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Abstract

Although technological complexity seems to be a crucial determinant of economic development, it remains insufficiently explored. Relying on micro information stored in individual patent applications and by applying the network view of countries linked to the technologies they develop, we create a global technology space and derive complexity measures that position countries in this space. Our measures of technological diversification and the ubiquity of technologies present in a country's technology portfolio are further used as an input to explain the role of technological complexity in countries' income and economic development. We show that a country's position in the global technology space affects its level of income and growth. The main channel through which it happens is the exclusiveness and uniqueness of the technological portfolio a country has, as compared to the remaining countries.

Keywords: *Technological complexity; Ubiquity; Diversification; Networks; Specialization; Economic Development*

JEL classification: *O57, F1, O11, O14, O3, O4*

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1. Introduction

Intuitively, technological complexity is a crucial factor and a determinant of development. However, it still remains only implicitly present in the attempts to explain economic growth and technological progress. Despite obvious differences in technological development of countries and their potential consequences for economic development, technology is treated in a very general way or its richness is brutally reduced. The main reason behind this is the difficulty of capturing technological complexity in theoretical models and measuring it in empirical studies.

In this work, we provide a methodology of constructing a global technology space and deriving complexity measures that position countries in this space. Our measures of technological diversification and the ubiquity of technologies present in a country’s technology portfolio are further used as an input to explain the role of technological complexity in countries’ income and economic development.

Our work is motivated by recent findings concerning the production structure and its role in economic development (Hausmann & Hidalgo, 2010). The logic behind the economic complexity as a driving force of economic development is straightforward: Countries making more products which are less ubiquitous are more likely to achieve higher income and growth. Expecting that the same is true for technological capabilities, which are a missing link in the analysis of economic complexity framework by Hausmann and Hidalgo (2010), we extend this framework by creating a global technology space and, after ranking countries based on the level of their technological complexity, the main questions we aim to answer in this analysis include: What is the relationship between the level of a country's technological diversification and the ubiquity of technologies present in its technology space? How economic development is affected by the complexity of a country’s technology space? What is the link between the technological complexity and the level of growth?

The main contribution of this work is that, by applying the network view of countries linked to the technologies they develop, we create a global technology space, which replicates the system of technological capabilities. Relying on micro information stored in individual patent applications, we are able to represent the richness of the technological structure at the global level without reducing the level of detail. Consequently, our results show that a country's technological diversification and the ubiquity of technologies present in its technology space have positive and negative impact on income and growth respectively.

In order to build the technology space and the subsequent measures of technological complexity, we use information included in patent applications. In particular, we rely on technological fields to which an invention corresponds. This information is coded through the International Patent Classification (IPC) classes. The source of our data is the European Patent Office (EPO) Worldwide Patent Statistical (PATSTAT) Database and the time considered spans from year 1991 to 2009. The elaboration of indicators used in the proceeding analysis relies on altogether over 11 Million priority patent applications that were filed to any patent office worldwide. The number of individual IPC codes considered was of nearly 30 Million.

The remaining of the paper is organized as follows: Section 2 positions the current work among the existing literature on the issue of technological progress, complexity and economic development. Section 3 introduces the methodological framework behind the design of the technology space and the technological complexity measures. Section 4 presents the data used. Section 5 presents the results of empirical analysis. Section 6 includes robustness checks of the results against alternative measures of technological complexity. Section 7 concludes.

2. Related literature

Our paper builds on the following strands of literature: first, it relates to the large body of research devoted to the determinants of economic growth. In particular, it seeks to create a link to the attempts of capturing the concept of technology and technological change into the empirical models of economic growth. Second, by introducing the new measures of technological development, it extends the research on the technological complexity and its economic consequences. Finally, by implementing the tool of network analysis it creates a connection with the relatively recent attempts to introduce this perspective to study economic phenomena. Below we provide a short overview of the above mentioned strands of literature and explain the linkages with the current work.

Despite a longstanding interest in the determinants of economic development and growth, causal inference drawn from the empirical evidence remains questionable and the magnitude and robustness of estimates for a wide range of factors are still under debate. Initially, empirical research on the sources of economic growth followed two theoretical classes of models (Capolupo, 2009). The first class considers capital accumulation as the driving force behind economic growth. Here, for example, the role of capital accumulation (Barro, 1991; Barro & Lee, 2001; Cohen & Soto, 2007; Erosa, Koreshkova, & Restuccia, 2010; Murphy, Shleifer, & Vishny, 1991; Oded & Omer, 2004; Sasaki, 2011) and the pattern of its use (Fitzgerald & Hallak, 2004) have drawn considerable attention. However, despite the theoretical role assigned to capital accumulation, the empirical results are highly unsatisfactory (Capolupo, 2009). After the criticism of the idea that production factors accumulation lies behind economic development (Islam, 1995, 2003; Klenow & Rodriguez-Clare, 2005; Prescott, 1998), alternative explanations have emerged. These new approaches seek explanations behind economic inequalities in, for example, differences in political system (Azam, Bates, & Biais, 2009; Besley, Persson, & Sturm, 2010; Castro, Clementi, & Macdonald, 2009; Cooper, 1972; Persson & Tabellini, 2006), the role of institutions (Andrianova, Demetriades, & Shortland, 2009; Branstetter, Fisman, Foley, & Saggi, 2011; Papaioannou & Siourounis, 2008) or finally in the technological change (Aghion & Howitt, 1997; Eaton & Kortum, 1996; Niosi, 2008; Romer, 1990).

Having a strong theoretical support, this argument has spurred a large stream of empirical research (Jorgenson, 1996). One of the obvious ways of looking at the relationship between technological change and growth is through the level of R&D investment. In a very extensive way, Griliches (1973, 1979, 1995) showed how investments in new technology can be translated into economic growth. This work is based on the proposition that aggregate input of intellectual capital, together with the inputs of individual producers serve as a determinant of output. In a stylized form, R&D intensity increases the rate of innovation (commonly proxied by the number of patents) and finally increased productivity at a firm level (Crepon, Duguet, & Mairessec, 1998) and, finally, economic growth at a country level (Zachariadis, 2003).

The explanations of the relationship between technological progress and economic development go beyond the argument of R&D or patenting intensity and range from explanations concerning the variance in infrastructure to entrepreneurial skills (Lloyd-Ellis & Bernhardt, 2000; Röller & Waverman, 2001). However, a number of studies explaining the differences in the level of economic development between countries make a strong assumption of identical technologies for all the countries (Mankiw, Romer, & Weil, 1992; Romer, 1987), although substantial differences in overall levels of productivity among countries have been documented (Christensen, Cummings, & Jorgenson, 1981; Denison, 1967; Dougherty & Jorgenson, 1996). According to Islam (1995, 2003), technology levels across countries differ enormously across countries and the highest value is about forty times larger than the lowest. Also the stock of varieties (Klenow & Rodriguez-Clare, 2005) and the different composition of GDP across countries and across sectors (Caselli, 2005) are responsible for the differences in income and economic growth. Moreover, the differences in specialization patterns are economically meaningful as well (Groizard, 2009; Hausmann, Hwang, & Rodrik, 2007; Saviotti & Frenken, 2008). By developing an index that measures the "quality" of countries' export baskets, Hausmann et al. (2007) shows that countries with more sophisticated set of goods that perform better. Thus, technological differences among countries must be taken into account in econometric modeling of differences in economic development. Consequently, the issue of technological complexity in economic development is increasingly attracting more attention, although the concept is neither easy to capture in theoretical models (Blauwhof & Leydesdorff, 1993; Growiec & Schumacher, 2007; Pintea & Thompson, 2007; Pollak, 2010) nor to measure (Griliches, 1995).

