c,n-1}k_{t,n-1}, \\ k_{t,n} &= \frac{1}{k_{t,0}}\sum_{c=1}^{N_c}\sum_{p=1}^{N_p}\mathfrak{M}_{c,p,t}k_{p,n-1}k_{c,n-1}. \end{aligned} \tag{13}$$

The three complexity indices: $k_{c,n}$, $k_{p,n}$, $k_{t,n}$ correspond to the geographical, manufacturing, and technological dimensions. The value of each index is determined by the simultaneous action of the other two indices.

The advantage of extending the Method of Reflections to three complexity indices helps to settle the convergence problem. Caldarelli [11, p. 6] formulates that "the major problem in the HH algorithm is that it is a case of consensus dynamics, i.e., the state of a node at iteration t is just the average of the state of its neighbors at iteration $t-1\ldots\ldots$ such iterations have the uniform state as the natural fix point..." However, this criterion is not applicable to the case of nonlinear iterative sequence as defined by the set of equation (13).

Figure 1 can also be considered a schematic representation of an autocatalytic cycle with three components. This model is also used for describing the evolution of biological ecosystems [49]. The interplay of indices provides a reference to the interplay of the three actors — university, industry, and government — in a Triple Helix model of innovations. Feed-forward and feed-back cycles may strengthen or weaken a corresponding index in the process of iterations as in the case of an autocatalytic system.

By adding the same terms to the left- and right-hand side of each of equations (13) one can write this system as follows:

$$k_{c,n}-k_{c,n-1}=-k_{c,n-1}+\frac{1}{k_{c,0}}\sum_{p=1}^{N_p}\sum_{t=1}^{N_t}\mathfrak{M}_{c,p,t}k_{p,n-1}k_{t,n-1},$$

$$k_{p,n} - k_{p,n-1} = -k_{p,n-1} + \frac{1}{k_{p,0}} \sum_{c=1}^{N_c} \sum_{t=1}^{N_t} \mathfrak{M}_{c,p,t} k_{c,n-1} k_{t,n-1},$$
$$k_{t,n} - k_{t,n-1} = -k_{t,n-1} + \frac{1}{k_{t,0}} \sum_{c=1}^{N_c} \sum_{p=1}^{N_p} \mathfrak{M}_{c,p,t} k_{p,n-1} k_{c,n-1}. \tag{14}$$

Ternary country, product, and technology complexity indices are defined in accordance with the definition of HH's MR as follows:

$$\begin{aligned} \mathrm{TCI}_c &= \frac{k_c - \langle k_c \rangle}{\mathrm{stdev}(k_c)}, \\ \mathrm{TCI}_p &= \frac{k_p - \langle k_p \rangle}{\mathrm{stdev}(k_p)}, \\ \mathrm{TCI}_t &= \frac{k_t - \langle k_t \rangle}{\mathrm{stdev}(k_t)}, \end{aligned} \tag{15}$$

where k_c, k_c, k_c are the limits of iterations

$$\begin{aligned} k_c &= \lim_{n \to \infty} k_{c,n}, \\ k_p &= \lim_{n \to \infty} k_{p,n}, \\ k_t &= \lim_{n \to \infty} k_{t,n}. \end{aligned} \tag{16}$$

Although the values of the non-normalized indices $k_{c,n}$ grow infinitely, the values of the Ternary Complexity Indicator (TCI) empirically converge to a limit which can be conceptualized as the state of equilibrium obtained through interactions of three different dimensions

3.4. *Constructing the three-dimensional array*

In order to define the array $\{\mathfrak{M}_{c,p,t}\}$ we have to build the three-dimensional array $\{x_{c,p,t}\}$ with respect to c, p, t dimensions in which c refers to countries (or other geographical units), p refers to product classes, and t refers to technology (patent) classes, and then binarize it. We define the matrix elements of a three-dimensional matrix $\{x_{c,p,t}\}$ as follows:

$$y_{c,p,t} = x_{c,p} Z_{p,t} a_{c,t}. \tag{17}$$

Here, $x_{c,p}$ is a country–product matrix, $a_{c,t}$ is a country-patent matrix, and $Z_{p,t}$ is a binary matrix which relates product groups to patent classes (hereafter referred to as a concordance matrix) derived from a patent–product concordance table [15] with elements that are assigned the value one if the patent class t relates to product group p and zero otherwise.

