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Transformational Complexity, Systemic Complexity and Economic Development

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Abstract

The paper develops two new notions of economic complexity based on the study of interactions between different capabilities. (1) *Transformational complexity* denotes a country's pace of structural transformations over time, arguing that an economy is more t-complex if a large number of factors (capabilities) are able to drive the system out-of-equilibrium and towards new growth paths. (2) *Systemic complexity* represents a country's overall density of causal relationships that link together its main capabilities, based on the idea that an economy is more s-complex if its growth path is simultaneously driven by several co-evolving factors. Making use of the Johansen cointegration approach, and using annual time series data for the period 1970-2015, we apply the new notions of complexity to the study of economic development for 134 countries. The results show that systemic (transformational) complexity is positively (negatively) correlated with the ECI index and with GDP per capita. This suggests that economic complexity can be achieved following different growth paths, depending on countries capabilities and the interactions among these.

Keywords: Economic complexity; ECI; growth and development; coevolution; cointegration analysis

JEL codes: O1, O3, O4

1. Introduction

Economic development is a process of transformation that goes hand in hand with increasing complexity (Antonelli, 2011). Economies that have the necessary capabilities to undertake structural changes progressively become more complex, thus achieving a more dynamic economic performance in the long-run. By contrast, countries that lack such capabilities are not able to carry out the required transformations, and more often experience poverty traps that hamper their process of economic development (Robert and Yoguel, 2011).

A recent strand of research develops and extends this seminal idea, showing that economies that are able to produce more complex and more sophisticated products can export them to several other countries, and they can in this way achieve rapid and sustained economic growth (Hidalgo et al., 2007; Hidalgo and Hausman, 2009). This recent approach to the study of economic complexity shows the important relationship between a country's web of products, on the one hand, and its export and economic growth, on the other. A well-known result of this recent empirical research is the economic complexity index (ECI), which ranks world economies according to their complexity level, and points out the implications for their economic performance (Hausman et al., 2014).

This approach is motivated by, and implicitly based upon, two underlying assumptions. The first is that economic growth is driven, first and foremost, by countries' ability to produce and export complex products. We certainly agree that this dimension is crucial. However, the economic growth and development literature has previously pointed out a variety of other dimensions that are also relevant to foster economic growth in the long-run. Growth research has in particular highlighted the important role of human capital (Azariadis and Drazen, 1990; Verspagen, 1991), physical capital and infrastructures (Castellacci, 2011), innovation and imitation ability (Howitt and Mayer-Foulkes, 2005; Acemoglu et al., 2006), and an advanced industrial structure (Kelly, 2001). A key insight of growth and development theory is in particular that several growth engines are simultaneously important to

explain cross-country differences in income per capita, and that these factors interact with each other leading to feedback effects and cumulative dynamics (Castellacci and Natera, 2013; Castellacci, 2018). The second underlying assumption of the ECI approach is that if a country is able to produce and export complex products, then it must certainly be the case that it has the set of capabilities that are necessary to develop these sophisticated products. In other words, the existence of advanced capabilities is inferred from (reflected in) the country's export specialization performance. However, extant research does not explicitly point out, measure and analyze what these different capabilities are, how they relate to each other, and how they foster economic development. A large empirical research has previously shown that the capabilities that are important for economic growth can indeed be measured by using widely available cross-country datasets, and that different capabilities have distinct effects on economic growth (Castellacci and Archibugi, 2008; Fagerberg and Srholec, 2008).

In the present paper, we build upon the economic complexity approach, but we seek to extend it by explicitly measuring and analyzing a set of relevant capabilities of nations, the relationships among them, and their impact on income per capita growth in the long-run. Our research is motivated by the fact that economic growth is a multi-dimensional and co-evolutionary process, in which several growth engines *interact* with each other in a complex manner. It is therefore paramount to extend economic complexity research by considering a broader set of relevant dimensions and the interaction between the underlying capabilities.

This extension is important, we argue, because it makes it possible to point out that there may be different paths to achieve greater complexity and economic development, depending on the core set of capabilities that each national system has, and that it is able to develop over time. To illustrate, some countries have a growth strategy that is explicitly focused upon the development of advanced R&D capabilities and sophisticated export specialization patterns (by and large resembling the main idea underlying the ECI approach); other countries, though, have a growth path that is primarily led

by the co-evolution of human capital and the ability to imitate foreign advanced technologies; yet other economies are driven by the joint dynamics of industrial transformations, capital accumulation and embodied technical progress. By taking into account a broader set of capabilities, we seek to show that there may be distinct possible co-evolutionary paths leading to higher levels of complexity and economic development.

Motivated by these considerations, the present paper develops two new notions of economic complexity. The first notion is *transformational complexity* (TC): this measures a country's pace of structural transformations over time, based on the idea that an economy is more t-complex if a large number of factors (capabilities) are able to drive the system out-of-equilibrium and towards new growth paths. The second notion is *systemic complexity* (SC): this provides a measure of a country's overall density of causal relationships that link together its main capabilities, based on the idea that an economy is more s-complex if its growth path is simultaneously driven by several co-evolving factors. To operationalize these notions, we make use of the Johansen time series cointegration approach (Johansen, 1991). Specifically, we estimate a vector-error correction model (VECM) for all countries in the world, using annual time series for the entire period 1970-2015. The econometric estimates of a VECM system of equations for each country makes it possible to point out the existence and strength of causal relationships that link together different growth engines, and how each of these affects the growth of income per capita in the long-run.

More precisely, for any given country, we define transformational complexity as the number of long-run causal relationships that have moved the economic system out of its initial long-run equilibrium. On the other hand, we define systemic complexity as the total number of "strongly causal" relationships that our econometric model identifies for a given national economy (White and Lu, 2010). We name it *systemic* because it seeks to measure the overall complexity of the economic system, i.e. the number of factors that are structurally linked to GDP per capita the long-run.

We construct these new indicators for a very large sample of countries, and using a large number of different model specifications in order to assess the robustness of the resulting patterns. The results show that systemic complexity is on the whole positively correlated with the ECI index of Hausman et al. (2014) as well as to GDP per capita, although there are notable differences among country groups. On the other hand, transformational complexity is negatively related to the ECI index and to income per capita, indicating that countries starting from a lower level of export specialization and, more in general, economic development, have on average experienced a more rapid pace of structural transformations and out-of-equilibrium dynamics than economies that were already wealthy (complex) at the beginning of the period.

In a nutshell, the main contribution of this article is that it develops new notions of economic complexity that are based on an inherently *dynamic* understanding of complexity, because they are defined on the basis of the econometric results of time series cointegration analysis. Our focus is on economic transformations and dynamic out-of-equilibrium processes, in line with seminal works in the complexity literature (Antonelli, 2011). And by considering a broad number of relevant dimensions, and the interactions among these over time, our approach seeks to extend and complement the recent ECI approach, showing that countries can indeed achieve increasing levels of complexity in a variety of different ways.

