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Climbing the ladder of technological development

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ABSTRACT

Despite being the main thriving force behind economic growth and industrial development, technological innovation remains highly concentrated on a handful of countries. It is therefore of a great interest to know how countries accumulate and develop their innovative capabilities, what kind of obstacles they need to overcome, and whether it is possible to identify opportunities to develop new areas of technological specialization. In this paper we analyze countries' patterns of technological diversification and specialization along the development process. We provide evidence regarding the importance of existing technological capabilities and the relationship among technologies in shaping possible paths of technological development. We show that the likelihood of diversification is higher for those technologies that are related to countries' existing profile of competences. Moreover, we show this effect to be stronger at earlier stages of development. Additionally, we show that countries tend to follow clear patterns of specialization along the development path, by moving towards more complex and valuable technologies.

1. Introduction

Technological innovation is the main thriving force behind economic growth, industrial development, and the rise of living standards. However, only a handful of countries are actively developing new technologies. The United States, Western European countries, Japan and South-Korea host a small fraction of the world's population but are responsible for most technological advances. This unequal distribution of innovative activities sets the role played by different countries in the global value chain. Countries that innovate are able to capture a larger share of the value added, while others are trapped in less profitable activities. Climbing the ladder of economic development also requires climbing the ladder of technological development. But how do countries accumulate and develop their innovative capabilities? What kind of obstacles do they need to overcome? How could they identify opportunities to develop new areas of technological specialization?

These questions have attracted a lot of interest in the innovation literature. An extensive literature has analyzed the process of accumulation of technological capabilities in developing countries (see among others Bell and Pavitt, 1992; Enos, 1991; Lall, 1992; Dahlman et al., 1987; Fransman and King, 1984; Lee and Lim, 2001; Kim, 1999). We have also a good understanding of patterns of sectoral and technological change (Breschi et al., 2000; Malerba and Orsenigo, 1996) and how their dynamics are shaped by cumulative and path dependent processes (Dosi, 1988; Dosi et al., 1988; Malerba, 1992; Patel and Pavitt, 1997).

Despite this extensive literature, we still have a limited understanding of how countries build new technological capabilities along the different stages of their economic development. In fact, cross-country quantitative studies exploring patterns of technological diversification and specialization have been very limited, and often restricted to the analysis of a handful of developed economies (see for instance Boschma et al., 2014, Archibugi and Pianta, 1994 and Cantwell and Vertova, 2004). As a result, we lack a robust and comprehensive bulk of evidence providing a general characterization of the type of technologies countries are more likely to produce, whether they tend to follow coherent patterns of technological specialization as they develop, and to what extent technological change is bounded to pre-existing technological capabilities.

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This paper will address these issues by analyzing countries' patterns of technological diversification and specialization along the development process, as reflected by their patenting activity at the United States Patent and Trademark Office (USPTO). We use disaggregated data on patenting activity by type of technology for 65 countries and covering a period of 15 years (1993–2007). We estimate an econometric model that differentiates between diversification and specialization patterns. In this way we are able to understand both, the general trends in terms of technological production (i.e. specialization patterns) and to single out factors affecting the emergence of new technologies (i.e. diversification patterns).

We contribute to the literature by providing a richer and more comprehensive characterization of countries' patterns of technological development, which includes: a wider and more heterogeneous collection of countries, a novel characterization of technologies aimed at capturing their complexity and economic value, and a measure of cognitive proximity (or relatedness) among technologies as a key determinant of the likelihood of technological diversification.

Our findings provide evidence regarding the importanceof existing technological capabilities (Bell and Pavitt, 1992 and 1997, and Bell, 2009) and relatedness among technologies (Jaffe, 1986; Breschi et al., 2003) in shaping possible paths of technological development. We show that the likelihood of diversification is higher for those technologies that are related to countries' existing profile of competences. Moreover, we show this effect to be stronger at earlier stages of development. On the other hand, we show that countries tend to follow clear patterns of specialization along the development path, by moving towards more complex and valuable technologies. Overall, our findings are in line, and complement related evidence showing that well-performing countries tend to have a productive structure oriented towards the production of more sophisticated and valuable goods (Lall 2000; Hidalgo et al., 2007; Hidalgo and Hausmann 2009; Hausmann and Hidalgo, 2011; Hausmann et al., 2007; Felipe, 2012).

The paper is structured as follows: the next section presents the literature review and outlines the conceptual framework. In Section 3 we illustrate the data and describe the methodology, while Section 4 presents the results. The last section discusses the findings and sketches some policy implications.

2. Theoretical background

2.1. On technological diversification and development

Within the innovation literature, country-level studies have focused on exploring patterns of technological specialization and/or diversification of advanced economies. For instance, Archibugi and Pianta (1991) found an inverse relationship between countries' technological size (measured as cumulative R&D expenditure) and the degree of sectoral concentration of technological activities. They covered the period 1975–1988 and used patent information for around a dozen of countries, mostly OECD members. Cantwell and Vertova (2004), and Vertova (1999 and 2001) investigated patterns of technological specialization by looking at the patenting activity of a handful of developed economies between 1890 and 1990. They found a similar pattern regarding the relationship between countries' technological size and the degree of concentration in patenting activity, and additionally, that only few countries were able to specialize in fast-growing technological fields.

Besides the patent-based evidence, a more detailed overview of the topic has been provided by empirical studies using international trade data. For example, Lall (2000) explored export patterns of developing economies using bilateral trade data. He found that countries with an export portfolio oriented towards technology-intensive products tend to grow faster in the world trade. Similarly, Rodrik (2008) argued that a structural transformation in the export basket from traditional to non-traditional products constitutes the main engine of growth. Hausmann et al. (2007) developed an index to measure the quality of countries' export baskets and showed that countries specializing in products which lay higher on this quality spectrum tend to perform better. Moreover, Hidalgo et al. (2007) and Hidalgo and Hausmann (2009), Hausmann and Hidalgo (2011) found evidence that countries' export patterns become more sophisticated and complex as they develop. All in all, the above studies seem to agree on the fact that the distribution of the productive structure of well-performing countries tends to be biased towards the production of more sophisticated or/and valuable goods.