Following HH, one can reduce matrix $\{y_{c,p,t}\}$ to a binary form by extending Balassa's RCA index to three dimensions as

$$\mathrm{RCA}_{c,p,t} = \frac{y_{c,p,t}/\sum_{p,t} y_{c,p,t}}{\sum_c y_{c,p,t}/\sum_{c,p,t} y_{c,p,t}} = \frac{y_{c,p,t}/Y_c}{y_{c,p,t}/\sum_c Y_c}. \quad (18)$$

The corresponding array elements $\{\mathfrak{M}_{c,p,t}\}$ are assumed to be one if this extended Balassa's RCA is larger than or equal to unity and otherwise zero. $\mathrm{RCA}_{c,p,t}$ defines the weight of partial patent–product output $y_{c,p,t}$ in a country's production function relative to the weight of the same patent–product output for all the countries in the set.

4. Data

We performed test calculations with the three indicators — HH's ECI, Tacchella's *et al.* Fitness, and TCI for a set of 41 countries, which includes 29 of the 35 OECD member states, three BRICS countries — Brazil, China, Russia, plus nine smaller economies: Croatia, Egypt Georgia, Lithuania, Malaysia, Morocco, Moldova, Romania, and Ukraine. The initial conditions are empirically defined:

(1) Data for the products exported by the 41 countries are harvested from https://comtrade.un.org/data/_in the format of the Standard International Trade Classification (SITC) revision 3 at the 2-digit level.
(2) The patent data organized in terms of 35 technology groups were retrieved from the WIPO statistics database at http://ipstats.wipo.int/ipstatv2/index.htm. We used resident count by filing office since domestic patents fully comply with technology development of the country.
(3) Technology classifications based on the codes of the International Patent Classification (IPC) were obtained from http://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo_ ipc_technology.pdf.

Correspondence tables connecting SITC Rev.3 and NACE rev. 2 classifications through the sequence: NACE Rev. 2 — ISIC Rev. 4, ISIC Rev. 4 — ISIC Rev. 3.1, ISIC Rev. 3.1 — ISIC Rev. 3, ISIC Rev. 3 — SITC Rev. 3, SITC Rev. 3 — NACE Rev.2 are found at Eurostat Reference and Management of Nomenclatures (RAMON) Index of correspondence tables http://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL_A concordance table between IPC 8 and NACE Rev.2 concordance table was obtained from http://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL.

5. Results

The values of TCI for the first 20 iterations in the set of 41 countries are provided in Appendix A. The first 20 iterations for seven major economies (for 2015) selected

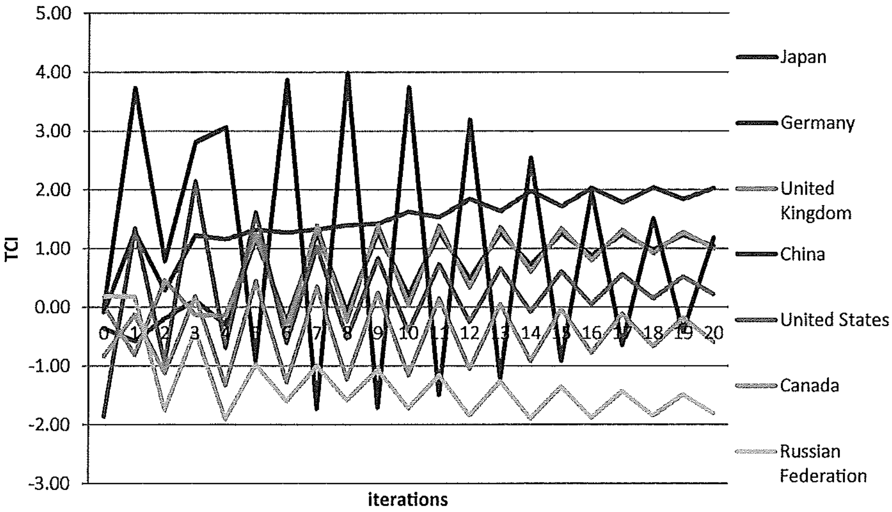


Fig. 2. The first 20 successive iterations of the Ternary Complexity Index for seven selected countries (for 2015).

Table 1. Pearson correlations between the values of TCI, Fitness, ECI, initial diversity score, and ln(GDP per capita) in current USD (for 2015).