One of the first attempts to create a technological complexity, or rather a technological proximity measure, was by Jaffe (1986) who, by exploiting firm-level data on patenting in different technology classes, located firms in a multi-dimensional technology space. Jaffe's (1986) approach to define the level of technological diversification has found a wide application. For example, Bloom et al. (2005) empirically distinguish a firm’s position in technology space and product market space using information on the distribution of its patenting across technology fields. In a similar way, Cincera (2005) uses an improved Jaffe's index to measure R&D spillovers among between firms and their effect on productivity. However, although widely adopted, and it is not clear to what extent the uncentered correlation index between the firms' technological vectors is a correct measure of technological proximity or complexity (Griliches, 1995). Hence, the concept of technological complexity remains hard to define empirically and this issue can be solved by experimenting alternative approaches.

A novel approach to deal with economic complexity has been recently proposed by Hidalgo and Hausmann (2009). By interpreting trade data as a bipartite network in which countries are connected to the products they export, they quantify the complexity of a country's economy by characterizing the structure of this network. The key measures of complexity include countries diversification and the ubiquity of products they produce and export. The most important finding of this work is that economic complexity measures are correlated with a country's level of income, and that deviations from this relationship are predictive of future growth (Hausmann & Hidalgo, 2010; Hidalgo, Klinger, Barabási, & Hausmann, 2007). Arriving to these results was possible due to the application of network analysis, which besides biology and physics, slowly makes its road in the field of economics and has been applied to a wide range of topics ranging from international trade (De Benedictis & Tajoli, 2011; Garlaschelli & Loffredo, 2005) through internationalisation of inventive activity (De Prato & Nepelski, 2012, 2014) to corporate ownership (Vitali, Glattfelder, & Battiston, 2011).

This success of network analysis in studying economic phenomena comes from the fact that its tools are well suited to study complex systems, which are understood as being composed of many agents with numerous interactions. One of the key characteristics of such systems is that the entire system often shows characteristics that cannot be captured and described at the individual level. This concerns mainly the emergence, i.e. where macro behaviour emerges from the interactions of the agents at the micro level. Hence, this approach represents a good instrument to analyse the connection between the micro, or sectoral, level and the aggregate level, as it builds on a very small level of detail and, without reducing it, captures the complexity of reality. This, in turn, allows to make a number of observations and to draw conclusions which could not be reached without looking at the whole system rather than at individual relationships and interactions. These advantages of network analysis also motivate the use of a network perspective and derived measures to study technological complexity and its relationship with economic development.

3. Methodological framework

Despite their limitations, patent data are the most accurate source of information on technological and inventive activities, which allows to make relatively accurate cross-country comparisons with respect to technological development (Griliches, 1990). Thus, we make use of information included in patent applications to construct the technology space and, then, to locate countries in this space. In particular, we rely on technological fields to which an invention corresponds to. This information is coded through IPC classes. Below, we explain the methodological framework that we apply and discuss the process of extracting the information included in the patent documents to be used in the process of building the technology space and constructing measures of technological complexity.

Technology space

Similarly to the product space developed by Hidalgo et al. (2007) and further exploited by Hidalgo and Hausmann (2011; 2009), in order to construct the technology space, we apply the concept of bipartite networks. A bipartite network consists of a graph whose elements include three sets: two sets of nodes and a set of lines representing relations between nodes. In a formal way, bipartite network N is defined as

$$N = (V_c, V_\tau, L) \tag{1}$$

where $V_c = (v_{c1}, v_{c2}, ..., v_{cC})$ and $V_\tau = (v_{\tau 1}, v_{\tau 2}, ..., v_{\tau \mathrm{T}})$ are two partite sets of nodes of size C and T respectively. L is the set of lines connecting the nodes in two sets (Gross & Yellen, 2004).

In our framework, set one, V_c, consists of countries and set one, V_τ, includes 664 IPC technological classes. Formally, this network is represented by the adjacency matrix $L_{c\tau}$, where $L_{c\tau} = 1$, if country c is a producer of technology τ and 0 otherwise.

Measures of technological complexity

Taking the technology space as a starting point, in order to construct measures of technological complexity, we apply the method of reflections, introduced and described by Hidalgo and Hausmann (2011; 2009). This method describes the nodes of the two sets, countries and technologies, by a series of variables. In order to generate these variables, we follow an iterative process in which to define one type node, for example countries, information on the other type of nodes, i.e. technologies, is used.

In a formal way, the method of reflections is defined as the following set of observable variables:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{\tau} L_{c\tau} k_{\tau,N-1} , \tag{2}$$

$$k_{\tau,N} = \frac{1}{k_{\tau,0}} \sum_{c} L_{c\tau} k_{c,N-1} , \tag{3}$$

for $N \geq 1$. The initial conditions are given by the degree, i.e. number of links, of countries and technologies:

$$k_{c,0} = \sum_{\tau} L_{c\tau} , \tag{4}$$

$$k_{\tau,0} = \sum_{c} L_{c\tau} . \tag{5}$$

By iterating this process, each country can be described by the vector $\vec{k}_c = (k_{c,0}, k_{c,1}, ..., k_{c,N})$ and each technology by the vector $\vec{k}_\tau = (k_{\tau,0}, k_{\tau,1}, ..., k_{\tau,N})$. In economic terms, the degree of country $c, k_{c,0}$, and the degree of technology $\tau , k_{\tau,0}$, represent the level of a country's diversification and the ubiquity of a technology respectively. Following this line of reasoning, considering countries, even variables, $k_{c,0}, k_{c,2}, k_{c,4} ...$, reflect their diversification level and odd variables, $k_{c,1}, k_{c,3}, k_{c,5} ...$, reflect the ubiquity of technologies in which countries specialize. The reverse is true for technologies, i.e. even variables characterize the ubiquity of technologies and odd variables the diversification of countries that produce these technologies.

In the subsequent analysis, in order to locate countries in the technology space, we use k_{c0}, i.e. technological diversification of country c expressed by the total number of technological classes in which a country is active, and $k_{c,1}$, i.e. the ubiquity of technologies developed by country *c* expressed by the number of countries that are also producers of the same technologies.