More recently, the role of relatedness among products and technologies and its effect on the diversification process of regions and firms has gained considerable attention, as reflected by the number and diversity of studies incorporating this concept (Hidalgo and Hausmann, 2009; Frenken et al., 2007; Frenken and Saviotti, 2008). The main idea behind the concept of relatedness is that firms' diversification possibilities (or regions/countries) are affected by the degree to which products or technologies are connected to one another, where the link between two technologies/products is usually measured as how much they share in terms of common scientific knowledge, technical principles, heuristics, and common needs in general. The concept of relatedness suggests that technological change may follow a path dependent process, in which production of new knowledge is bound to the existing knowledge (Dosi, 1988; Patel and Pavitt, 1997).

At country level, the pioneering study of Hidalgo et al. (2007) shows that countries are able to develop products which are close (in terms capabilities needed to produce them) to their current basket of products, providing evidence on the importance of product relatedness. Additionally, Saviotti and Frenken (2008) show that developing related products is beneficial in the short term, while long-term growth comes from the emergence of unrelated sectors.

At regional level, strong support has been found to the role of relatedness in driving either technological or sectoral development. For example, Boschma et al. (2015) and Rigby (2015) showed that technological relatedness was a crucial driving force behind technological change in U.S. cities. Colombelli et al. (2014) found that the development of new nanotechnologies is linked to the structure of the existing local knowledge base. Similarly, but focusing on industrial diversification of regions, Neffke et al. (2011), Boschma et al. (2015), and Essletzbichler (2015) showed that regions are more likely to enter into industries which are related to those already in place.

At firm level, results show that firms tend to follow coherent patterns of diversification. Jaffe (1986) and Breschi et al. (2003) found that firms' tend to diversify into groups of technological activities that share a common or complementary knowledge base. Yip (1982) studied firms' choices between internal development and acquisition and found that the likelihood of entry into new markets increases as those markets are more related to firms' own characteristics. MacDonald (1985) analyzed patterns of diversification within U.S. manufacturing firms, finding they were more likely to enter rapidly growing industries, and industries that were related to their primary activities through supply relationships or marketing similarities. Additionally, Teece et al. (1994) showed U.S. manufacturing firms maintain certain level of coherence while diversifying.

As shown above, robust evidence at both firm and regional level has convincingly shown the presence of a link between diversification and relatedness. However, comprehensive quantitative evidence at country level is lacking. The few existing studies

reviewed above focus on product relatedness, while there are no country-level studies of technological diversification that have incorporated yet the role of relatedness.

In the next subsection we review the potential drivers and constraints for technological diversification/specialization, and the role of relatedness in this process. In doing so, we build a conceptual framework to understand the role of relatedness for technological diversification.

2.2. Technological diversification, relatedness, and stages of development

The process of technological accumulation observed at the country-level is a reflection of firms' capacity to accumulate and develop new technologies. Within the innovation literature, several factors have been acknowledged to affect firms' incentives to diversify or specialize in particular technologies. They include cases where diversification/specialization may be triggered by firms' attempts to move towards more profitable positions, which can be motivated either by inter-industry differences in the rates of return to R&D investment, as in the literature of technological opportunities (Jaffe 1986; Klevorick et al., 1995; Laursen 1999; and Malerba, 2002, 2004), or by differences in the dynamism of the demand conditions, as in Schmookler (1966). Technological diversification can be also the result of firms' efforts to mitigate or avoid the effects of risk and volatility, which can negatively affect firms' productivity (Koren and Tenreyro 2007 and 2013). Additionally, entry barriers due to the requirement of high initial investments, in either technological or scientific knowledge, can deter diversification initiatives (Perez and Soete, 1988).

Besides these incentives, firm's potential for technological diversification depends heavily on its prior capabilities (Patel and Pavitt, 1997), which allows them to acquire, accumulate, and process the knowledge required for engaging in such a process. Understanding how the existing capabilities of a firm are related to the capabilities needed to develop new technologies is therefore crucial. We can identify two main channels through which this proximity affects firm's possibilities for technological diversification: economies of scope in the use of knowledge, and firms' absorptive capacity.

The economies of scope in the 'use of one piece of knowledge' imply that the same type of knowledge could be used as an input in multiple technological fields (Penrose, 1959; Teece, 1982). Therefore, the more related two technological fields the bigger the share of common heuristics and scientific principles they rely on (Breschi et al., 2003), and consequently, the bigger the possibility to take advantage of the already acquired knowledge. For instance, economies of scope can affect barriers to entry by reducing investment costs, and the costs of acquiring the scientific and technological knowledge required to assimilate and carry out the innovation.

The concept of absorptive capacity refers to the fact that prior knowledge confers the ability to recognize the value of new information, assimilate it, and exploit it to commercial ends (Cohen and Levinthal, 1990). In particular, higher absorptive capacity allows for a better understanding of the challenges and opportunities for knowledge exploitation, and the benefits and costs associated with it. Firm's absorptive capacity affects its perception of the technological opportunities a given technology may offer, and its ability to form accurate expectations about the demand and risks associated with any diversification strategy. Hence, the more related a technology is with firms' absorptive capacity, the more likely it will accurately assess the benefits and costs associated with its adoption.

Based on the above theoretical arguments we set out our first research aim, focused on the role of relatedness in the process of technological diversification. We test to what extent technological capabilities within countries, and the relatedness among technologies, shape the possibilities of technological diversification. In particular, we aim at testing whether the likelihood of diversification into new technologies decays as the 'technological distance' to existing capabilities increases. In line with the recent evidence on technological diversification at regional level we expect that pre-existing technological capabilities shapes patterns of technological diversification of a country.