	TCI	ECI	Fitness	Diversity	LN (GDP/capita)
TCI					
ECI	−0.728**				
Fitness	−0.165	0.192			
Diversity	0.038	−0.098	0.882**		
LN(GDP/capita	−0.541	0.516	−0.112	−0.078	

Notes: **Correlation is significant at the 0.01 level (2-tailed).
*Correlation is significant at the 0.05 level (2-tailed).

from the set are shown for illustrative purposes in Fig. 2. Using real data, the iterative sequence for all countries in the set empirically converged to a limit. Whereas the interpretation of different iterations in the ECI calculation is difficult, in our approach these iterations can be considered as steps of the autocatalytic cycles which bring the system increasingly into the equilibrium.

Table 1 shows the Pearson correlations between the values of TCI, Fitness,[b] ECI, initial diversity scores, total export values, and the logarithm of nominal GDP per capita in current US$ (for 2015). There is a significant correlation between TCI and ECI and a weak correlation between the pairs of TCI, ECI and Fitness, which can be attributed to the fact that TCI and ECI, on the one side, and Fitness, on the other

[b]FCI measures the Fitness of countries and product complexity; here we use Fitness as analog to ECI.

side, capture different kinds of information[c]. The three indices correlate to different extents with the value of total export. Furthermore, there is no significant relationship between total exports and income. Fitness is significantly correlated with the initial diversity score. ECI and TCI do not correlate with diversity. Note that it can be mathematically shown that HH's complexity is not correlated with the countries' diversity [29], so that one expects ECI to be uncorrelated to the product diversity of countries. Indeed, we find $r = -0.098$ (n.s.).

Both ECI and TCI correlate significantly with the logarithm of GDP per capita, but this is not the case for the correlation between Fitness and GDP. (Applying the Ln function to Fitness [13] also does not improve the situation.) This is not surprising since Fitness is strongly correlated with diversity and the correlation between diversity and GDP per capita is weak. However, TCI outperforms ECI in terms of the correlation with the logarithm of GDP per capita. This may be attributed to the additional accounting of the variety in the technology dimension in TCI. ECI has been reported to be good at predicting future growth in the long run, but not so reliable in short-term predictions This may indicate that the advantage of complexity is more likely to be realized over time [38].

Using an OLS linear regression growth model for a 10-year time period, we tested our data by regressing the rate of growth on the initial level of a country's income and complexity index, according to the Equation provided by Hidalgo and Hausmann [23, p. 10574], as follows:

$$\mathrm{Growth}(t + \Delta t) = A + B \cdot \mathrm{LN}(\mathrm{GDP}(t)) + C \cdot \mathrm{CI}. \tag{19}$$

Here, *Growth* stands for GDP per capita growth (% for the period), CI can stand for ECI, Fitness or TCI. Table 2 shows the results for the three indicators (t-values are

Table 2. OLS 10-year linear regression growth model.

Predicted variable	Growth (2004, 2014)	Growth (2004, 2014)	Growth (2004, 2014)	Growth (2004, 2014) (null model)
Predictors				
LN(GDP/capita)	−53.1	−51.318	−52.564	−53.225
(current USD)	(−7.534)	(−6.148)	(−7.096)	(−7.87)
TCI	−0.656			
	(−0.073)			
ECI		−4.23		
		(−0.398)		
Fitness			−0.371	
			(−0.234)	
Constant	595.089	578.145	595.969	596.236
	(8.826)	(7.258)	(9.094)	(9.212)
Observations	41	41	41	41
R^2	0.613	0.615	0.614	0.613

[c] Cristelli *et al.* [12] mentioned the correlation between Fitness and GDP around 0.45 for 2015 data of 148 countries. One should consider that the correlation with GDP may also depend on the number of countries included in the set (e.g., Ivanova *et al.* [28]).

provided in parentheses). All three indices demonstrate approximately similar results with respect of adjusted R^2 value of the regression.

The last column of Table 2 refers to the model which accounts only for the initial value of GDP per capita (null model):

$$\text{Growth}(t + \Delta t) = \beta_0 + \beta_1 \text{LN}(\text{GDP}(t)). \tag{20}$$

It can be seen from Table 2 that adding complexity dimension slightly improves the situation. The best improvement is provided by the Fitness index which accounts for 34% of the variations. To obtain a better fit one can further introduce additional factors used to explain economic growth.