The paper is organized as follows. Section 2 reviews the relevant literature; section 3 outlines the main conceptual dimensions of the model, and the indicators used to measure these in the empirical analysis; section 4 presents the methods used to empirically apply the two new notions of economic complexity; section 5 illustrates and discusses the empirical results; section 6 concludes by discussing the main contributions and their implications for research in this field.

2. Literature

Several decades ago, classical authors like Myrdal and Kaldor pointed out that economic growth is a complex process that is driven by dynamic feedback effects among several factors interacting with each other (Robert and Yoguel, 2011). Some of these classical insights have later been extended and refined by evolutionary economics models, which investigate the micro-dynamics processes that explain why economic systems transform and structurally change over time, following a complex and out-of-equilibrium dynamics (Castellacci, 2007).

According to complexity theories (Antonelli, 2011), the growth of economies is akin to dynamical systems characterized by multiple local attractors. Chance events (e.g. policy shocks) can be magnified by positive feedbacks among economic variables, which may drive the system from a given equilibrium towards a new local attractor (Colombelli and Von Tunzelmann, 2011).

These original insights of complexity theories have recently fostered the emergence of a new strand of research that investigates economic complexity by focusing on the characteristics of products that are developed and exported by a given national economy. Hausman and Hidalgo (2011) develop a model that generates patterns of increasing complexity, based on the idea that the network structure of economic output and countries' export activities become more complex over time as economies specialize in more differentiated and more advanced products. The underlying idea is that countries with a broader range of capabilities will be more diversified, and therefore better able to produce a wider set of products by combining these related capabilities for the development of more complex products.

More sophisticated products are also less ubiquitous, i.e. they are typically produced and exported by a few countries only (Hidalgo and Hausman, 2009). The reason for this is that the quality and complexity of products that a country can export is closely related to the set of capabilities that characterizes its national system, and economies that are below a given threshold level of capabilities

will not easily be able to upgrade their product space and improve their international competitiveness (Hidalgo et al., 2007). Combining information on exported products' sophistication and ubiquity, Hidalgo, Hausman and collaborators have recently developed the so-called *Economic Complexity Index* (ECI), a summary measure of a country's ability to export advanced products, mirroring the complexity of its productive structure (Hausman et al., 2014).

These studies also show that product complexity is closely related to the level of economic development and that, in particular, the set of capabilities available at a given time is a good predictor of subsequent economic growth (Hidalgo and Hausman, 2009). Felipe et al. (2012), in an empirical application of the economic complexity approach, show that high-income countries are major exporters of the most complex products, and that export shares of the most complex products increase with income levels. In a related study, Hartmann et al. (2017) point out that economic complexity is also negatively related to income inequality.

This approach has recently been extended and refined in a series of papers, which argue that it is important to consider the non-linear nature of the relationship between product complexity and country competitiveness. This is relevant because it points out that country's competitiveness is highly dependent on the ability to develop complex products rather than to produce several different products of lower value (Caldarelli et al., 2012; Cristelli et al., 2013; Tacchella et al., 2013).¹

The recent strand of research on economic complexity provides the conceptual background for the present study. However, our work intends to depart from and extend extant research in two main respects. The first is that most recent empirical applications of the economic complexity approach make use of a static operationalization of the concept of complexity, in the sense that they typically study product / export complexity of a national economy at a given point in time, as well as differences

¹ Balland and Rigby (2017) have recently presented an original application of the ECI approach to study the geography of complex knowledge in the US, applying the ECI methodological approach to patent invention and citation data.

of complexity indexes over time. The present work seeks to develop new indicators of economic complexity that are based on an inherently *dynamic* notion of complexity, because they are defined on the basis of the econometric results of time series estimations (see next section). In other words, our focus is on economic transformations and dynamic out-of equilibrium processes, in line with seminal works in the complexity literature (Antonelli, 2011; Colombelli and Von Tunzelmann, 2011).

The second extension is that our approach to economic complexity is inherently *multidimensional*. Extant research in the ECI approach has until now mostly focused on countries' ability to produce and export sophisticated products, which implicitly reflects the set of underlying capabilities that are necessary to commercialize complex products overseas. This dimension is certainly important. However, the economic growth and development literature has previously pointed out a variety of other dimensions that are also relevant to explain countries' competitiveness and growth in the long-run. A key insight of economic growth theory is in particular that several growth engines are simultaneously important to explain cross-country differences in income per capita, and that these factors interact with each other leading to feedback effects and cumulative dynamics (Azariadis and Drazen, 1990; Verspagen, 1991; Howitt, 2000; Kelly, 2001; Galor, 2005; Howitt and Mayer-Foulkes, 2005; Acemoglu et al., 2006). In a recent system dynamics model, Castellacci (2018) shows that economic development arises from the complex interactions of countries' ability to innovate and develop new products, transform its industrial structure, build up advanced physical infrastructures and human capital, and export sophisticated products. In line with these models, the empirical approach adopted in this paper is based on the idea that economic development is a multi-dimensional co-evolutionary process, in which several growth engines interact with each other in a complex manner.

3. Model and indicators

Our empirical model provides a stylized description of a dynamical complex system composed of a vector of key capabilities, each of which corresponds to a growth engine previously studied in the economic development and growth literature. Each of these capabilities can affect the growth of GDP per capita, and be in turn affected by the latter. The various capabilities may also interact with each other (Castellacci, 2018). These interactions may therefore lead to feedback effects and non-linearities in the development process, and they may thus explain why economic systems transform, moving from previously established equilibria towards new local attractors (Colombelli and Von Tunzelmann, 2011). One major difference of our empirical approach *vis-à-vis* the ECI approach noted in the previous section is that we do not simply assume that some capabilities are present if an economy is characterized by a complex web of products, but we seek to measure these capabilities directly, using publicly available and widely used indicators (e.g. Castellacci and Archibugi; 2008; Fagerberg and Srholec, 2008). All our variables and indicators are annual data for 134 countries for the period 1970-2015.

The main target (dependent) variable in our analysis is economic growth. We use two indicators to measure this: (1) GDP per capita (constant, PPPs); (2) labour productivity. The set of explanatory factors considers some of the most important engines of growth that have previously been studied in the economic growth literature.

Physical capital: the accumulation of physical capital has traditionally been singled out as one of the crucial engines of growth (Castellacci, 2011). However, it may also play an important role in a Schumpeterian perspective since investments in physical capital enable innovative activities and technology diffusion through so-called embodied technical progress. A higher level of physical capital and technological infrastructures enable a faster and more efficient implementation of foreign advanced technologies. We measure this through a standard indicator of gross fixed capital formation (% of GDP).

Human capital: this is one of the most important and most frequently studied factors of economic development. As noted in recent threshold externalities models, human capital typically interact with technological changes, and such co-evolutionary relationship is important to explain countries' shifts across different stages of development (Azariadis and Drazen, 1990; Verspagen, 1991; Galor, 2005). We use two common indicators to measure human capital: (1) Tertiary enrolment ratio (% gross); (2) tertiary education's life expectancy (years).