4. Data

To compute patent-based indicators used in the current study, we use raw patent data provided by the EPO Worldwide Patent Statistical Database, commonly referred to as the PATSTAT database. This database provides a worldwide coverage of patent applications submitted to around 180 Patent Offices in the world. The present analysis is based on indicators built by extracting and elaborating patent application data from the April 2012 release of the PATSTAT database, taking into account patent applications filed to all Patent Offices included in PATSTAT.

The time period taken into account covers from January 1st, 1991 to December 31st, 2009. The reason for selecting this period of time is that of institutional transformations that took place, for example, in the Soviet Union and Central Europe, and caused changes to the global patent system. In particular, as we allocate patent to countries based on the inventor's country of residence and not to the country to whose patent office an application was filled, the possibility of collecting reliable patent information and reconstructing the inventive performance of some countries would have been challenged.

We use WIPO IPC 2006.01 classification version to extract information on the technology classes coded in patent applications, which includes 664 individual technological classes.[1] Our checks took into account IPC codes belonging to alternative IPC classification schemes. These checks confirmed that another classification scheme does not affect the results.

The elaboration of indicators used in the proceeding analysis relies on altogether over 11 Million priority patent applications that were filed to any patent office worldwide between January 1st, 1991 to December 31st, 2009 (Table 1). The number of individual IPC codes, which we consider in constructing the technology space and the subsequent measures of technological complexity was nearly 30 Million.

Obtaining the information on technology classes and assigning it to a country is far from being straightforward. Thus, raw data coming from PATSTAT are elaborated through a series of methodological steps, starting with those consolidated in literature (de Rassenfosse, Dernis, Guellec, Picci, & van Pottelsberghe de la Potterie, 2013; Picci, 2010; Turlea et al., 2011) to deal with some remaining criticalities, mainly related to the process of exchange of information among patent offices, which affects patent data. First, as the needed variables are intended to provide measure of the inventive capability of countries, rather than of the productivity of patent offices, the subset of 'priority patent applications' is initially taken into account, to avoid double counting and the limitation coming from considering granted patents (OECD, 2008, 2009). The year is assigned along with the information coming with the filing date given when the application was first filed at a patent office by an applicant seeking patent. Second, to the extent of the present analysis the issue of missing information is in fact still relevant, when it comes to identify the country of residence of applicants (or inventors), and several methodological steps are followed in order to collect missing country information from other records related to the patent application, and to proxy it with that of the country where the application has been filed only as a last resort. A detailed description of the methodology can be found in de Rassenfosse, Dernis, Guellec, et al. (2011).

Further difficulties arise from the fact that first, there is usually more than one IPC class assigned to an invention and, second, it is relatively common that the list of inventors and/or applicants frequently includes individuals or entities residing in different countries (De Prato & Nepelski, 2014). In order to overcome these obstacles, we treat patent data by taking into account all levels of the IPC classification. If a patent is assigned to more than one IPC code, not only the main (first) IPC code is taken into account but all of them. The application is divided equally among all IPC codes, i.e. fractional counting, avoiding thus double counting. Only after the fractional counting the IPC codes are rounded at the class level the resulting sum is then assigned to a country. Regarding the assigning patents to countries, there are two common methodologies: it is possible to refer to either the declared country of residence of the inventor(s) (‘inventor criterion’)

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[1] More information can be found under:
http://www.wipo.int/classifications/ipc/en/ITsupport/versions.html

of a patent, or to that of the applicant(s) (‘applicant criterion’) (OECD, 2008). Several applicants could hold rights on a patent application, and they would have legal title to the patent once (and if) it is granted. In the same way, several inventors could have taken part in the development process of the invention, and be listed in the patent application. A fractional count is applied in order to assign patents to countries in cases where several inventors (or applicants) with different countries of residence have to be considered for the same application. In general, the choice of the criterion depends on the perspective from which innovative capability is being investigated. In this study, the adoption of the inventor criterion has been chosen, as it allows to represent a country technological capabilities more accurately (de Rassenfosse et al., 2011; Turlea et al., 2011).

Data on GDP at purchasing power parity (PPP) per capita originates from the International Monetary Found (IMF, 2012). In this analysis, we use GDP data for the period between 1991 and 2009.

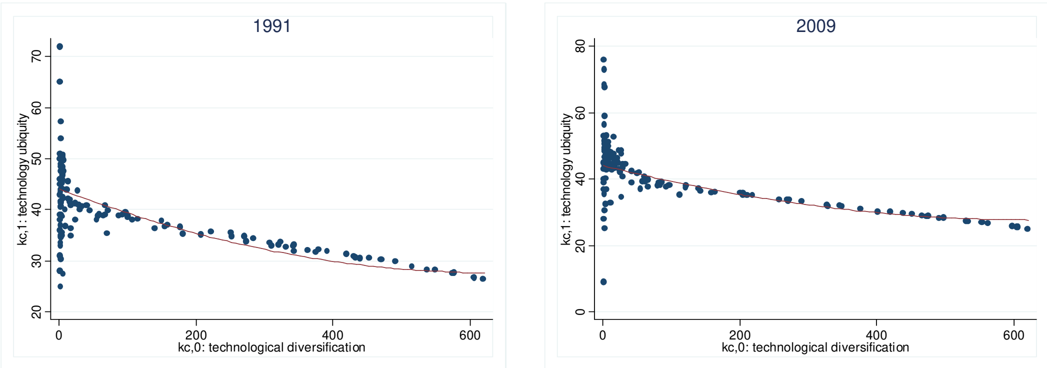
5. Empirical analysis

Technological complexity

We start our analysis of technological complexity by looking at the relationship between a country's diversification (k_{c0}) and the ubiquity of technologies, which it develops (k_{c1}). Figure 1 represents this relationship for two time periods, i.e. 1991 and 2009. Despite a considerable number of countries that have a very low level of diversification, we can observe a relatively strong negative relationship between the two measures of complexity, which is also confirmed by a significantly negative correlation (see Table 3). More interestingly, this negative relationship has increased over time, indicating that the technological level of countries diverged (see Figure 4). In other words, whereas some countries continued to increase their technological competencies and hence complexity, others stagnated.

In practical terms, the most technologically diversified country was Japan, whose technology space counted 610 out of total 664 technological classes in 2005. In comparison, the technology space of Estonia counted only 31 classes. At the same time, however, technologies included in the Japanese technology space were present in technology spaces of, on average, 26 other countries, whereas Estonia had over 40 potential competitors in each technological field it was active in. Thus, following the relationship between countries technological diversification and the ubiquity of their technologies identified above, with respect to the characteristics of technology space, we expect that less ubiquitous technologies are more complex at the same time. As a result, they will be present in the technology space of fewer countries. Consequently, as in the case of economic complexity analyzed by Hausmann and Hidalgo (2011), technologically diversified countries tend to also be active in less ubiquities fields of technology. In an analogical way, we also expect that these characteristics of the technology space and complexity of technologies will have an impact on the economic development of countries. We tackle this question in the subsequent sections.