Traditional growth models account for three factors of growth — increase in labor and labor quality, increase in capital, and increase in technology [41, 43]. We introduced additional country-specific factors to more completely account growth variations, such as gross capital formation, population growth, exchange rate, life expectancy, and unemployment rate. Here population growth, life expectancy, and unemployment rate refer to labor and labor quality, domestic investments refers to capital, trade openness and exchange rate relate to institutional quality, and complexity index refers to an increase in technology. Income per capita serves as a base level of economic development.

$$\begin{aligned}\text{Growth}(t + \Delta t) = \beta_0 &+ \beta_1 \text{LN}(\text{GDP}(t)) + \beta_2 \text{Ln}(\text{GCF}(t)) + \beta_3 \text{Ln}(\text{Pop}(t)) \\ &+ \beta_4 \text{Ln}(\text{ER}(t)) + \beta_5 \text{Ln}(\text{LE}(t)) + \beta_6 \text{Ln}(\text{UE}(t)) + \beta_7 \text{CI}(t),\end{aligned} \tag{21}$$

where *Growth* — GDP per capita growth 10-year period (2004–2014), *GDP* — income per capita; *GCF* — Gross capital formation (% GDP) current USD; *Pop* — population (annual %) growth; *ER* — exchange rate (local currency unit per USD, period averaged); *LE* — life expectancy (years); *UE* — unemployment rate (% of total labor force); *CI* — complexity indicator (ECI, Fitness or TCI). The results of calculations are presented in Table 3. One can mention that all three measures give approximately the same fit.

According to Table 3, the ECI and Fitness coefficient in the regression have a negative sign, meaning that higher values imply lower growth. This may be due to an error term. When regressing growth on independent variables some of the elements may be endogenous. The residual term then can comprise time-invariant component which can be attributed to country-specific fixed effects. To get rid of it and get the better fit for the OLS coefficients one can subtract individual means from the equation for each country in the set. It can be shown that this approach is, in effect, to treat individual effects as coefficients on dummy variables and run least square. OLS 10-year linear regression growth model with country fixed effects removed using panel data for 2003–2005 and 2013–2015 is presented in Table 4.

Note that this time TCI, ECI, Fitness coefficients are all positive. OLS regression with TCI measure substantially improves over regression with ECI or Fitness measures. Also Growth is more sensitive to the change in TCI in comparison with

Table 3. OLS 10-year linear regression growth model with additional growth related variables.

Predicted variable			
Predictors	Growth (2004–2014)	Growth (2004–2014)	Growth (2004–2014)
LN(GDP per capita)	−55.292	−55.24	−55.966
(current USD)	(−3.523)	(−3.51)	(−3.546)
TCI	5.9		
	(0.652)		
ECI		−5.54	
		(−0.512)	
Fitness			−0.259
			(−0.153)
LN(Gross capital formation)	39.43	32.277	35,357
(% GDP) current USD	(0.772)	(0.621)	(0.672)
LN(Population growth)	−33.332	−39.251	0.074
(annual %)	(−0.489)	(−0.575)	(−0.534)
LN(Exchange rate)	−9.055	−8.575	−8.97
	(−1.741)	(−1.64)	(−1.692)
LN(Life expectancy)	−136.325	−92.182	−121.652
	(−0.381)	(−0.251)	(−0.33)
LN(Unemployment rate)	−59.267	−57.576	−55.70
(% of total labor force)	(−2.417)	(−2.373)	(−2.3)
Constant	1265.775	1102.908	1224.129
	(0.938)	(0,793)	(0.882)
Observations	41	41	41
R^2	0.684	0.682	0.680

Table 4. OLS 10-year linear regression growth model with country fixed effects removed.

Predicted variable			
Predictors	Growth (2004–2014)	Growth (2004–2014)	Growth (2004–2014)
$LN(GDP_{pc}) - \langle LN(GDP_{pc}) \rangle$	−469.139	−442.814	−441.612
	(−4.481)	(−4.043)	(−4.054)
$TCI - \langle TCI \rangle$	5.542		
	(1.956)		
$ECI - \langle ECI \rangle$		2.224	
		(0.309)	
$Fitness - \langle Fitness \rangle$			0.644
			(0.621)
$LN(GCF) - \langle LN(GCF) \rangle$	170.515	167.794	171,564
	(3.547)	(3.304)	(3.361)
$LN(Pop) - \langle LN(Pop) \rangle$	57.08	80.385	82.516
	(0.637)	(0.85)	(0.878)
$LN(ER) - \langle LN(ER) \rangle$	−301.474	−280.335	−282.162
	(−2.82)	(−2.5)	(−2.525)
$LN(LE) - \langle LN(LE) \rangle$	−205.19	−70.712	−42.013
	(−0.385)	(−0.125)	(−0.075)
$LN(UE) - \langle LN(UE) \rangle$	14.794	14.458	16.883
	(0.848)	(0.816)	(0.924)
$constant - \langle constant \rangle$	5.631	5.394	5.596
Observations	(5.006)	(4.574)	(4.582)
	41	41	41
R^2	0.587	0.540	0.544