Innovation: technological innovation represents the key factor highlighted by Schumpeterian growth models, which is assumed to become more important as national economies evolve from early to more advanced stages of economic development (Howitt, 2000; Howitt and Mayer-Foulkes, 2005). The capability to innovate is also necessary to produce and export non-ubiquitous and sophisticated products (Hidalgo et al., 2007). Our empirical analysis makes use of three related indicators to measure countries' innovative capabilities: (1) Research and development expenditure (GERD as % GDP); (2) Number of scientific and technical journal articles (per million people); (3) Patents granted at USPTO (per million of inhabitant).

Industrial structure: during the development process, national economies typically undergo a process of structural change and industrial transformation in which labour and capital resources are gradually shifted from low-tech and traditional activities (e.g. agriculture) towards more technologically advanced manufacturing sectors. Furthermore, a more advanced industrial structure does also represent an important factor enabling the absorption of foreign advanced technologies and their inter-industry diffusion (Durlauf, 1993; Kelly, 2001). In our analysis, we measure this aspect through a standard indicator of countries' industry value added share (% of GDP).

Openness: the openness of the economic system is important for economic growth for two related reasons. The first is that openness facilitates international trade, through both export and FDI, which is an important channel of productivity growth. The second is that international trade and FDI also

represent important pre-conditions for the international diffusion of advanced technologies. When trade openness is matched with the other structural factors noted above (physical infrastructures, human capital, innovation, advanced industrial structure), a country's absorptive capacity is enhanced and international technology diffusion through the import and imitation of foreign advanced technologies becomes an important driver of economic growth (Papageorgiou, 2002; Stokke, 2004). We employ three distinct indicators to measure this dimension: (1) $(\text{Import} + \text{Export})/\text{GDP}$; (2) Inward FDI Flow (% of GDP); (3) Inward FDI stock (% of GDP).

In summary, our empirical model investigates the dynamic relationships that link each of these variables to economic growth, the feedback effect that GDP per capita growth has on these dimensions, as well as the interactions and co-evolutionary processes linking together the five growth engines. In a nutshell, by estimating this model in a time series context we expect to find that economies that are characterized by a large number of causal relationships and feedback effects are more complex than countries in which our model will indicate the existence of only few causal relationships among these different growth factors.

4. Methods: new variables of economic complexity

The two new notions of complexity that we develop in this paper are based on a time series approach to economic growth. Specifically, time series cointegration analysis studies the relationships between non-stationary time series (Engle and Granger, 1987; Johansen, 1991). If two or more variables are integrated of the same order, there may be a linear combination of them whose residuals are stationary (meaning that the two series are not stationary but one (or more) linear combination of them is). In this case, the variables are *cointegrated*. Based on a Vector Error Correction (VEC) econometric specification, the Johansen cointegration method distinguishes between long-run and short-run

structure of the cointegrated series, and it is able to identify the long-run causal effect of any given explanatory variable on a dependent variable's growth rate over time. Two steps are involved in this method. First, a VEC model specification studies the existence of cointegration relationships among the K variables of interest:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \nu + \eta t + \varepsilon_t \quad (1)$$

where Y_t is the vector that contains the K (dependent and explanatory) variables of the model, Π is the matrix that contains the Error Correction Terms (ECT), Γ_i are the matrices indicating the transitory effects (part of the short-term structure), p is the lag order, ν and ηt are the deterministic components, and ε_t are independently and identically distributed (i.i.d.) errors with mean zero and a finite variance σ^2 .² Second, estimation and identification of the model is performed. The ECT term contains relevant information about the long run structure of the system, and it can be expressed as:

$$\Pi = \alpha\beta' \quad (2)$$

where β is a matrix composed of the cointegrating relations, which represent the long-run equilibrium relationships among the dependent and explanatory variables in the model; and α contains the set of long-run Granger causality effects, indicating the extent to which each variable reacts to deviations from its long-run equilibrium path (Granger, 1988).

² Engle and Granger (1987) show that if variables are cointegrated, the Π matrix in equation 1 should have a reduced rank r , such that $K > r > 0$. Johansen's (1991) cointegration rank test determines those r cointegrating relationships by adopting Trace Test and Maximum Likelihood specifications. Under the null of finding an additional cointegrating relation, it uses a recursive test starting with $r = 0$ until the first rejection is encountered.

The Johansen cointegration approach is able to determine three distinct types of causality: (1) *Short-run (weak) causality* (indicated by the Γ_i matrices) points out how variables react to external shocks in the short-term; (2) *Long-run causality* detects whether variables react to deviations from the long-run equilibrium β , i.e. moving the system out of its long-run equilibrium path; (3) *Strong causality* is given by the joint presence of short-run and long-run causality (Costantini and Marini; 2010; White and Lu, 2010). The two new notions of economic complexity that we develop here are based on the econometric concepts of long-run causality and strong causality, respectively.

To introduce these, consider again the VEC model (system of equations (1)), and focus on the equation that expresses the growth rate of a country (ΔGDP_t) as a function of the explanatory factors outlined in the previous section: openness (OP), human capital (HK), innovation (I) and industrial structure (IS). The VEC equation is:

$$\Delta GDP_t = \alpha_1(GDP_{t-1} - \theta_1 OP_{t-1} - \theta_2 HK_{t-1} - \theta_3 I_{t-1} - \theta_4 IS_{t-1}) + \sum_j (X \Delta GDP_{t-j}) + \sum_j (X \Delta OP_{t-j}) + \sum_j (W \Delta HK_{t-j}) + \sum_j (V \Delta I_{t-j}) + \sum_j (Z \Delta IS_{t-j}) + v + \eta t + \varepsilon_t \quad (3)$$

where the vector $[\theta_1; \theta_2; \theta_3; \theta_4]$ denotes the long-run cointegration relationships, and α_1 provides a measure of *long-run causality* (see above), i.e. the extent to which the growth rate of the economy responds to a (level) change in openness, human capital, innovation or industrial structure. By looking at the sign and significance of the coefficient α_1 we can therefore study the growth trajectory followed by each economy over the period 1970-2015.³ Precisely, a *negative* value of the coefficient α_1 would imply that changes in the country's openness (or human capital, innovation activity or industrial structure) have had an equilibrium correcting effect, but no permanent impact on the growth rate of

³ Significance of these coefficients can be assessed by applying a Wald Test with a Chi-Squared statistical distribution. Reliability of the models could be evaluated by observing stationary cointegrating relations, testing that the roots of the companion matrix is smaller than one and that errors are uncorrelated and normally distributed.

the economy along its transition path. On the other hand, a *positive* value of the estimated coefficient α_1 for country i would indicate that a 1% change in the openness of that country (or its human capital, innovation or industrial structure) has had a permanent $\alpha_1\%$ influence on the rate of growth of its GDP per capita over the four-decade period. In other words, the existence of this type of permanent effect indicates that the economy has experienced a structural transformation: the permanent effect of a variable on GDP per capita growth denotes that the economic system has moved away from its long-run (equilibrium) path – i.e. just like a complex dynamic system moves from one local attractor to another (Colombelli and von Tunzelmann, 2011).