Figure 1: Relationship between countries' diversification and ubiquity of their technologies, 1991 & 2009



Country values of technological diversification of countries, $k_{c,0}$, and their average level of technology ubiquity $k_{c,1}$ in years 1991 and 2009. N = 137. Technology and country of invention origin assigned by fractional counting according to the inventor criterion. Source: Own calculations based on EPO PATSTAT Database, 2012.

Technological complexity and economic development

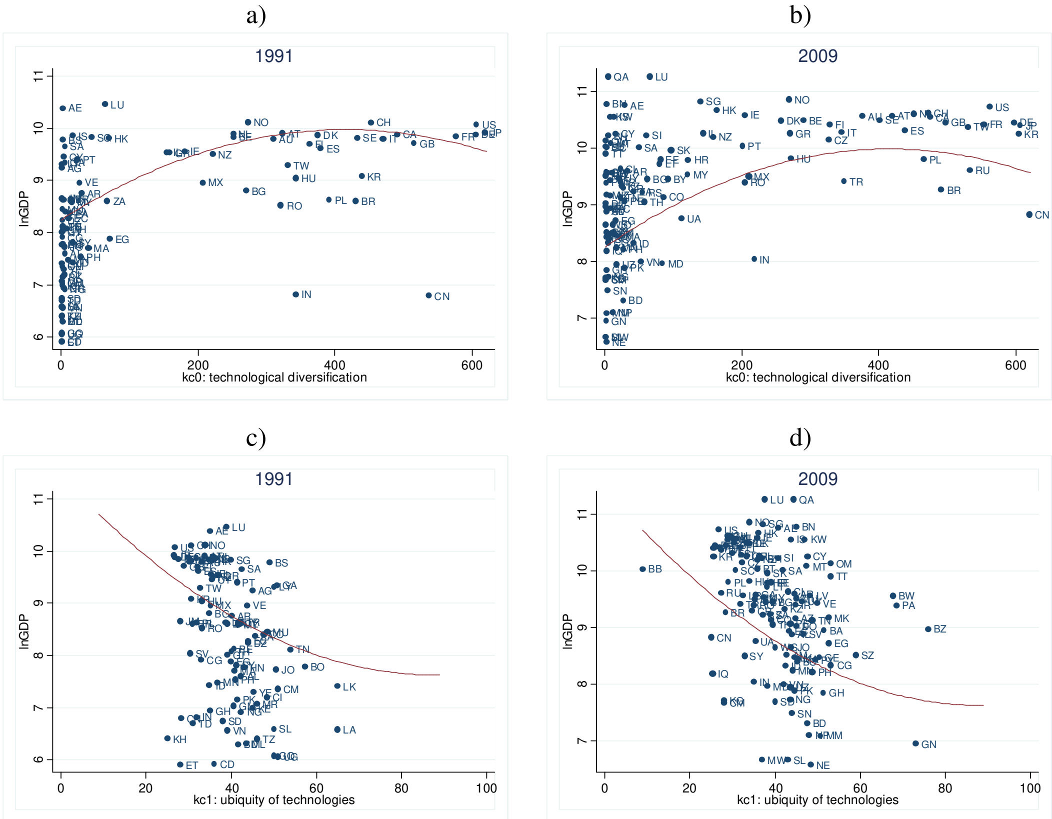
What is the relationship between technological complexity of a country and its economic development? Again, to get some insight into this question, we first look at the visual representation of the link between a country level of income and its technological diversification (Figure 2 a&b) and the ubiquity of technologies it develops (Figure 2 c&d) in year 1991 and 2009. Both measures of technological complexity behave in the expected way. Whereas the level of income is positively correlated with the number of technologies in a country's technology space, the average ubiquity of technologies it develops has a negative impact on GDP. Although we can observe some deviations, which might be related to the size of a country and its patenting performance, e.g. Luxemburg or Singapore, the general trend remains rather steady over time (see Figure 5).

In order to empirically address the relationship between technological complexity of a country and its economic development, we are interested in estimating the following equation:

$$Y_{c,t} = \alpha_c + \eta_t + K'_{c,t} + \nu_{c,t}\,. \qquad (6)$$

The dependent variable is $Y_{c,t}$ stands for income per capita in country c at period t. Country-fixed effects, α_c, and time-fixed effects, η_t, capture time-invariant country characteristics and global trends respectively. The main variable of interest is represented by the vector $K'_{c,t}$, which includes country specific level of technological complexity, i.e. its technological diversification ($k_{c,0}$) and the ubiquity of technologies which it develops ($k_{c,1}$). Other country and time-varying factors are included in the error term $\nu_{c,t}$.

Figure 2: Relationship between countries' diversification and GDP and between ubiquity of their technologies and GDP, 1991 & 2009



Relationship between technological diversification of countries, $k_{c,0}$, and income (a, b) and average level of ubiquity of their technologies $k_{c,1}$ and income (c, d) in years 1991 (N = 96) and 2009 (N = 119). Technology and country of invention origin assigned by fractional counting according to the inventor criterion. Source: Own calculations based on EPO PATSTAT Database, 2012.