ECI and Fitness. Fixed effects panel data models offer a solution to endogeneity problem by absorbing time-invariant regressors. The model can consistently be estimated as long as the residual term is uncorrelated with the used regressors.

The ranking of countries (provided in the Appendix) is different for the three indices. The Fitness index, which relies on the diversity score, places countries as China, Germany, Austria, and the UK lower than Poland, Moldova, Egypt, and Croatia, though the countries in the first group have more diversified portfolio of manufacturing. ECI places Ireland, Poland, and Egypt above Canada and China. In our opinion, the ranking of countries according TCI is realistic since manufacturing capabilities are additionally weighted according the respective knowledge bases of the countries.

6. Extension to Continuous Time

In addition to improving the prediction, TCI can be considered as an ecosystem's approach to constructing a complexity indicator for comparative statics (e.g., time series). Let us apply the eco-systems metaphor to model the structure of economic complexity indicators. Assuming that the set of equation (14) present a discrete time form of the continuous equations in which $k_n = k(t+1)$ and $k_{n-1} = k(t)$ and denoting $k_{c,n}$, $k_{p,n}$, and $k_{t,n}$ as vectors $\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}$, respectively, and the array $\{\mathfrak{M}_{c,p,t}\}$ as $\mathfrak{M}$, one can write the set of equations (14) in continuous form as follows:

$$\begin{aligned} \frac{dx_i}{dt} &= -x_i + \alpha\,\mathfrak{M}\boldsymbol{yz}, \\ \frac{dy_j}{dt} &= -y_j + \beta\,\mathfrak{M}\boldsymbol{xz}, \\ \frac{dz_k}{dt} &= -z_k + \gamma\,\mathfrak{M}\boldsymbol{xy}. \end{aligned} \tag{22}$$

Here, $i = 1, \ldots, N_c$, $j = 1, \ldots, N_p$, $k = 1, \ldots, N_t$. A negative sign at linear terms in the right-hand side of equation (22) means that the corresponding increment of the left-hand side value (country product diversity, and product and technology ubiquity) will decline unless the appropriate nonlinear term is present.

The set of equation (22) presents a modification of the generalized L–V equation:

$$\frac{dx_i}{dt} = x_i f_i(\boldsymbol{x}), \tag{23}$$

where the vector $\boldsymbol{f}$ is defined as

$$\boldsymbol{f} = -\boldsymbol{I} + \boldsymbol{A}\mathrm{x}. \tag{24}$$

Here, $\boldsymbol{I}$ is a unity matrix and $\mathbf{A}$ is a community matrix.

Generalized L–V equations can exhibit various kinds of dynamics, including attractors, chaos, and limit cycles [26]. The same kinds of dynamics can be also be expected for equation (22). Whereas interaction of two dimensions shape each other in a coevolution that may lead to relatively stable trajectories, the addition of a third dimension can make these trajectories unstable (hyper-stable, meta-stable, etc.; [32]).

7. Conclusion

A major advantage of the eco-systems approach in constructing complexity measures is the possibility of entertaining models of systems dynamics and self-organization. Hitherto, this approach has not often been applied in innovation studies. An important feature of an eco-system is co-evolution. With respect to constructing economic complexity measures one can account for the co-evolution among different dimensions of innovation systems. In other words, complexity measures can be constructed by following the evolutionary dynamics of innovation eco-systems resulting from interactions among independent dimensions. We show that complexity indicators can be constructed in analogy to eco-systems. Iterative sequences can be approximated by generalized L–V equations in which the three dimensions — countries, products, and technologies — interact and reach a dynamical equilibrium.