This is the basis to define empirically the first of our new notion of economic complexity: **transformational complexity (TC)**. We define TC of country i as the number of positive and statistically significant α_j coefficients that we find in the estimation of equation 3 for that country. In other words, TC is a measure of the number of long-run causal relationships that a given country has experienced throughout the period, each of which has moved the economic system out of its initial long-run equilibrium, and towards a new local attractor. The underlying idea is that an economy that does not experience any structural transformation in the long-run tends to remain stable and to gravitate along the same local attractor. By contrast, a country that experiences several structural transformations over time is subject to a more intense process of structural change, moving frequently towards new local attractors, and thereby becoming more t-complex over time – in the sense that a high number of factors are able to lead to permanent changes in the economy’s growth path.

The second new notion of economic complexity that we introduce can also be empirically defined by using the estimation results of equation 3. As noted above, *strong causality* is defined as the joint presence of short-run and long-run causality, i.e. the joint significance of the coefficients α_j and of the coefficients of the lagged terms X , W , V and Z . This concept does not distinguish between equilibrium-correcting and out-of-equilibrium relationships (as the concept of long-run causality

does), but it points out whether a given explanatory variable has had a strong causal effect on GDP growth, which simultaneously entails a short-run adjustment *and* a long-run effect (see Costantini and Marini; 2010; White and Lu, 2010).

Based on this, we empirically define our second notion of economic complexity. **Systemic complexity (SC)** of country i is the total number of (statistically significant) strong causality relationships that we obtain from the estimation of equation 3 for that country. We name it “systemic” because it seeks to measure the overall complexity of the economic system, i.e. the number of factors that are structurally linked to GDP per capita and its growth in the long-run. To illustrate the underlying idea, a country whose GDP growth only depends on, say, the openness of the economy (e.g. an export-led economy) has *low systemic complexity* because many other potentially relevant growth engines – such as human capital accumulation, innovation, and industrial structure – do not have any effect on its development path over time. By contrast, a country whose GDP growth causally depends on openness, innovation and industrial structure – and where these growth engines are also causally related to each other, has *high systemic complexity*, because the dynamics of this economic system is driven by a dense web of causal relationships.

In short, the two new notions of economic complexity that we empirically apply here are both based on the Johansen time series cointegration approach (and specifically the estimation of equation 3 above), but they refer to two distinct notions. Transformational complexity (TC) measures a country’s pace of structural transformations over time, based on the idea that an economy is more t-complex if several growth engines are able to drive the system out-of-equilibrium and towards new growth paths. On the other hand, systemic complexity (SC) provides a measure of a country’s overall density of causal relationships between its main growth engines, based on the idea that an economy is more s-complex if its growth path is simultaneously driven by several coevolving variables. In the next section, we will illustrate further these notions with a few examples, examine their relationships with previous

indicators of economic complexity (e.g. ECI), and analyze the extent to which these are related to economic performance.

Before presenting the results, it is important to point out a further methodological aspect. The results of Johansen cointegration estimations may be affected by the model specification that is employed. To assess the robustness of the results, we have therefore not relied on a single model specification, but we have estimated equation 3 for a total of 216 distinct model specifications (for each country). First, we have used different indicators to measure the explanatory variables of the model (see previous section). Second, we have included different time dummies for each country. During the last forty years, most world economies have undergone important economic and political transformations, and many of them have sometimes experienced episodes of crises and stability. These structural breaks have important effects on the aggregate time series dynamics, and must therefore be considered in the econometric analysis. The inclusion of *permanent* time dummies, for long-lasting external shocks allows us to control for the presence of these exogenous events in the empirical exercise. Since the inclusion of such time dummies may affect the estimation results, we have experimented with different sets of time dummies for each model specification.⁴

5. Results

As noted in the previous section, to assess the robustness of the results we have estimated equation 3 for 216 different model specifications (each of which presents a different combination of indicators as well as time dummies) for each country in the sample. This means that we have estimated equation

⁴ Besides the time dummies, the deterministic component of the model also includes an indicator measuring the institutional quality of each country as exogenous control variable in the model. The decision of inserting this institutional variable as an *exogenous* factor is based on a previous study (Castellacci and Natera, 2013), which shows that institutional variables move at a different pace than techno-economic variables, so that in a time series context it is appropriate to assume that the former affect the latter but not *vice versa*.

3 for a total of 28,944 times, and thereby coded the results of these time series estimations in a meta-analytic dataset that we have used to assess the robustness of the results. In the construction of this dataset, we have retained observations for all those models that pass the required cointegrations tests, and disregard the model specifications that do not. This section will first present a few selected examples and graphs to illustrate the underlying intuition, and then report the results of meta regression analysis to show the main patterns in a more robust manner.

5.1 Descriptive results and selected illustrations

Table 1 reports the results of the estimation of the VECM (equation 3) for one selected model specification and for three selected countries at different stages of development: Nepal, US and South Korea. We are not going to discuss these estimations results in further details here, but we simply report them to provide an illustration of the estimation output that we have obtained for each model specification and each country, and that we have subsequently used to calculate the SC and TC variables using the method outlined in the previous section.

For the same three countries, figure 1 shows a series of diagrams representing the main growth engines, how they are related to each other, and how they affect GDP per capita dynamics (placed at the centre of each diagram). The arrows depicted in these figures represent the (statistically significant) causal relationships that we have found in the estimation of equation 3 (i.e. *long-run causality* for the TC index, and *strong causality* for the SC index; see definition in previous section). To illustrate, figure 1 shows for instance that Nepal is characterized by a rather low degree of (both systemic and transformational) complexity, since the time series estimations only identify one causal relationship among the variables. On the other hand, the US and South Korea provide examples of countries that have a high degree of systemic complexity, meaning that their economic systems are driven by the complex dynamic co-evolution of several growth engines. South Korea, differently from the US, also

show high transformational complexity, i.e. it experienced a process of rapid and structural change during the period 1970-2015.

Moving beyond these simple selected illustrations and shifting the focus to the more general cross-country patterns, table 2 reports some descriptive statistics of the SC and TC variables (averages of all country-model observations included in our meta-analytic dataset). Both variables are discrete (because they are defined by ‘numbers’ of causal relationships), ranging between 0 (min) to 20 (max). SC has a mean value of 9.35, meaning that we have found on average a total of around 9 “strong causality” relationships, for each country and each model specification. TC has instead a mean value of 4.6, indicating the number of positive “long-run causality” relationships that moved the system out of equilibrium during the investigation period (on average, for each country and each model specification).