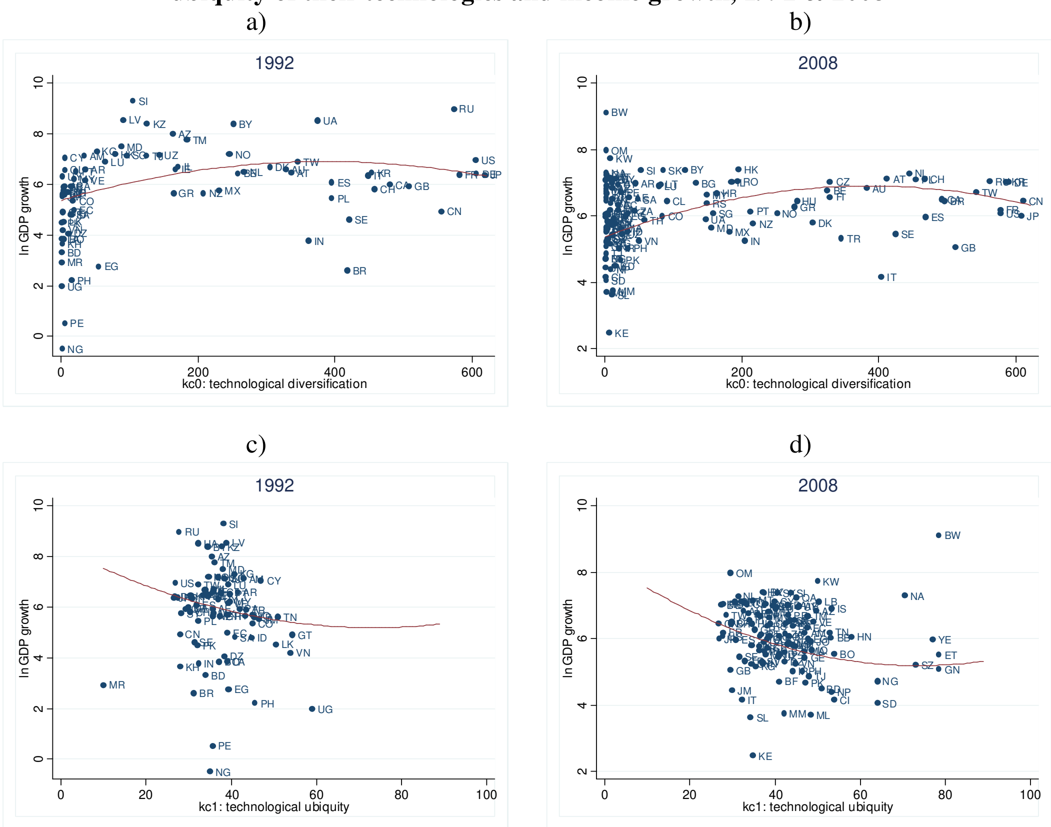
The results of the estimations of the static model defined in (6) are reported in Table 4. According to the pooled cross-sectional OLS estimates shown in column (1), the positive relationship between the level of income and a country's diversification (k_{c0}) is confirmed. Moreover, considering the value of R^2, the overall explanatory strength of this variable is relatively strong. Similarly, we find confirmation of the negative impact of the potential number of countries competing in the same technological fields, measured by the average ubiquity of technologies developed by a country (k_{c1}), and the level of economic development (column (2)). The results of these two basic regressions remain unchanged once we control for the technological diversification and the ubiquity of technologies in one estimation (column (3)). Moreover, to a large extent, these results are nor affected if we control for country effects and for (columns (4)-(6)) and time effects (columns (7)-(9)). The only exception concerns the average ubiquity of technologies developed by a country (k_{c1}). Once we isolate the within effect of technology ubiquity by adding country dummies, the coefficient changes its sign from negative to positive. This does not happen when time effects are considered. A potential explanation of this behavior is the relatively strong explanatory power of country-dependent characteristics with respect to country income. This is confirmed by a high value of R^2, which approaches 1, in each estimation including country-effects. In comparison, factors included in the estimation controlling only for a country's technological complexity account for nearly 25% of cross-country variation in income.

Technological complexity and economic growth

Turning to the next question of our analysis, we want to investigate the relationship between technological complexity and income growth. Figure 2 visualizes the link between technological diversification (a&b) and the ubiquity of technologies a country develops (c&d) and the level of income growth in year 1991 and 2009. Although the relationship between these two measures of complexity is less pronounced as in the case of income, we can see that there are some clear trends that can be read out of the presented data. In particular, technological diversification seems to positively affect the level of economic growth, the level of technology ubiquity has the opposite effect.

According the results of pair-wise correlation (see Table 3), whereas the correlation between the former one and income growth is strongly positive (0.37 at 99% significance level) the latter one is negatively correlated with economic progress level of technological (-0.23 at 99% significance level). When we look at the evolution of this relationship, we can see that, with some fluctuations, the correlation between the two measures of technological complexity on income growth has remained qualitatively stable.

Figure 3: Relationship between countries' diversification and income growth and between ubiquity of their technologies and income growth, 1992 & 2008



Relationship between technological diversification of countries, $k_{c,0}$, (a, b) and average level of ubiquity of their technologies $k_{c,1}$ and annual income growth (c, d) in years 1992 (N = 72) and 2008 (N = 119). Technology and country of invention origin assigned by fractional counting according to the inventor criterion. Source: Own calculations based on EPO PATSTAT Database, 2012.

In order to estimate the relationship between technological complexity and income growth, we are interested in the following equation:

$$G_{c,t} \equiv \ln Y_{c,t} - \ln Y_{c,t-1} = \alpha_c + \eta_t + K'_{c,t} + \nu_{c,t} \,. \qquad (7)$$

In this case, the dependent variable is $G_{c,t}$, which represents the logarithmic annual growth of income per capita in country *c* at period *t*. As previously, we control for country- (α_c) and time-fixed effects (η_t) and the main variable of interest is represented by the vector $K'_{c,t}$, which includes country specific level of technological complexity. Error term is represented by $\nu_{c,t}$.

The results of the estimation of the above model are reported in Table 5. As in the previous case, we begin with a pooled cross-sectional OLS regression (columns (1)-(3)). Regressions in which we control only for the individual effect of the technological complexity measures confirm our expectations concerning their impact on growth of GDP. Whereas we find a positive relationship between the income growth and a country's diversification (k_{c0}), reported in column (1), we obtain the opposite result concerning the level of technology ubiquity. In a joint regression (column (3)), only k_{c0} coefficient remains statistically significant. In contrast to the estimation of technological complexity and income, the explanatory power of the two variables of income growth is considerably weaker, i.e. the value of R^2 is 0,14 versus 0,25 in the income regression.

These results do not alter significantly when we control for country-effects (columns (4)-(6)) or time effects (columns (4)-(6)). Moreover, in the latter case, the value of the coefficient corresponding to the impact of the average ubiquity of technologies developed by a country (k_{c1}) on its income growth comes back to its "expected", i.e. negative, sign and remains significant at the 99% level.

6. Robustness check

A robustness check of the results presented in the previous section would require, for example, an alternative data source. However, as already mentioned (Griliches, 1995), a comparable source of information on countries' technological activity and performance to patent statistics does not exist yet. Thus, in order to test the robustness of our results, we compute alternative measures of technological complexity to the ones derived through network analysis and the methods of reflections.

One of the most popular measure of diversification is the Herfindahl–Hirschman index, which commonly applied in antitrust and also in technology management studies (Liston-Heyes & Pilkington, 2004), is a measure of concentration. In a formal way, the Herfindahl–Hirschman index can be defined as:

$$HH_{c,t} = \sum_{\tau=1}^{N} (s_{c,\tau,t})^2 \ , \tag{8}$$

where $s_{c,\tau,t}$ is the share of technology τ in the technological pool of country c at time t. The straightforward interpretation of the index is that its value is 0 if a country has only one technology and becomes close to 1 if a country's technology space is composed of equally divided technological groups.

Another count method for measuring diversification is the entropy index. The entropy measure of diversification weights each $s_{c,\tau,t}$ by the logarithm of $\frac{1}{s_{c,\tau,t}}$ and can be expressed as follows:

$$E_{c,t} = \sum_{\tau=1}^{N} s_{c,\tau,t} \ln(\frac{1}{s_{c,\tau,t}}) \ . \tag{9}$$

As in the previous case, if a firm is exclusively present in one technological class, its entropy is zero and its value increases with the number of distinct technological classes. In contrast, the Herfindahl–Hirschman, the entropy measure is designed to decompose the total diversification measure into meaningful elements of total diversification (van Kranenburg, Hagedoorn, & Pennings, 2004). Thus, the advantage of the entropy measure is that it relied on the contribution of diversification at each level of classified group aggregation to the total.