The innovative process is not the outcome of an individual process of learning and capability accumulation, it is placed and determined within a larger system that supports and benefits from it (Freeman, 1987; Lundvall 1992; Nelson and Rosenberg, 1993; Edquist and Lundvall, 1993; Niosi et al., 1993; Patel and Pavitt, 1994; and Metcalfe, 1995).The national productive and innovative environment determines not only the opportunities and costs of diversifying/specializing into different technological activities, but also the way firms perceive opportunities and estimate costs. On the one hand, technological opportunities, risks, or demand conditions vary considerably across countries and technologies, creating differential incentives to diversify/specialize. For instance, Furman et al. (2002) find considerable differences across countries in terms of R&D productivity and type of inputs devoted to innovation, while Marin and Petralia (2015) show that sectors with high technological opportunities (TOs) in LACs differ greatly from those having high TOs in developed economies. Patel and Pavitt (1997) showed that the rate of technological accumulation is heavily affected by the country competitive environment. Lee and Lim (2001) pointed out the differences between developed and emerging economies, showing that the latter have higher propensity to innovate under specific technological regimes.

On the other hand, the scope and quality of capabilities available within a country affect firms' possibilities to take advantage of the economies of scale in the use of knowledge, or to appropriately assess the benefits and costs of new technologies. Even if the advantages of any particular technology are similar across countries, the lack of indigenous capabilities may shift costs of exploration upwards, as firms' should develop internally the entire set of competences otherwise available, among other options, via local technology alliances (see for instance Ahuja 2000; and Rowley et al., 2000). The lack of capabilities may also affect how accurately benefits and costs of new technologies are estimated, to the point that possible development paths become unfeasible or unreasonable (given the perceived benefits and costs). As Nelson and Winter (1982, page 172) point out: "Real search processes take place in specific historical contexts, and their outcomes clearly depend in part on what those contexts contain in the way of problem solutions that are available to be 'found'."

Hence, technological diversity within and outside the firm may influence firms' capacity for combining and recombining their stock of existing knowledge, which may lead to new, and probably more valuable innovations (Fleming, 2001; Katila and Ahuja, 2002). Also, external knowledge may allow the firm to overcome lock-in traps (see Levitt and March 1988 and Levinthal and March 1993). There is of course the possibility to profit from valuable but 'distant' external knowledge, perhaps available in a different country, however, as Phene et al. (2006) show, firms have difficulties in absorbing and utilizing knowledge that is geographically distant. This is particularly true for developing economies, where the early experiences of international technological transfer showed that knowledge does not travel easily (Enos, 1991). Although the increasing codification of knowledge has certainly made the diffusion of technologies across borders easier, additional obstacles such as the growing complexity of the knowledge value chains still heavily hampers this process (Nelson, 2008). This also explains the renewed interest of scholars to the role of indigenous capabilities (Mazzoleni and Nelson, 2007).

Based on above theoretical arguments we formulate our second set of research aims. First, we test whether the effect of technological relatedness decays as countries develop: advanced economies can rely on a more diverse and rich technological environment than developing ones, which allows them to incur into more distant recombinations of knowledge. Second, we test whether countries systematically upgrade their technological structure following a coherent pattern of specialization, by increasing their participation in the production of more valuable and complex technologies as they develop.

3. Data and methods

We start this section by describing the data sources and variables we will use through the analysis. Later, we explain our methodological approach, aimed at characterizing countries' patterns of specialization and diversification.

3.1. Data sources and variables

We use patent data as an indicator of innovative capabilities. Data on patenting activity was obtained from the "Patent Network Dataverse" developed by the Institute for Quantitative Social Science at Harvard University (Li et al., 2014) using original data from the USPTO. Patenting activity in the US has been used extensively in economics and innovation studies to address issues of global scope, this responds not only to the importance and size of the US technological market but also to the consistent and systematic way patents applications have been evaluated over the years; making data collected at the USPTO very suitable for comparisons, both across countries and time. We take advantage of the vast and rich information contained in patents regarding the technological domain (or technological class) patents belong to, and use it to construct variables aimed at capturing different aspects of technologies. We also make use of the Annual Survey of Manufactures (ASM) from the US census bureau to include economic measures such as the value added of sectors technological classes contribute to. Patents are widely used in the innovation literature because they provide a systematic and quantitative measure of new technological inventions. Nevertheless, the use of patent activity in the US as a measure of innovative capabilities is not exempt of criticisms; we acknowledge these limitations and also propose a way to deal with them in the methodological subsection.

Evaluating countries' technological trajectories requires being able to track and quantify countries' technological capabilities and their changes over time. We measure patterns of specialization by computing countries' Revealed Technological Advantage (RTA) for each technological class (see Soete, 1987). In particular,

$$RTA_{cjt} = \frac{Patents_{cjt}/\sum_j Patents_{cjt}}{\sum_c Patents_{cjt}/\sum_{cj} Patents_{cjt}}$$

$$S_{cjt} = I[RTA_{cjt} > 1]$$

Where c stands for country, j for technological class, t for the time period (in three years intervals), and I[.] represents the indicator function. We assign the nationality of a patent by looking at inventors' addresses; and consider a patent to be part of country c portfolio of competences whenever an inventor resides there. This index provides information on countries' patterns of technological specialization by comparing the share each technology represents in countries' own profile of patenting activity, relative the world average. Then the dependent dichotomic variable S_{cjt} identifies technological classes where country c has a relatively high rate of patenting (i.e. RTA value above unity) when compared to the world average. We identify instances of diversification by considering those cases in which countries started patenting in particular technological domains. This can be done by focusing on cases where there was no patenting activity in the previous period, or at the beginning of the sample.