< Table 1, figure 1 and table 2 here >

5.2 Relationships between transformational and systemic complexity

In order to get a better understanding of the characteristics and relevance of the new notions, we have carried out a set of bivariate analyses, in which we have used the meta-analytic dataset to estimate the relationship between SC, TC, the ECI index, and GDP per capita. We first study the relationship between systemic and transformational complexity. Table 3 reports the results of Poisson regressions on the pooled dataset (21,440 country-model observations). The results indicate that this relationship is positive and significant. This means that economies that transformed more rapidly during the period 1970-2015 (higher TC) are also those that have achieved a higher level of systemic complexity (higher SC). Transformational complexity is thus a necessary condition to achieve greater systemic complexity in the long-run. In fact, estimations of the same regression in the seven country groups

show that this positive relationship is stronger for the groups of East and South Asian economies, many of which underwent rapid transformations during the last four decades. On the other hand, the estimated positive relationship between SC and TC is weaker for OECD countries, arguably because these had already achieved a high degree of systemic complexity at the beginning of the period, and hence did not necessitate to undertake severe structural transformations as other middle-income and developing economies did (see e.g. the illustration for the US in figure 1 above).

< Table 3 here >

5.3 Relationships between systemic complexity, ECI index and GDP per capita

Next, we analyze the relationships between systemic complexity, on the one hand, and the ECI index and GDP per capita, on the other. This analysis is important because the ECI index is a well-known and widely used indicator of economic complexity (Hausman et al., 2014). It is therefore relevant to assess whether, and to what extent, SC and the ECI are related to each other. Figures 2 and 3 plot these relationships for a selected model specification, whereas tables 4 and 5 report meta-analytic Poisson regression results on the pooled dataset.

The results in table 4 indicate that SC is positively related with ECI index, meaning that systemic complexity is on the whole correlated with product and export complexity (which is the notion underlying the ECI index). A reasonable interpretation of this pattern is that the latter is one of the factors that countries can exploit to achieve the former. The other columns in table 4 also suggest, though, that there is some heterogeneity across country groups. The positive correlation between SC and ECI is particularly strong for the group of East-Asian economies, arguably because these countries' export-led model is well caught by the ECI index. On the other hand, the estimated coefficient turns into negative for other middle-income and less developed economies, whose results

are reported on the right-hand side of the table. For these countries, there is substantial divergence between ECI and SC, which may be interpreted by arguing that some economies may still achieve some degree of systemic complexity without necessarily having a complex and sophisticated web of export products.

Table 5 shows estimation results of the correlation between SC and GDP per capita (average of the period). The relationship is positive and significant, indicating that systemic complexity is associated with better economic performance in the long-run. That is to say, countries in which several growth factors (and the underlying capabilities) interact with each other and foster income per capita growth, are able to achieve a more dynamic performance than countries that rely on only one or few growth engines (Castellacci, 2018). Table 5 also indicate the existence of some differences across country groups. Similarly to what noted above, the positive correlation between SC and GDP per capita is much stronger for the groups of East and South-East Asian economies, as well as for OECD countries. Hence, higher systemic complexity is mostly associated with stronger economic performance for fast developing and industrialized countries. By contrast, the estimated correlation turns into negative for other middle-income and less developed economies (although the size of these correlation coefficients is quite small).

< Figure 2, table 4, figure 3 and table 5 here >

5.4 Relationships between transformational complexity ECI index and GDP per capita

Finally, we shift the focus to the variable of transformational complexity, and we analyze its relationship with the ECI index and GDP per capita, respectively. Following the same exposition strategy as above, figures 4 and 5 illustrate these correlations for a selected model specification, while tables 6 and 7 report Poisson regression results of the relationships on the pooled dataset.

The results show that TC is on the whole negatively related with ECI in the pooled sample. However, this average correlation masks somewhat distinct patterns across country groups. The relationship is in fact weakly positive for the first three groups (OECD, Latin America and East-Asia). For these economies, a stronger degree of product and export complexity (higher ECI) is weakly associated with a greater ability to transform over time (higher TC). By contrast, the estimated correlation parameter is negative and significant for the less developed country groups, and particularly strong for Eurasian and African economies. Results for these country groups show that it is possible to combine a low level of product and export complexity (low ECI) with a high pace of structural transformations (high TC) over time. This may be the case if national systems, though in the absence of a strong and competitive international trade sector, rely instead on other growth engines (e.g. human capital, physical infrastructures, industrial transformations, and/or imitation ability) that may be able to set up a process of transformation in the long-run.

Further, regression results in table 7 show that TC is also negatively related with GDP per capita (average of the period). Here again, there are distinct patterns across country groups. The estimated parameter is in fact positive and strong for South Asian economies, indicating that these countries' ability to undertake rapid structural transformations is related to a better economic performance in the long-run. On the other hand, the estimated relationship is negative and significant for most other country groups, and particularly strong for African countries. These suggest that countries that had a low income per capita level during the period (and hence also a low degree of systemic complexity) had to undertake structural transformations to a greater extent than national systems which already had a higher level of economic development and systemic complexity.

< Figure 4, table 6, figure 5 and table 7 here >

6. Conclusions

The paper has developed two new notions of complexity and economic development that are based on time series analysis of the set of causal relationships driving economic growth in the long-run. Instead of studying the characteristics that define the complexity of a national system at a given point in time, the new notions that we have presented in this paper are inherently dynamic. S-complexity is based on the study of a country's overall web of causal relationships during a long period of time; while t-complexity denotes how rapidly an economic system has undergone structural transformations in the long run. We conclude the paper by summarizing its two main empirical results, and the related implications and possible future extensions.

First, as discussed in the previous section, the new variables that we have built up are empirically correlated with the well-known ECI index of product and export complexity, although there are notable differences between the two approaches. On the one hand, systemic complexity is positively correlated with the ECI index, indicating that countries that have the capabilities to produce and export complex and sophisticated products are on average also characterized by a dense web of causal relationships in which several growth factors co-evolve and drive economic growth. On the other hand, transformational complexity is negatively correlated with the ECI index. The reason for this, we argue, is that economies that do not have an advanced export specialization pattern, must compensate this structural weakness by focusing on the development of other growth engines (and the underlying capabilities), such as e.g. human capital, industrial and infrastructure upgrading, and / or the imitation of foreign advanced technologies. Hence, even in the absence of a strong and developed international trade sector, economies may still increase their complexity over time by focusing on other factors of development.

Our results show that the estimated correlations between SC, TC and ECI are strong for the group of OECD and East-Asian economies, and less so (or even take the opposite sign) for other middle-income and less developed countries. Hence, for the latter groups, there seems to be a marked divergence between the measurement of product and export complexity (ECI) and variables based on the multi-dimensional notions of s- and t-complexity. This suggests that some economies may still achieve some degree of systemic and transformational complexity without necessarily having a complex and sophisticated web of export products. In other words, there exists different paths and strategies to achieve economic development, and this is an important point of reflection that our paper suggests to develop further in future research. On the whole, the new notions of complexity presented in this work do not intend to challenge the ECI approach and its index, but rather extend and complement it by emphasizing the multi-dimensional and complex nature of the growth and development process.