The above specified measures of diversification extend vector $K'_{c,t}$, which includes country specific level of technological complexity. Additional estimations of the impact of technological complexity on economic development and growth, which include the additional variables, are reported in Table 6 and Table 7 respectively.

According to Table 6, the H-H index of technological diversification has a negative (column (1)) and the measure of entropy (column (2)) a positive impact on the level of economic growth. Coefficients of the two alternative measures of diversification of a country technology space are significant at the 99% level. However, when considering the value of R^2, the entropy index performs better, as compared to the H-H index in explaining the cross-country variations in income.

In the H-H index estimation, the adjusted-R^2 equals 0.21, as compared to 0.31 in the entropy index. Moreover, the entropy index seems to perform better than our primary measures of technological complexity, i.e. the level of technological diversification (k_{c0}) and the average ubiquity of technologies developed by a country (k_{c1}). Whereas k_{c0} and k_{c1} taken together account for nearly 25% variation in income, the entropy index is more effective by around 6%. This is confirmed when we consider all measures of technological complexity together (Table 6, column (3)). However, this advantage is weakened when we consider country- and time-effects.

According to Table 7, out of the two alternative measures of technological complexity, entropy index performs better than the H-H index in explaining the differences in income growth. Moreover, the regression with entropy index has a higher value of adjusted-R^2, as compared with the regression including the level of technological diversification (k_{c0}) and the average ubiquity of technologies developed by a country (k_{c1}) (see Table 5, column (3)). Thus, it is quite clear that the entropy index together with the complexity measures derived through the method of reflection are "competing" among each other as the best predictor of income growth. However, the final decision is rather complicated, considering the behavior of the variables when additional effects are taken into account. Whereas the inclusion of country dummies cancels out the importance of the H-H and entropy indices, time effects have the opposite effect on the level of technological diversification (k_{c0}) and the average ubiquity of technologies developed by a country (k_{c1}).

The possible explanation behind this behavior is that both H-H and entropy indices are rather designed to consider the shares of a technology class in the total technology portfolio, and hence better capture the absolute changes in the technological activity, proxied by the number of patents. The significance of the measures of complexity derived through the method of reflections are, on the other hand, more sensitive to the total number of patents. This is particularly the case when we deal with two groups of countries where one group has very low and the other very high measures of complexity. This is illustrated at the beginning of this analysis, where it was shown that there is a relatively large group of countries that score very low on both measures (Figure 1). Moreover, as both types of technological complexity put emphasize on different aspects, i.e. entropy index performs a self-analysis, whereas the measures of diversification and technology ubiquity compare a country against all the other countries, we need to recognize their differences and the value they deliver. Thus, a final conclusion with respect to the question of which measure of technological complexity is more accurate to study the level of income and its growth is rather difficult, as the check against other measure does not disqualify the primary measures used in this study.

7. Conclusions

To better understand the characteristics of the technology space and the role of technological complexity in economic development, we apply the network perspective that links countries to technologies they develop and rank them according to the level of their diversification and the ubiquity of technologies they develop. We show that there is negative relationship between the two measures of technological complexity and that they significantly impact a country's economic development and growth.

Despite delivering some novel insights, our work suffers from some limitations. First of all, patent data, despite its richness of information, suffers from its own obvious drawbacks. Most importantly, for technical reasons, we ignore the value of patents, and do not take into account neither a country's IPR environment, which also strongly affect the possibility of observing and mapping the technology space of a country. Second, one limitation of the applied methodology and measures of technological complexity is that they do not account for the size of technological activity. Our checks confirmed, for example, that by putting only a small threshold either on the total number of patents produced by a country or the minimum number of patents in one technological field, the sample of countries is significantly reduced. Hence, due to the fact that mainly developed countries are active technology producers, we expect that controlling for the size of inventive and technological activity would not substantially change our results. Third, due to the fact that there is no theoretical foundation explaining the formation and evolution of technology space, we cannot provide any empirical insights into its development. We believe, however, that addressing this question in both the theoretical and empirical way is worthwhile.

In conclusion, our analysis provides a unique reflection on and a systematic view of a methodology to map a country's technology space and to assess its position with respect to the remaining countries. As a result, it serves as a basis for formulating some conclusions that could not be drawn without the application of the proposed methodology. We confirm that the level of technological complexity has a positive impact on the level of economic development and growth. The main channel through which it happens is the exclusiveness and uniqueness of the technological portfolio a country has, as compared to the remaining countries. In other words, the bargaining power and the rents extracted from the interactions with other countries will depend on a country's relative position against the remaining countries, i.e. the global technology space. Thus, while strengthening technological and scientific capabilities, countries need to take into account broader environment, where many are competing for scarce resources.

8. Appendix: Tables and figures

Table 1: Number of priority patent applications IPC classes processed

Year	Number of priority patent applications	Number of IPC classes treated
1991	470.674	1.290.836
1992	439.322	1.222.801
1993	452.866	1.261.776
1994	445.286	1.250.856
1995	469.993	1.330.653
1996	487.695	1.370.996
1997	510.413	1.424.622
1998	534.983	1.483.549
1999	552.158	1.562.000
2000	593.825	1.815.541
2001	622.670	1.887.685
2002	605.715	1.766.195
2003	627.445	1.832.714
2004	632.849	1.745.016
2005	663.111	1.656.958
2006	674.221	1.718.230
2007	699.879	1.768.180
2008	733.374	1.804.734
2009	692.950	1.712.195
Total	10.909.429	29.905.537

Source: Own calculations based on EPO PATSTAT Database, 2012

Table 2: Descriptive statistics

	Obs	Mean	Std. Dev.	Min	Max
$k_{c,0,}$ – Diversification	2636	115,294	174,8	1,000	621,000
$k_{c,1}$ – Technology ubiquity	2636	39,944	9,595	8,000	89,000
H-$H_{c,}$ – Herfindal index	2636	0,261	0,322	0,003	1,000
Entropy index	2636	2,673	1,846	0,000	5,689
Ln GDP PPP per capita	2214	8,834	1,200	5,801	11,319
Ln annual growth of GDP	1813	5,913	1,354	-1,965	9,829