In order to construct the technology-level variables, we need to define the so-called Technological Space (TS). The TS was first addressed empirically by Jaffe (1986), Jaffe (1989), who calculated relatedness among two given technologies by looking at how often they were used in combination with a third technology. In a similar manner, we construct the TS following the "product space" (PS) framework developed by Hidalgo et al. (2007). Within this framework, the TS can be seen as a network-based representation of the technological production, where nodes define technologies and ties among them indicate their degree of relatedness (see also Rigby 2015; Boschma et al., 2013; and Boschma et al., 2015). We identify 344 technologies using the USPTO patent classification and measure relatedness by counting co-occurrences of technologies (or technological classes) among patents. In particular, the degree of relatedness between technology *i* and *j* is measured as follows:

$$R_{ijt} = \frac{C_{ijt}}{\sqrt{S_{it}S_{jt}}}$$

Where C_{ijt} counts the co-ocurrences of technologies *i* and *j*, and S_i and $S_j$count the number of ocurrences (size) of technologies at period t. This is often referred to as the cosine similarity measure and it has been widely applied in recent work (see Eck and Waltman 2009 for a detailed analysis). Therefore, the more often two technological classes appear together within the same patent, the more related they are, after controlling for the effect of size. This measure is therefore intended to capture the degree of common heuristics and scientific principles technologies share, by looking at how often they appear together in inventions.

We follow Hidalgo and Hausmann (2009) and Balland and Rigby (2017) to measure the complexity of technologies. The main idea is that, by analyzing the structure of the bipartite network connecting countries to the technologies they produce; complex technological structures can be characterized as those producing a wider range of exclusive technologies (i.e. non ubiquitous, produced by few countries). A country with a complex technological structure will not only produce technologies in many different technological domains, but they will do so in technologies requiring capabilities found only in a handful of countries. Therefore, the construction of an Index of Technological Complexity (ITC) requires combining information on both, the 2-mode degree distribution of a country (diversity) and the 2-mode degree distribution of the technologies it produces (ubiquity). We follow their 'method of reflections' and iteratively calculate:

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_t M_{cj} k_{j,N-1}$$

$$k_{j,N} = \frac{1}{k_{j,0}} \sum_c M_{cj} k_{c,N-1}$$

The matrix M_{cj} takes value 1 if country c is a significant producer of technology j, and zero otherwise. We consider country *c* to be a significant producer of technology *j* if its RTA > 1. $k_{c,0}$ and $k_{j,0}$ measure levels of diversification of a country (the number of technologies produced by that country), and the ubiquity of a technology (the number of countries producing that technology). Each additional step incorporates feedback effects and produces more precise estimates of the knowledge complexity of countries by using information on the complexity of technologies they produce. By the same token, $k_{j,N}$estimates the knowledge complexity of a technology using information on the complexity of countries that produce this technology. For a detailed description

Table 1
Technology-level Variables.

Variable Name	Description	Source
Value Added	Value added of industries technologies contribute to (in billions of dollars)	ASM
Size	Number of patents within the technological class (in logs)	USPTO
Herfindhal Index	Herfindhal concentration index of patenting activity	USPTO
ITC	Index of Technological Complexity (as in Hidalgo and Hausmann, 2009)	USPTO

of the procedure and the properties of the indicator see Hidalgo and Hausmann (2009) and Balland and Rigby (2017).[1]

We also include three more variables: the Herfindhal concentration index (across countries) of each technological class, their size, and the value added of industries technological classes contribute to. The variable measuring class size aims at controlling for scale effects. Even though the level of patenting activity has been used to measure technological opportunities, as in Laursen (1999); here we don't go beyond any interpretation other than capturing differences in the propensity of patenting activity among technological classes. As it is customary, we use the Herfindhal index as an indicator of the amount of competition among countries within a particular technological domain. The third variable (i.e. value added) aims at capturing the economic value of technological classes. We measure it by computing the value added of industries technological classes contribute to. Note that the USPTO provides a concordance linking technological classes to standard industrial classifications; which can be used to match technological classes with characteristics of the industries in the US.[2] We use this concordance to generate a weighted average of the value added technologies contribute to, using information of the value added by industry, more specifically:

$$VA_i = \sum_s W_{is} VA_s$$

Where i indexes technological classes and s industrial sectors. W_{is} is a weighting matrix which assigns a weight proportional to the amount of patents within class i contributing to industry s. Table 1 summarizes all the tech-level variables.

In addition to the variables described above, we include a measure providing information about the proximity of countries' existing capabilities to every technology. For each technological class, we quantify the degree to which countries' current technological production 'surrounds' that given technology. This measure uses information about the relatedness among technologies as well as countries' profiles of indigenous capabilities to calculate, for any given technology, the proportion of related technological classes countries' shows patenting activity on. It varies from 0 to 1, with higher values indicating there are competences nearby a given technological domain (where distance is measured in terms of proximity within the TS), and it is calculated as follows[3]:

$$Density_{cjt} = \frac{\sum_i R_{ijt} X_{cit}}{\sum_i R_{ijt}}$$

Where X_{cit} takes value 1 if country c shows patenting activity in technology i at time t, and 0 otherwise. This variable will be used to disentangle whether and how indigenous capabilities, as well as relatedness among technologies, affect possibilities for technological diversification.

Table 2
Main Descriptive Statistics.

	Mean	SD	Min	Max
Specialization	0.21	0.41	0	1

	PA_{cjt-1}	NPA_{cjt-1}	Total
$S_{cjt} = 1$	0.748	0.252	1.00
$S_{cjt} = 0$	0.290	0.710	1.00

Technology Level Variables

	Mean	SD	Min	Max
Value Added	79.34	40.47	5.53	184.7
Log Size	5.68	1.53	0.51	9.52
Herfindahl	0.36	0.13	0.11	0.92
ITC	0	1	−4.45	3.96
Density	0.40	0.19	0	1.00

Correlation Table

1				
−0.303	1			
−0.104	−0.054	1		
0.340	−0.660	−0.171	1	
−0.120	0.017	0.133	−0.173	1

Number of Countries: 65.
Number of Technologies: 344.
Coverage: 1993–2007 (5 intervals of 3 years each).
Number of Observations: 92300.

Table 2 shows descriptive statistics of the aforementioned variables. After combining all different sources of information we end up with a sample of 65 countries covering a 15 years period, from 1993 to 2007.