Second, our results also highlight some important relationships between s-complexity, t-complexity and the level of income per capita. On the one hand, systemic complexity is positively correlated with GDP per capita. This is in line with our idea that countries in which several growth factors interact with each other are able to achieve a more dynamic performance than countries that rely on only one or few growth engines. On the other hand, we find that transformational complexity is negatively correlated with GDP per capita. In line with what noted above in relation to the ECI index, the interpretation of this pattern is that countries starting at a lower level of economic development are also characterized by a less complex economic structure, and have for this reason larger scope and greater need to undertake structural changes and transformations over time, compared to national economies that were already wealthy (complex) at the beginning of the period.

However, these empirical patterns also show some notable differences across country groups. The positive estimated parameters are much weaker, and sometimes negative, for some of the groups of

middle-income and less developed economies. This may perhaps suggest that these countries, starting below a minimum threshold level, do not have sufficiently strong capabilities to set in motion dynamic processes of structural change and transformations that would lead them to achieve higher levels of complexity. This explanation is plausible, but the present paper has not explored and developed it in depth. Future research should investigate further the factors that explain why some countries are able to undertake a virtuous process of transformation whereas others remain trapped at earlier levels of complexity and economic development.

References

- Acemoglu, D., Aghion, P. and Zilibotti, F. (2006): “Distance to Frontier, Selection and Economic Growth”, *Journal of the European Economic Association*, 4: 37-74.
- Antonelli, C. (2011): “The economic complexity of technological change: knowledge interaction and path dependence”, in Antonelli, C. (Ed.), *Handbook on the Economic Complexity of Technological Change*, Edward Elgar Publishing.
- Azariadis, C. and A. Drazen (1990): “Threshold Externalities in Economic Development”, *Quarterly Journal of Economics*, 105: 501-526.
- Balland, P.-A. and Rigby, D. (2017): “The geography of complex knowledge”, *Economic Geography*, 93(1): 1-23.
- Caldarelli, G., Cristelli, M., Gabrielli, A., Pietronero, L., Scala, A. and Tacchella, A. (2012): “A network analysis of countries’ export flows: Firm grounds for the building blocks of the economy”, *PLOS One* 7(10).
- Castellacci, F. (2007): “Evolutionary and new growth theories: Are they converging?”, *Journal of Economic Surveys*, 21(3): 585-627.
- Castellacci, F. (2011): “Closing the Technology Gap?”, *Review of Development Economics*, 15(1): 180-197.
- Castellacci, F. (2018): “Co-evolutionary growth: A system dynamics model”, *Economic Modelling*, 70: 272-287.

- Castellacci, F. and Archibugi, D. (2008): “The technology clubs: The distribution of knowledge across nations”, *Research Policy*, 37 (10): 1659-1673.
- Castellacci, F. and Natera, J. M. (2016): “Innovation, absorptive capacity and growth heterogeneity: Development paths in Latin America 1970-2010”, *Structural Change and Economic Dynamics*, 37: 27-42.
- Castellacci, F. and Natera, J. M. (2012): “The dynamics of national innovation systems: A panel cointegration analysis of the coevolution between innovative capability and absorptive capacity”, *Research Policy*, 42(3): 579-594.
- Colombelli, A. and von Tunzelmann, N. (2011): The persistence of innovation and path dependence”, in Antonelli, C. (Ed.), *Handbook on the Economic Complexity of Technological Change*, Edward Elgar Publishing.
- Costantini, V. and Marini, C. (2010): “The causality between energy consumption and economic growth: A multi-sectoral analysis using non-stationary cointegrated panel data”, *Energy Economics*, 32: 591-603.
- Cristelli, M., Gabrielli, A., Tacchella, A., Caldarelli, G. and Pietronero, L. (2013): “Measuring the intangibles: A metrics for the economic complexity of countries and products”, *PLOS One*, 8(8).
- Durlauf, S.N. (1993): “Nonergodic Economic Growth”, *Review of Economic Studies*, 60: 349-366.
- Engle, R.F. and Granger, C.W.J. (1987): “Co-integration and error correction: representation, estimation, and testing”, *Econometrica*, 55: 251-276.
- Fagerberg, J. and Srholec, M. (2008): “National innovation systems, capabilities and economic development”, *Research Policy*, 37 (9): 1417-1435.
- Felipe, J., Kumar, U., Abdon, A. and Bacate, M. (2012): “Product complexity and economic development”, *Structural Change and Economic Dynamics*, 23: 36-68.
- Galor, O. (2005), “From Stagnation To Growth: Unified Growth Theory”, in: Aghion, P.. and S. Durlauf (eds.), *Handbook of Economic Growth*, Elsevier, North Holland.
- Granger, C.W.J. (1988): “Some recent development in a concept of causality”, *Journal of Econometrics*, 39 (1-2): 199-211.
- Hartmann, D., Guevara, M., Jara-Figueroa, C., Aristaran, M. and Hidalgo, C. (2017): “Linking economic complexity, institutions, and income inequality”, *World Development*, 93: 75-93.
- Hausmann, R. and Hidalgo, C. (2011): “The network structure of economic output”, *Journal of Economic Growth*, 16: 309-342.
- Hausmann, R., Hidalgo, C., Bustos, S., Coscia, M., Simoes, A. and Yldirim, M. (2014): *The Atlas of Economic Complexity: Mapping Paths to Prosperity*, MIT Press.

- Hidalgo, C., Klinger, B., Barabasi, A.-L. and Hausmann, R. (2007): “The product space conditions the development of nations”, *Science*, 317: 482-487.
- Hidalgo, C. and Hausmann, R. (2009): “The building blocks of economic complexity”, *Proceedings of the National Academy of Sciences*, 106(26): 10570-10575,
- Howitt, P. (2000): “Endogenous Growth and Cross-Country Income Differences”, *American Economic Review*, 90: 829-846.
- Howitt, P. and D. Mayer-Foulkes (2005): “R&D, Implementation and Stagnation: A Schumpeterian Theory of Convergence Clubs”, *Journal of Money, Credit and Banking*, 37: 147-177.
- Johansen, S. (1991): “Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models”, *Econometrica* 59: 1551–1580.
- Kelly, M. (2001): “Linkages, Thresholds, and Development”, *Journal of Economic Growth*, 6: 39-53.
- Papageorgiou, C. (2002): “Trade as a Threshold Variable for Multiple Regimes,” *Economics Letters*, 71 (1): 85-91.
- Robert, V. and Yoguel, G. (2011): “The complex dynamics of economic development”, in Antonelli, C. (Ed.), *Handbook on the Economic Complexity of Technological Change*, Edward Elgar Publishing.
- Stokke, H. (2004): “Technology adoption and multiple growth paths: An intertemporal general equilibrium analysis of the catch-up process in Thailand”, *Review of World Economics*, 140 (1): 80-109.
- Tacchella, A., Cristelli, M., Caldarelli, G., Gabrielli, A. and Pietronero, L. (2013): “Economic complexity: Conceptual grounding of a new metrics for global competitiveness”, *Journal of Economic Dynamics and Control*, 37: 1683-1691.
- Verspagen, B. (1991): “A new empirical approach to catching up or falling behind”, *Structural Change and Economic Dynamics*, 2 (2): 359-380.
- White, H. and Lu, X. (2010): “Granger causality and dynamic structural systems”, *Journal of Financial Econometrics*, 8(2): 193-243.