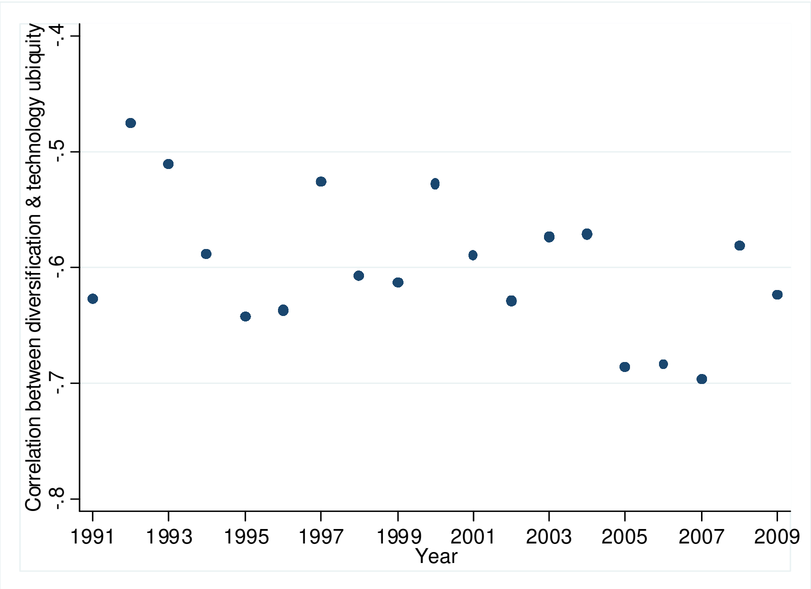
Source: Own calculations based on EPO PATSTAT Database, 2012 and IMF World Economic Outlook Database.

Table 3: Pair-wise correlation between variables

	1)	2)	3)	4)	5)	6)
1) $k_{c,0t}$ – Diversification	1.000					
2) $k_{c,1t}$ – Technology ubiquity	-0.574*	1				
3) H-$H_{c,}$ – Herfindal index	-0.490*	0.361*	1			
4) $Entropy_{c,}$	0.802*	-0.538*	-0.848*	1		
5) ln $GDP_{c,}$ PPP p. capita	0.499*	-0.333*	-0.455*	0.560*	1	
6) $G_{c,}$ – log annual growth of GDP PPP p. capita	0.374*	-0.230*	-0.352*	0.443*	0.763*	1

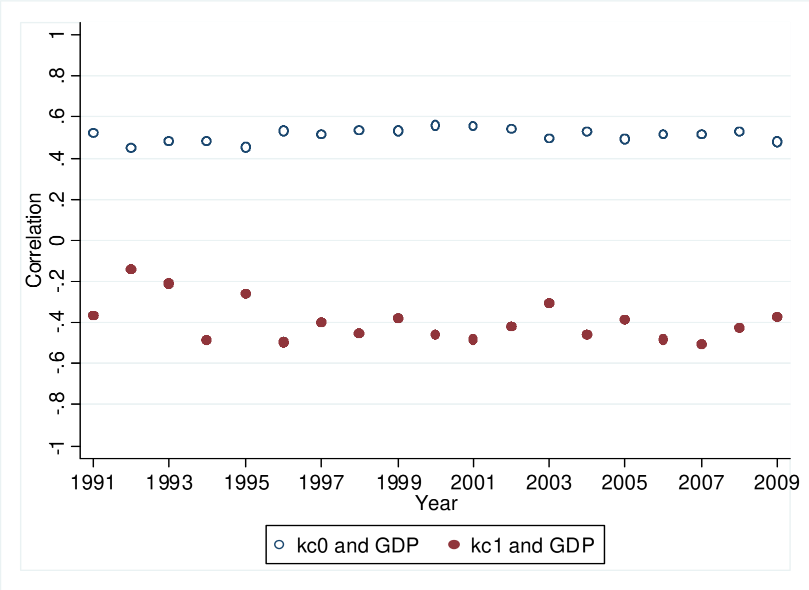
*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.
Source: Own calculations based on the data from EPO PATSTAT Database 2012 and IMF World Economic Outlook Database 2012

Figure 4: Correlation between countries' diversification and ubiquity of their technologies between 1991 and 2009



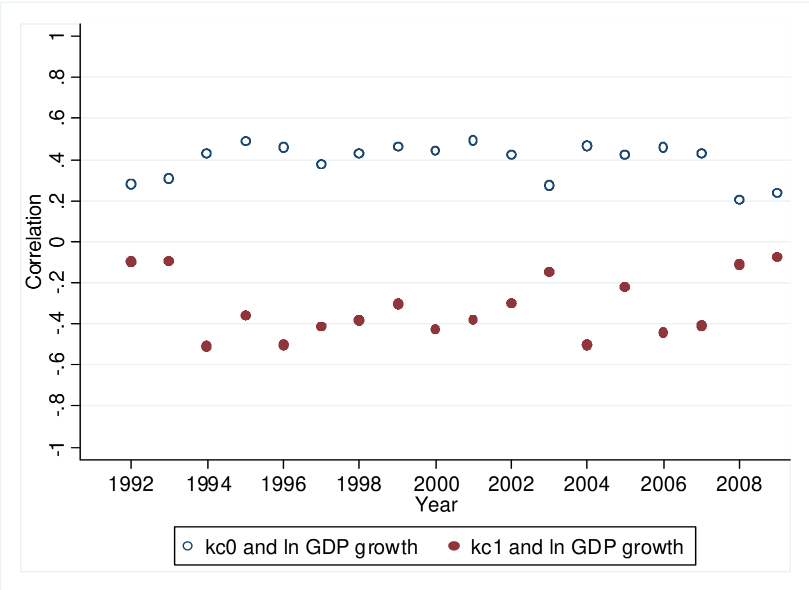
Evolution of the level of correlation between the average value of technological diversification of countries, $k_{c,0}$, and the average level of technology ubiquity $k_{c,1}$ between 1991 and 2009. Technology and country of invention origin assigned by fractional counting according to the inventor criterion. Source: Own calculations based on EPO PATSTAT Database, 2012.

Figure 5: Correlation between GDP and countries' diversification and products' ubiquity



Evolution of the level of correlation between technological diversification of countries, $k_{c,0}$, and GDP and between average level of technology ubiquity $k_{c,1}$ and GDP between 1991 and 2009. Technology and country of invention origin assigned by fractional counting according to the inventor criterion. GDP at Purchasing Power Parity per capita expressed in natural logarithm. Source: Own calculations based on EPO PATSTAT Database, 2012 and IMF World Economic Outlook Database.

Figure 6: Correlation between annual GDP growth and countries' diversification and products' ubiquity



Evolution of the level of correlation between technological diversification of countries, $k_{c,0}$, and annual growth of GDP and between average level of technology ubiquity $k_{c,1}$ and annual growth of GDP between 1991 and 2009. Technology and country of invention origin assigned by fractional counting according to the inventor criterion. GDP at Purchasing Power Parity per capita expressed in natural logarithm. Source: Own calculations based on EPO PATSTAT Database, 2012 and IMF World Economic Outlook Database.