Basic statistics show that only a 25% of the cases represent instances of diversification, in the way defined it earlier (i.e. when $S_{cjt} = 1$ with no prior patenting activity, in the table below NPA_{cjt-1} identify countries with no prior patent activity in that technology while PA_{cjt-1} identify those who had). Additionally, note that there exist a high correlation between the ITC and the size of technological classes, meaning that in order to appropriately capture any patterns involving the complexity of technologies it will be necessary to net out, or control for, the effect of size.

Let's consider a finer description of the data used in this study. Fig. 1 below, characterizes the technological production of three selected countries at different stages of development; Argentina, Korea, and Germany. It shows, for the main technological variables and last period of the sample, how countries are distributing their technological production.

All graphs show on the horizontal axis a ranking of technological classes ordered according to the variable in question. For instance, the first graph entitled 'Complexity' orders technologies from the less to the most complex along the horizontal axis. Vertical axes display the cumulative share of countries' technological production. Therefore, the first graph shows that Argentina accumulates almost 80% of its technological production among the 20% less complex technologies, while Korea and Germany concentrate only around 45%. A similar pattern characterizes the distribution of valuable technologies, where Argentina more than doubles the concentration of its technological production within the 20% less valuable technologies (around 40%), when compared to Korea and Germany (less than 20%). The last two graphs also depict different patterns of technological specialization across countries. Remarkably, Korea shows a technological profile biased towards the production of technologies that are relatively big in size.

The next section describes the methodological approach of the paper, which among other things, aims at providing an answer to

[1] Values were scaled around the mean. We iterated the method of reflections 20 times. At the last step the correlation with the previous iteration was above 0.999.
[2] Concordances can be found here: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/data/
[3] This measure has been widely applied in recent studies, see Hidalgo et al. (2007), and Boschma et al. (2015) for instance.

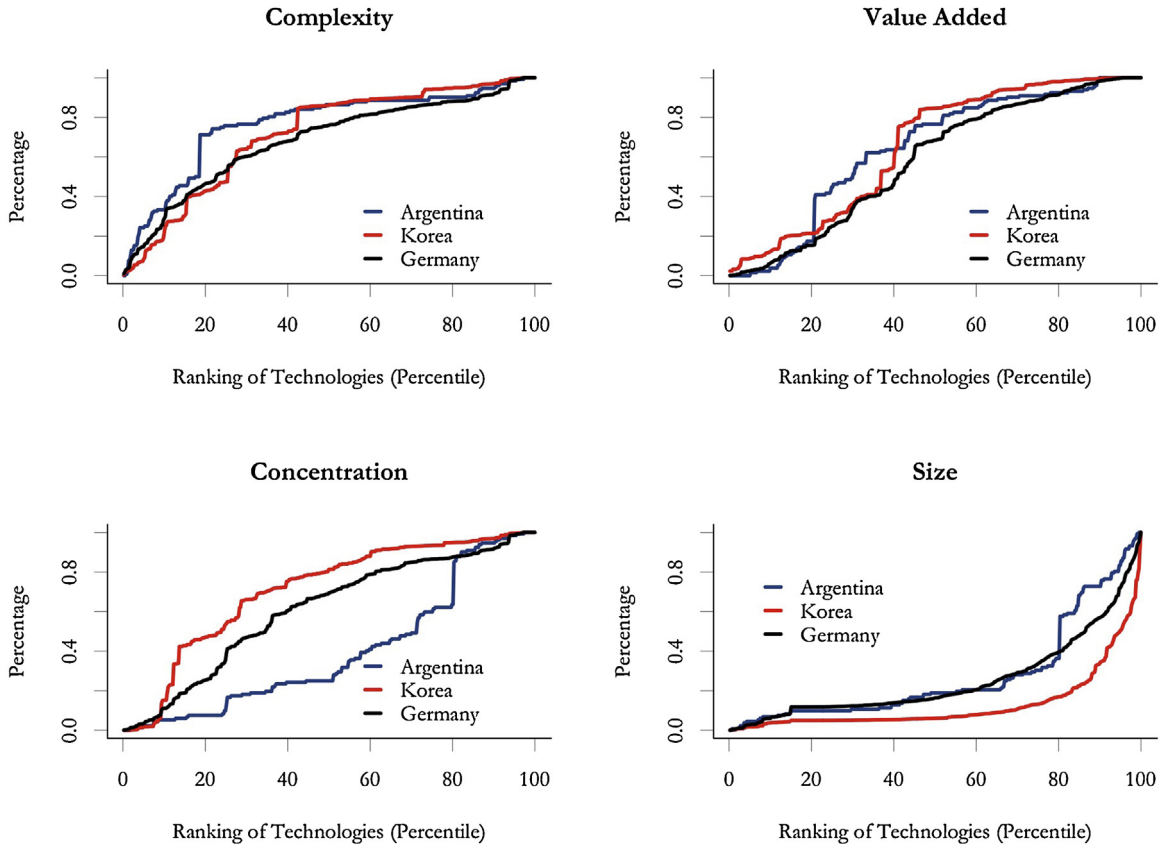

Fig. 1. Characterising Countries' Technological Production: Some Examples.

the question of whether these seemingly intuitive patterns hold on in general, and when possible sources of bias are controlled for.

3.2. Methodology

In this subsection we outline the methodological approach to address our main research aims. On the one hand we aim at characterizing countries' patterns of technological diversification by estimating how the likelihood of entering into new technological activities decays as the 'technological distance' to existing technological capabilities increases. Additionally, we evaluate whether this effect decays as countries develop. On the other hand, we test to what extent countries follow a coherent pattern of specialization, by increasing their participation in the production of more 'valuable' and 'complex' technologies as they develop.