Tables and figures

Table 1: Joahnsen cointegration results: vector error correction estimates (β -vector) for three selected countries and model specifications.

	Illustration 1: Nepal		Illustration 2: United States		Illustration 3: South Korea	
Conceptual dimension	<i>Indicator used</i>		<i>Indicator used</i>		<i>Indicator used</i>	
Physical capital	<i>Gross fixed capital formation</i>	8.663567 [0.37666]	<i>Gross fixed capital formation</i>	5148.657*** [10.0824]		
Human capital	<i>Tertiary school life expectancy</i>	-116.1061* [-1.58351]	<i>Tertiary school enrollment</i>	2027.823*** [10.8518]	<i>Tertiary school life expectancy</i>	-5824.063*** [-3.71210]
Innovation	<i>R&D expenditure</i>	-4059.405*** [-38.6388]	<i>Patents granted (USPTO)</i>	-86.04007*** [-9.78498]	<i>Scientific and technical articles</i>	-4.715714* [-1.60614]
Industrial Structure					<i>Industry value added (%)</i>	3048.044*** [9.25999]
Openness	<i>Openness Indicator</i>	-9.394975*** [-2.32080]	<i>FDI Stock Inward (% GDP)</i>	401.735*** [2.75176]	<i>FDI Stock Inward (%)</i>	2495.043*** [6.84246]

Time dummies included in the regressions but not reported in the table. T-statistics in brackets: *** 1% significance level, ** 5% significance level, * 10% significance level.

Figure 1: Illustrations of systemic complexity and transformational complexity for three selected countries and three selected model specifications (corresponding to results reported in table 1).

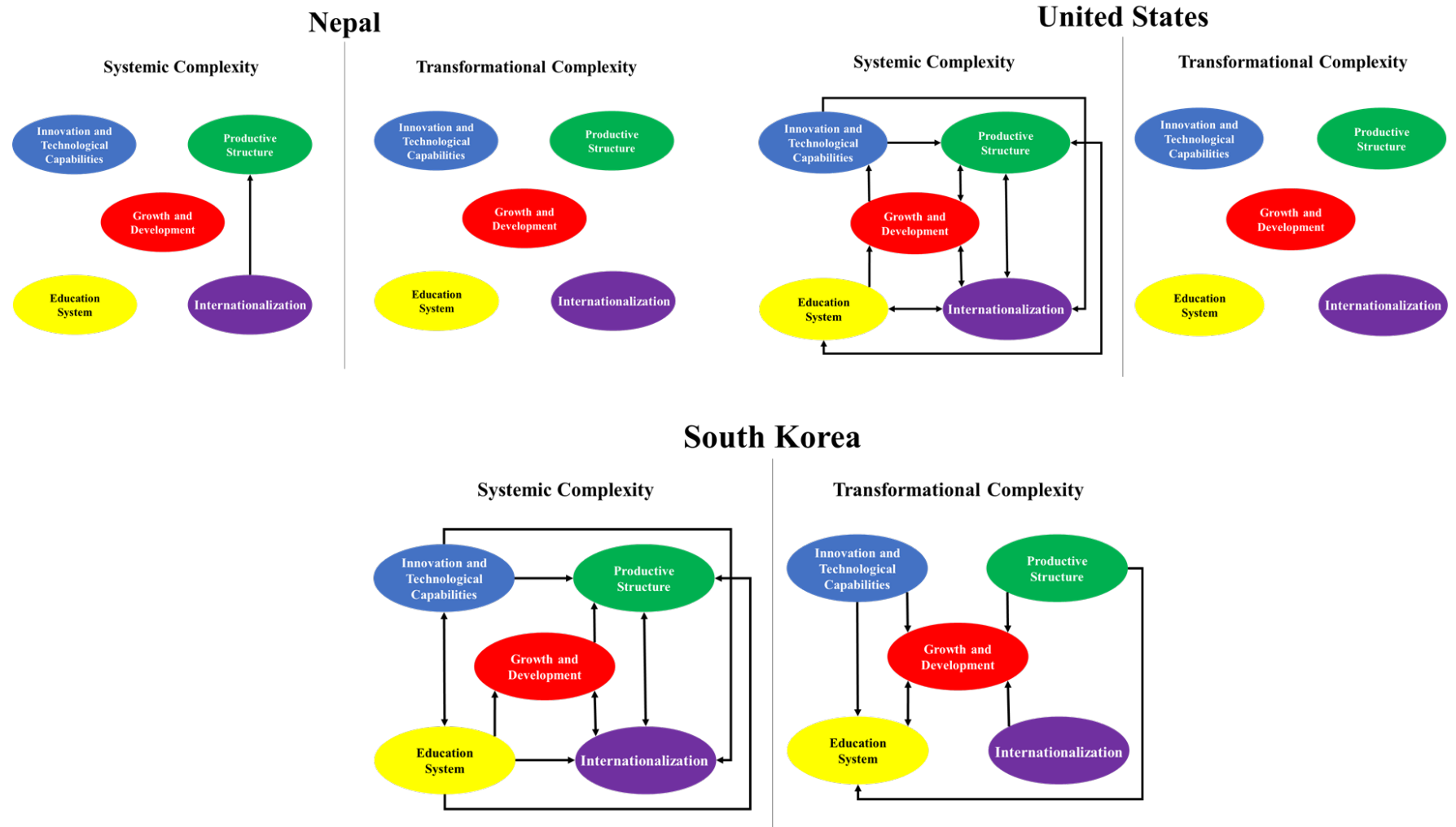


Table 2: Descriptive statistics of the two new complexity variables

	Mean	Maximum	Minimum	Std. dev.	Observations
Systemic complexity (SC)	9.35	20.00	0.00	3.57	11207
Transformational complexity (C)	4.64	20.00	0.00	3.88	11207

Table 3: Results of meta-analysis on the relationship between transformational complexity and systemic complexity.

	All countries	OECD	Latin America	East Asia	Eurasia	South Asia	North Africa & Middle East	Central and Southern Africa
	0.042041***	0.038516** *	0.045067***	0.049305** *	0.040626** *	0.048336** *	0.043137***	0.042251***
	[74.65453]	[31.57511]	[30.96297]	[25.07922]	[31.7486]	[16.98064]	[17.37163]	[35.8612]
R2	0.207185	0.199716	0.240569	0.244154	0.223705	0.341083	0.238545	0.238275
Adjusted R2	0.204216	0.186738	0.22436	0.215248	0.210379	0.285102	0.195399	0.225642
N	21440	4638	3542	2010	4386	946	1381	4537

Poisson regressions on pooled meta-analytic sample. Model specification dummies, and country group dummies included in the regressions but not reported in the table. T-statistics in brackets: *** 1% significance level, ** 5% significance level, * 10% significance level.

Figure 2: Plot of SC vs ECI.