TCI can shed light on the meaning and limitations of the complexity approach. While the interpretation of different iteration terms in ECI has remained vague [29], and FCI is defined bottom-up from the data, TCI can straightforwardly be interpreted as a discrete version of generalized L–V equations. This changes the status of the data since we can test a model using this data, and the model guides the interpretation of the different terms in the iterations. The dynamics can be considered as evolutionary stages of interaction dynamics among the three variables: geography, product, and technology (Storper, 1997). Sequential iterations can be considered as a series of successive communications among the variables. During a fixed period, there can be only a limited number of communications. If the equation has an asymptotically stable solution, the specification of this solution may serve as a limit to which iterative communications converge over time.

The introduction of this ecosystems approach in the domain of complexity measures raises further questions. Generalized L–V equations can comprise different dynamics, including limit cycles, chaos, and point attractors. The question of the relations of these dynamics to economic phenomena needs further investigation. A comparison of the results of model simulations of the three complexity measures suggests that TCI can be used for the prediction of the economic growth of countries. This may help decision makers to shape their policy. We believe that elaboration of a paradigm based on the systems-evolutionary dynamics of L–V can bring more predictive power to both the field of developing complexity indicators and innovation studies.

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Appendix A

Table A.1. Comparison of the country among TCI, ECI, and Fitness measures (2015).

Rank	*Country*	*TCI*	*Country*	*ECI*	*Country*	*Fitness*
1	Japan	2.124	Switzerland	2.969	United States	27,075
2	Korea, Rep.	1.857	Japan	2.243	Netherlands	24,975
3	Switzerland	1.570	Ireland	2.023	Poland	23,919
4	Germany	1.511	United Kingdom	1.716	Lithuania	22,239
5	United Kingdom	1.443	Korea, Rep.	1.578	Canada	22,039
6	Austria	1.237	Germany	1.415	Spain	20,919
7	China	1.133	United States	0.636	Egypt	20,897
8	Finland	1.102	France	0.599	Japan	20,629
9	Sweden	1.095	Austria	0.561	Denmark	20,510
10	Slovenia	0.901	Hungary	0.502	Korea, Rep.	20,393
11	United States	0.761	Sweden	0.470	Croatia	20,262
12	Luxemburg	0.583	Finland	0.447	Sweden	20,181
13	Slovak Republic	0.503	Luxemburg	0.436	France	19,361
14	France	0.414	Czech Republic	0.420	Latvia	18,898
15	Ireland	0.375	Slovenia	0.242	Moldova	18,492
16	Czech Republic	0.115	Denmark	0.123	Brazil	18,187
17	Romania	0.072	Poland	0.015	China	18,123
18	Morocco	−0.017	Netherlands	−0.117	Slovenia	18,009
19	Netherlands	−0.038	Malaysia	−0.257	Portugal	18,007
20	Denmark	−0.051	Spain	−0.285	Germany	17,884
21	Portugal	−0.067	Greece	−0.388	Czech Republic	17,313
22	Croatia	−0.115	Slovak Republic	−0.412	Hungary	16,519
23	Spain	−0.214	Croatia	−0.436	Austria	16,091
24	Iceland	−0.276	Egypt	−0.464	United Kingdom	15,737
25	Poland	−0.389	New Zealand	−0.509	Estonia	15,644
26	Norway	−0.411	Estonia	−0.563	Ireland	15,59
27	Latvia	−0.473	China	−0.586	Malaysia	14,643
28	Canada	−0.510	Romania	−0.654	Greece	14,631
29	Greece	−0.577	Portugal	−0.676	Luxembourg	14,474
30	Malaysia	−0.650	Georgia	−0.689	Morocco	14,176
31	Brazil	−0.686	Lithuania	−0.696	Australia	13,812
32	Estonia	−0.716	Brazil	−0.711	Finland	13,678
33	Lithuania	−0.876	Canada	−0.731	Slovak Republic	13,604
34	Hungary	−1.039	Moldova	−0.746	New Zealand	13,164
35	Australia	−1.085	Australia	−0.815	Russian Federation	13,027
36	New Zealand	−1.131	Latvia	−0.900	Romania	12,246
37	Russian Federation	−1.198	Iceland	−1.010	Georgia	12,012
38	Moldova	−1.350	Ukraine	−1.029	Ukraine	11,634
39	Egypt	−1.410	Norway	−1.170	Switzerland	10,952
40	Ukraine	−1.410	Russian Federation	−1.181	Norway	5,217
41	Georgia	−2.108	Morocco	−1.370	Iceland	4,335

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