To identify instances of diversification we restrict our sample those cases where a particular technology was not already produced in a country prior the period of analysis. By doing this, we are able to evaluate which factors affect the likelihood that technologies will emerge. As there is not a clear consensus on how to empirically identify instances of diversification we propose two different ways. First, restricting the sample to cases where there was barely or no activity at the beginning of the sample. In doing so, we can assess if technological production emerged in any of the subsequent periods. Second, we restrict the sample to cases where there was barely or no activity in the previous period, for each time period. This way we are able to consider only the previous period as a benchmark, where diversification instances should occur from one period to the next. We consider that a country has barely or no activity in patenting if RTA values are below 0.1 as in Hidalgo and Hausmann (2009).[4]

We use patented inventions at the USPTO as a proxy of innovative capabilities of countries, which is an imperfect measure, as it has been argued that: (a) They provide an incomplete characterization of the production of knowledge, mainly because firms may not patent and choose secrecy instead; (b) They may induce biases, as the rate of patenting differs greatly across sectors and time; (c) It is not possible to account for differences in the economic value of the inventions; (d) It is not clear whether patenting activity at the USPTO can be taken as an appropriate source of information to evaluate global patterns of knowledge production; as rates of participation may vary systematically across countries, leading to a misrepresentation of their competences.

Our methodological approach aims at both providing answers to our research objectives while overcoming the potential limitations of the data we work with. We propose to estimate two separate linear probability models (one to characterize diversification patterns and another to evaluate specialization patterns), which include tech-level dummies to overcome the potential biases that differences in patenting rates may have on our results (b). Consider the following specifications, with c indexing countries, j technological classes, and t time periods:

Diversification Equation (on the restricted sample):

$$S_{cjt} = \theta_1 Density_{cjt-1} + \theta_2 Density_{cjt-1} * GDP_{ct} + \sum_k \beta_k T_{jt}^k + \delta_c D_c + \delta_j D_j + \delta_t D_t + \varepsilon_{cjt} \quad (1)$$

Specialization Equation:

$$S_{cjt} = \theta_1 Density_{cjt-1} + \sum_k \beta_k T_{jt}^k + \sum_k \beta_k T_{jt}^k * GDP_{ct} + \delta_c D_c + \delta_j D_j + \delta_t D_t + \varepsilon_{cjt} \quad (2)$$

[4] Results are robust to changes in this cutoff.

Where S_{cjt} identifies technological classes country c has specialized in the production of (having an RTA above unity), GDP_{ct}accounts for the GDP per capita of countries,[5] $Density_{cjt-1}$ measures country c technological proximity to technology j, T_{jt}^{k} for k:1...4 contain all technology-level variables described in Table 1, D_i for i:c,j,t represent a set of country, technology, and time variables respectively, and ε_{cjt} is the error term. Note that we account for differences in the economic value of the inventions (c) by including among the tech-level variables the value added of sectors technological classes contribute to.

Note that the first equation aims at identifying whether the effect of having competences in related technologies is higher when entering into a new technological domain and additionally, whether this effect changes as countries develop. Tech-level variables along with country, technology, and time fixed effects are consider as control variables in this equation.

There are two key differences in the specialization equation. First, we aim at evaluating the distribution of the technological production, disregarding whether the production of that technology is new to the country or not (in this case we use the entire sample). Therefore we explore specialization profiles according to characteristics of the technologies, which are interacted with GDP per capita of countries to evaluate whether countries tend to follow coherent patterns of specialization as they develop. Second, unlike in the previous equation, the density variable is here introduced as a control variable along with the rest of the dummies. As in the previous specification, we don't want that any possible correlation between the density of technologies in the TS biases any of the coefficients of the technological variables.

It may still be the case that patents records at USPTO may not fully reflect countries' profiles of competences (d), meaning that the US technological market may not be an unbiased sample of the world production of patents and its distribution over countries. We address this issue by including a sample selection test to identify whether the particular selection of countries we use in the analysis may have influenced our results. This test, proposed by Wooldridge (1995), does not require imposing any restriction on distribution of the error term in the regression equation, and allows for arbitrary serial dependence. In order to carry it out we need to calculate the likelihood any given country is part of our sample at any period of time and according to different country-level characteristics, to later obtain the Inverse Mills Ratio (IMR) and include it the regression equation. A significance *t*-test on the additional variable will then be used to detect the presence of sample selection. As the construction of this test involves defining and describing a whole new set of country-level variables, we relegate a detailed outline of this procedure to the Appendix A.

The use of secrecy over patenting as a method of protection (a) cannot be measured unless a firm-level survey spanning different technological domains is conducted, however, there are no obvious reasons to believe that this may considerably affect our results, especially after having controlled for specific tech-level effects in the regression.

4. Results

In what follows we describe the results the econometric model. Table three below reports the results of the linear probability models. The first two columns correspond to Eq. (1) for the two different subsamples defined at the beginning of Section 3.2, while the third column corresponds to Eq. (2). Standard errors were clustered by country, technology, and time according to Cameron et al. (2011).

Results in columns one and two test the likelihood a country will diversify into the production of a particular technology. The former identifies technologies that were not already produced in a country by restricting to cases in which countries show a RTA value less than 0.1 in the previous period, while the later considers RTA values below 0.1 at the starting point of our sample. Both specifications show that having capabilities in related technologies is important when entering into a new technological domain, as reflected by the positive and significant coefficient of the *density* variable. The likelihood a new technological capability will emerge is higher the closer that technology is with respect to the profile of existing capabilities in that country. However, when the *density* variable is interacted with countries' *GDP per capita*, this effect diminishes, showing that having related capabilities is less important as countries develop. Results show that diversification in unrelated technologies is less likely to occur at early stages of development, or putting it in another way, that developing countries tend to diversify incrementally. As expected, it is less likely to find diversification into more complex and less concentrated technologies, as shown by the negative coefficients of the *ITC* and *Herfindahl index* variables. There are no significant differences in the likelihood of diversification with respect to the economic value of technologies (no significant coefficient of the *Value Added* variable).