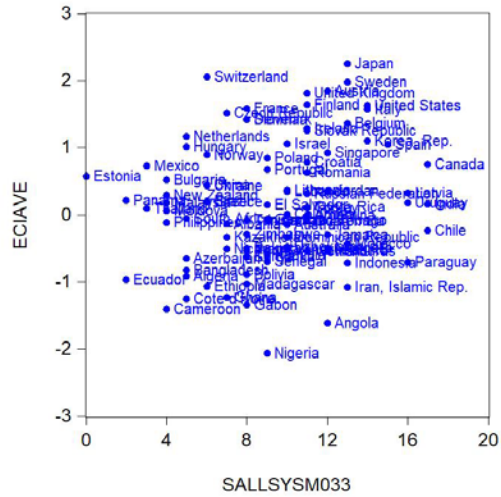


Table 4: Results of meta-analysis on the relationship between systemic complexity and ECI index.

	All countries	OECD	Latin America	East Asia	Eurasia	South Asia	North Africa & Middle East	Central and Southern Africa
ECI index	0.009901** [2.297522]	0.020614*** [2.659093]	0.049236*** [3.784805]	0.172918*** [14.09914]	-0.066668*** [-7.806269]	0.09561*** [3.183602]	-0.051399*** [-2.912741]	-0.037807*** [-3.068608]
R2	0.016804	0.047623	0.025508	0.117034	0.049889	0.134441	0.097595	0.04379
Adjusted R2	0.012678	0.031444	0.00449	0.081981	0.031796	0.051794	0.046464	0.020212
N	21440	4638	3542	2010	4386	946	1381	4537

Poisson regressions on pooled meta-analytic sample. Model specification dummies, and country group dummies included in the regressions but not reported in the table. T-statistics in brackets: *** 1% significance level, ** 5% significance level, * 10% significance level.

Figure 3: Plot of SC vs GDP per capita.

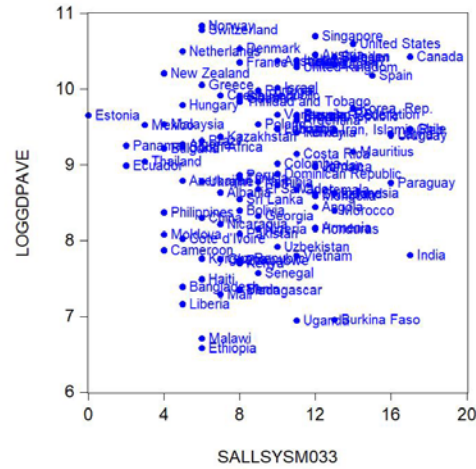


Table 5: Results of meta-analysis on the relationship between systemic complexity and GDP per capita.

	All countries	OECD	Latin America	East Asia	Eurasia	South Asia	North Africa & Middle East	Central and Southern Africa
GDP per capita	0.01079*** [2.8354]	0.117046*** [4.628869]	0.020069 [1.510298]	0.072567*** [9.276411]	-0.028862*** [-4.063786]	0.236518*** [8.043955]	-0.012237 [-0.477573]	-0.020968*** [-3.111824]
R2	0.015778	0.041351	0.02258	0.075337	0.045875	0.185913	0.107381	0.052038
Adjusted R2	0.011713	0.02508	0.000104	0.038629	0.029497	0.103502	0.050634	0.030638
N	21440	4638	3542	2010	4386	946	1381	4537

Poisson regressions on pooled meta-analytic sample. Model specification dummies, and country group dummies included in the regressions but not reported in the table. T-statistics in brackets: *** 1% significance level, ** 5% significance level, * 10% significance level.

Figure 4: Plot of TC vs ECI.

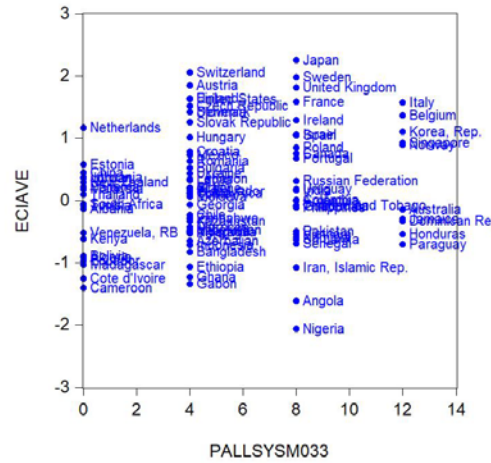


Table 6: Results of meta-analysis on the relationship between transformational complexity and ECI index.

	All countries	OECD	Latin America	East Asia	Eurasia	South Asia	North Africa & Middle East	Central and Southern Africa
ECI index	-0.02455*** [-4.003937]	0.064383*** [5.632524]	0.052556*** [2.835144]	0.069318*** [3.948574]	-0.122737*** [-10.20906]	-0.037315 [-0.869987]	0.001798 [0.068527]	-0.183536*** [-10.90006]
R2	0.014704	0.030061	0.022268	0.09014	0.040038	0.138478	0.106511	0.060422
Adjusted R2	0.010569	0.013584	0.00118	0.054019	0.021758	0.056217	0.055884	0.037253
N	21441	4638	3542	2010	4386	946	1381	4537

Poisson regressions on pooled meta-analytic sample. Model specification dummies, and country group dummies included in the regressions but not reported in the table. T-statistics in brackets: *** 1% significance level, ** 5% significance level, * 10% significance level.

Figure 5: Plot of TC vs GDP per capita.

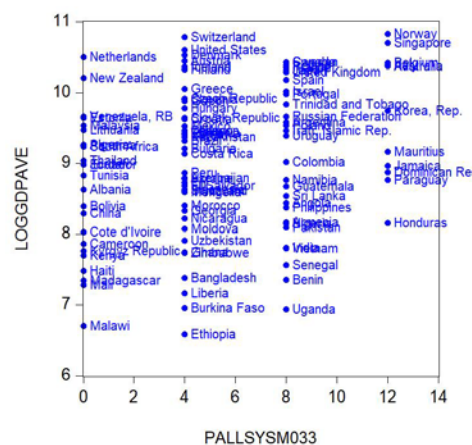


Table 7: Results of meta-analysis on the relationship between transformational complexity and GDP per capita.

	All countries	OECD	Latin America	East Asia	Eurasia	South Asia	North Africa & Middle East	Central and Southern Africa
GDP per capita	-0.059913*** [-11.19806]	0.071959* [1.947401]	-0.091716*** [-4.84323]	-0.001095 [-0.097696]	-0.070696*** [-7.108118]	0.198715*** [4.907219]	-0.328675*** [-8.989492]	-0.100938*** [-10.82617]
R2	0.017883	0.027488	0.02876	0.085976	0.031873	0.174746	0.129347	0.058873
Adjusted R2	0.013826	0.010982	0.006426	0.04969	0.015255	0.091205	0.073996	0.037627
N	21441	4638	3542	2010	4386	946	1381	4537

Poisson regressions on pooled meta-analytic sample. Model specification dummies, and country group dummies included in the regressions but not reported in the table. T-statistics in brackets: *** 1% significance level, ** 5% significance level, * 10% significance level.