Table 4: The relationship between country's diversification, technology ubiquity and income between 1991 and 2009

Dependent variable	OLS			Country FE			Time FE		
$Y_{c,t}$ – log GDP PPP p. capita	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$k_{c,0,t}$ – Diversification	0,003***		0,003***	0,001***		0,001***	0,003***		0,003***
	(0,000)		(0,000)	(0,000)		(0,000)	(0,000)		(0,000)
$k_{c,1,t}$ – Technology ubiquity		-0,042***	-0,006**		0,009***	0,010***		-0,050***	-0,015***
		(0,002)	(0,002)		(0,000)	(0,001)		(0,003)	(0,003)
Constant	8,403***	1,049***	8,664***	7,060***	5,569***	5,571***	7,973***	10,349***	8,628***
	(0,027)	(0,103)	(0,104)	(0,027)	(0,274)	(0,104)	(0,104)	(0,148)	(0,165)
Adjusted R-squared	0,249	0,110	0,245	0,946	0,949	0,949	0,288	0,184	0,296
Observations	2214	2214	2214	2214	2214	2214	2214	2214	2214

Notes: The dependent variable is the log of GDP at PPP per capita. Explanatory variable include country's diversification, i.e. $k_{c,0,t}$, and the average ubiquity of technologies developed by a country at time *t*. Models from (1)-(3) report pooled cross-sectional OLS estimates in the maximum number of countries-years. Models from (4)-(6) include country dummies and models from (7)-(9) include year constants. Standard errors are reported in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
Source: Own calculations based on the data from EPO PATSTAT Database 2012 and IMF World Economic Outlook Database 2012.

Table 5: The relationship between country's diversification, technology ubiquity and annual income growth between 1991 and 2009

Dependent variable $G_{c,t}$ – log annual growth of GDP PPP p. capita	**OLS** (1)	(2)	(3)	**Country FE** (4)	(5)	(6)	**Time FE** (7)	(8)	(9)
$k_{c,0,t}$ – Diversification	0,003***		0,003***	0,003***		0,003***	0,003***		0,002***
	(0,000)		(0,000)	(0,000)		(0,001)	(0,000)		(0,000)
$k_{c,1,t}$ – Technology ubiquity		-0,032***	0,001		0,018***	0,019***		-0,043***	-0,013***
		(0,000)	(0,004)		(0,003)	(0,003)		(0,000)	(0,004)
Constant	5,535***	7,188***	5,483***	6,719***	6,425***	6,384***	5,310***	7,353***	5,841***
	(0,037)	(0,131)	(0,177)	(0,865)	(0,863)	(0,858)	(0,137)	(0,182)	(0,216)
Adjusted R-squared	0,140	0,110	0,140	0,592	0,597	0,602	0,217	0,159	0,221
Observations	1813	1813	1813	1813	1813	1813	1813	1813	1813

Notes: The dependent variable is the log of annual growth of GDP at PPP per capita. Explanatory variable include country's diversification, i.e. $k_{c,0,t}$, and the average ubiquity of technologies developed by a country at time *t*. Models from (1)-(3) report pooled cross-sectional OLS estimates in the maximum number of countries-years. Models from (4)-(6) include country dummies and models from (7)-(9) include year constants. Standard errors are reported in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Source: Own calculations based on the data from EPO PATSTAT Database 2012 and IMF World Economic Outlook Database 2012.

Table 6: The relationship between country's technological diversification and annual income between 1991 and 2009

Dependent variable	**OLS**			**Country FE**			**Time FE**		
$Y_{c,t}$ – log GDP PPP p. capita	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
H-H$_{c,t}$ – Herfindal index	-1,729***		-0,087	-0,125***		-0,337***	-1,704***		0,067
	(0,072)		(0,157)	(0,034)		(-0,061)	(0,070)		(0,153)
Entropy$_{c,t}$		0,360***	0,271***		0,025***	-0,102***		0,361***	0,294***
		(0,011)	(0,039)		(0,011)	(0,021)		(0,011)	(0,038)
$k_{c,0,t}$ – Diversification			0,001***			0,002***			0,001***
			(0,000)			(0,000)			(0,000)
$k_{c,1,t}$ – Technology ubiquity			0,001			0,009***			-0,007***
			(0,003)			(0,001)			(0,003)
Constant	9,247***	7,802***	7,892***	7,129***	7,040***	5,912***	8,926***	7,457***	7,811***
	(0,028)	(0,039)	(0,185)	(0,279)	(0,279)	(0,274)	(0,109)	(0,103)	(0,205)
Adjusted R-squared	0,207	0,313	0,245	0,946	0,946	0,950	0,237	0,352	0,361
Observations	1813	1813	1813	1813	1813	1813	1813	1813	1813

Notes: The dependent variable is the log of GDP at PPP per capita. Explanatory variable include Herfindahl–Hirschman index of concentration in technological classes, Entropy index controlling for diversification of technological basket and technological diversification, i.e. $k_{c,0,t}$, and the average ubiquity of technologies developed by a country at time *t*. Models from (1)-(3) report pooled cross-sectional OLS estimates in the maximum number of countries-years. Models from (4)-(6) include country dummies and models from (7)-(9) include year constants. Standard errors are reported in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Source: Own calculations based on the data from EPO PATSTAT Database 2012 and IMF World Economic Outlook Database 2012.

Table 7: The relationship between country's technological diversification and annual income between 1991 and 2009

Dependent variable $G_{c,t}$ – log annual growth of GDP PPP p. capita	**OLS**			**Country FE**			**Time FE**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
H-$H_{c,t}$ – Herfindal index	-1.564***		0.412*	-0.251**		-0.250	-1.529***		0.584***
	(0.098)		(0.219)	(0.120)		(0.228)	(0.095)		(0.210)
$Entropy_{c,t}$		0.324***	0.396***		0.102***	-0.032		0.327***	0.412***
		(0.015)	(0.054)		(0.038)	(0.081)		(0.015)	(0.051)
$k_{c,0,t}$ – Diversification			0.000			0.003***			-0.000
			(0.000)			(0.001)			(0.000)
$k_{c,1,t}$ – Technology ubiquity			0.010***			0.019***			-0.003
			(0.004)			(0.003)			(0.004)
Constant	6.263***	4.959***	4.219***	7.869***	7.672***	6.639***	6.043***	4.677***	4.435***
	(0.037)	(0.536)	(0.255)	(0.870)	(0.867)	(0.889)	(0.138)	(0.139)	(0.278)
Adjusted R-squared	0.123	0.196	0.200	0.589	0.590	0.602	0.191	0.272	0.275
Observations	1813	1813	1813	1813	1813	1813	1813	1813	1813

Notes: The dependent variable is the log of annual growth of GDP at PPP per capita. Explanatory variable include Herfindahl–Hirschman index of concentration in technological classes, Entropy index controlling for diversification of technological basket and technological diversification, i.e. $k_{c,0,t}$, and the average ubiquity of technologies developed by a country at time t. Models from (1)-(3) report pooled cross-sectional OLS estimates in the maximum number of countries-years. Models from (4)-(6) include country dummies and models from (7)-(9) include year constants. Standard errors are reported in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Source: Own calculations based on the data from EPO PATSTAT Database 2012 and IMF World Economic Outlook Database 2012.

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