Column three summarizes the results of the specialization equation, which show that there is a significant and positive reinforcement of having developed related capabilities, as captured by the *density* coefficient. The latter means that technological production tends to cluster in the technological space. Additionally, it is less likely to find countries specializing in complex and valuable technologies. However, when we interact the tech-level variables with countries' *GDP per capita*, results show that the likelihood of specialization increases for complex and valuable technologies as countries develop (see positive and significant coefficients of *ITC* and *Value Added* variables when interacted with *GDP*). In sum, developed countries tend to show a distribution of their technological production biased towards the production of less concentrated, more complex, and more valuable technologies. Additionally, note that the coefficient of the sample selection test is not significant in all three specifications. The *log size* variable is always positive and significant as expected; the straightforward meaning is that in larger technological classes there are higher opportunities of diversification, and this is true at any stage of development.

Fig. 2 below summarizes our results regarding the importance of having related capabilities for diversification, and its differential impact along stages of development (darker colors correspond to higher probability values). Left panel of Fig. 2 shows how the likelihood of diversification changes as proximity to technological capabilities increases (as reflected by the *density* coefficient on the vertical axis) and along stages of development[6](i.e. *GDP per capita* on the horizontal axis). Note that the likelihood of diversification more than doubles (from 0.25 to over 0.5) if we move from related to unrelated technologies for low-income countries (i.e. while going up along the vertical axis from the left-lower corner). When considering high-income countries (rightmost part of the graph along the horizontal axis) the difference in the likelihood of diversification between related and unrelated technologies barely changes.[7]

[5] Constant (based in 2005) and PPP adjusted measures of GDP per capita were obtained from the World Development Indicators (WDI) database provided by the World Bank.

[6] Technology attributes were set to their average values. Predictions are made over all dummy variables and then averaged together.

[7] Note that while plotting predicted values we are keeping country and technology fixed effects constant, meaning that these figures do not incorporate shifts in the likelihood of diversification captured by fixed effects.

Table 3
Results of the Econometric Model.

	Diversification Equation (RTA < 0.1 in the previous period)	Diversification Equation (RTA < 0.1 at the beginning of the sample)	Specialization Equation
Density	0.208***	0.270***	0.87***
	(0.034)	(0.025)	(0.0392)
Density * GDP	−0.0011*	−0.0029***	
	(0.00058)	(0.00050)	
Tech-Level Variables			
Value Added	−0.0005	−0.00021	−0.00061*
	(0.00043)	(0.00030)	(0.00028)
Log Size	0.0185**	0.032***	0.0313***
	(0.0069)	(0.0048)	(0.005)
Herfindahl Index	−0.169***	−0.169**	−0.248***
	(0.033)	(0.036)	(0.067)
ITC	−0.025***	−0.0140***	−0.025***
	(0.0034)	(0.0021)	(0.004)
Value Added * GDP			0.000008**
			(0.000003)
Log Size * GDP			−0.000087
			(0.00016)
Herfindahl Index * GDP			−0.0059**
			(0.0022)
ITC * GDP			0.00067*
			(0.00029)
Sample Selection Test (Wooldridge 1995)	0.011 (0.008)	−0.0023 (0.005)	0.0107 (0.0136)
Adjusted R-Squared	0.079	0.090	0.27
Tech Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Number of observations	54370	58808	89440

Significance levels: 0.001 '***', 0.01 '**', 0.05 '*'. Standard errors were clustered by country, technology, and time according to Cameron et al. (2011).

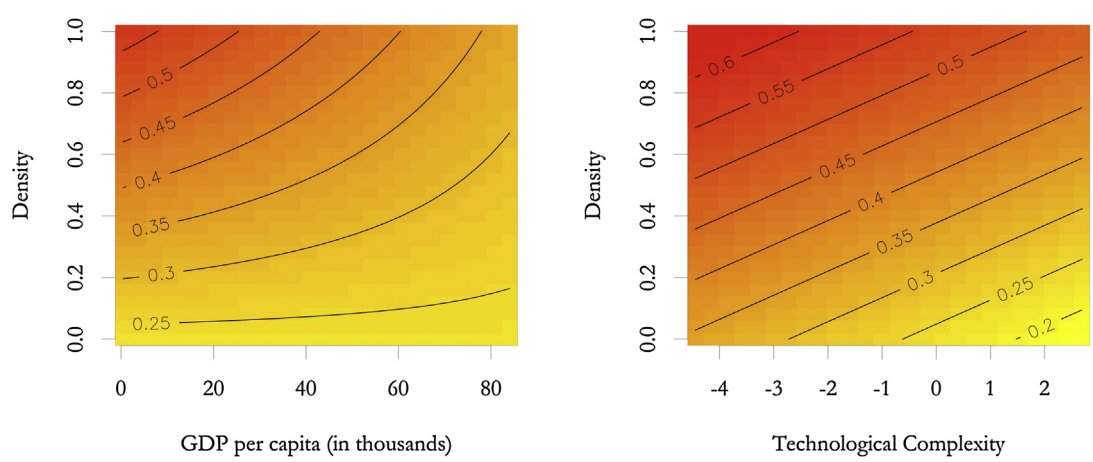

Fig. 2. Diversification Possibilities and Stages of Development.

Right panel of Fig. 2 exemplifies another aspect of our results. It shows how different characteristics of technologies such as their complexity and proximity to countries' indigenous competences (density) interact to determine possible paths of technological development. On average, the likelihood of diversification triples (from 0.2 to 0.6) if we move from complex and unrelated technologies (lower-right corner of the figure) to ubiquitous and related technologies (north-upper-left corner of the figure).

Results in Table 3 shows that different characteristics of technologies, such as their complexity and economic value, can be associated with specialization patterns along the stages of development. It is not so straightforward to see, however, to what extent these statistically significant results can be translated into meaningful changes of specialization profiles. Fig. 3 below shows specialization profiles (predicted values S_{cjt}) along different characteristics of the technologies and stages of development (as before, darker colors correspond to higher probability values). Left panel of Fig. 3 plots predicted probabilities for different values of technological complexity and GDP per capita, showing that it is four times more likely to find low-income countries specializing in less complex technologies than finding high-income countries producing that sort of technologies (it goes from values above 0.4–first line from the left – to less than 0.1–second line from the right). For high-income countries, as opposed to low-income ones, the mode is situated in the upper part of the graph. Similar results can be found for value added (Right panel of Fig. 3), where production of less valuable technologies is relatively more likely to be found in low-income countries (0.35 in low income vs 0.2 for high income countries).

We would like to emphasize that our results do not imply that technological diversification can't happen unless you have certain related level of existing technological competences. Note that inde-

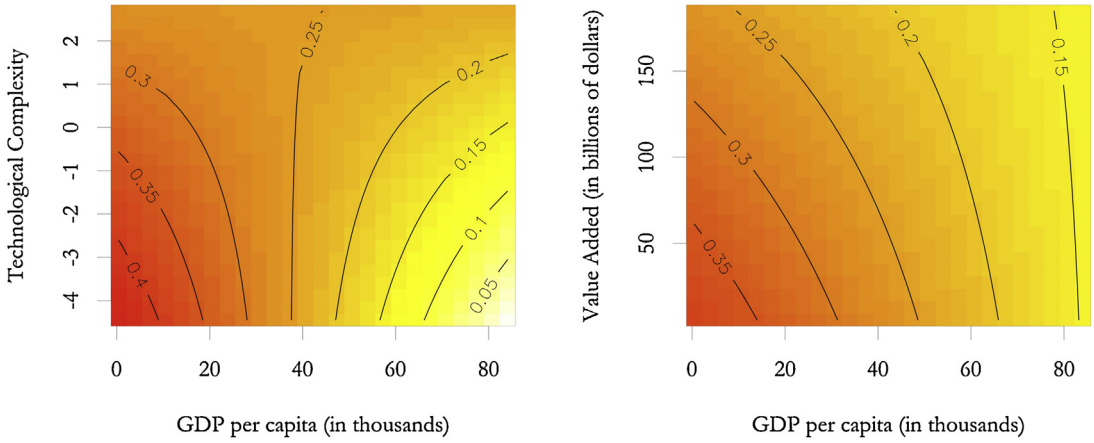

Fig. 3. Specialization Patterns and Stages of Development.

pendently of their proximity to existing competences, complexity, and value, each technology has different barriers to entry. As shown in Park and Lee (2006) and Lee (2013), latecomer countries can enter technological niches where windows of opportunities open up more frequently, so reducing barriers to entry. These opportunities emerge usually in technologies with short life cycle, where latecomers are less at disadvantage with advanced economies. In these niches, as shown by the experience of Korea, leapfrogging can occur (Lee and Lim, 2001). In our econometric specification these characteristics are absorbed by tech-level fixed effects, as they remain practically invariant over the time span we considered. We show in the Appendix C that our fixed effects are correlated with the technology-regime variables used in Park and Lee (2006) and Lee (2013).

To conclude, a potential concern with our econometric specification is that results may be biased given that we imposed a linear relationship in the way our variables of interest are affected as *GDP per capita* increases. An alternative option is to divide the sample according to the stage of development of countries (proxied by the *GDP per capita* level), and evaluate whether we observe a similar pattern. We carry out this analysis in the Appendix B and show that results are robust to changes in the specification of the model.

5. Concluding remarks

This study has examined how countries diversify and upgrade their technological production as they develop. We analyzed diversification and specialization patterns of 65 countries using disaggregated patent data by type of technology from the United States Patent and Trademark Office (USPTO) over a period of 15 years. Patenting activity of countries show that the development of new technologies is a highly cumulative and path dependent process, in which technological upgrading emerges out of pre-existing knowledge bases and patterns of specialization. The likelihood of diversification into a new technological activity is higher for those domains that are related to countries' existing profile of competences. Countries climb the ladder of technological development rung by rung, as new capabilities have to be built-up gradually. However, patterns of technological development change in two important ways as countries develop. First, diversification is more heavily constrained by related, indigenous capabilities at early stages of development. At later stages of the development process countries are able to make bigger jumps and develop new technologies that are less and less related to their current knowledge bases. Second, the type of technologies in which developed and developing countries are specialized is different. Along their economic development, countries tend to upgrade their technological structure by specializing into increasingly complex and more valuable technologies.

These results have several implications for development strategies of countries. It is important to understand that developing strong capabilities and leadership in technologies out of the blue is nearly impossible. It is tempting to try to become a leader in information technologies or biotech because these technologies are fashionable and profitable, but such a technology-targeted strategy is a lottery. What if countries do not have the specific knowledge and capabilities required to become a successful producer of the targeted technology? In many cases, such a blinded policy will end up in wasted taxes. This issue is particularly important for developing countries, where diversification possibilities are even more heavily constrained by indigenous capabilities. Our results suggest that a more efficient policy strategy consists of carefully assessing the pre-existing knowledge bases of a country, considering indigenous capabilities as a starting point. The specific analysis of the technological strengths and weaknesses of a country can reveal unexploited opportunities, which may lead to alternative development paths. The methods used in this paper can be applied to assess national knowledge bases and develop strategies for their diversification or upgrading.

Although we suggest that an inside-out strategy of technological development is more desirable than a technology-targeted policy, a word of caution is necessary here. It is important to note that a policy supporting only technologies that are very closely related to existing capabilities is also quite likely to fail. Such a development strategy won't be risky in the short run, but it can lock-in technological development of countries in the long run. This is especially true for developing economies, which tend to make shorter technological jumps (i.e., more related) in less sophisticated activities (i.e. less complex). Therefore, there is a threat for developing countries to become locked in the production of less sophisticated technologies, and innovation policies should not re-enforce this path-dependent process by narrowing down technological opportunities. It is important for developing countries to continuously aim at producing more complex technologies in order to upgrade their technological structure. Sometimes it will require supporting activities that are not necessarily the most related to existing capabilities. In this case, it will require bigger investments (also in complementary education or supporting infrastructure). Another important leg of this strategy is to engage actively in international knowledge networks in order to gradually build-up the necessary competencies.

An alternative strategy for latecomers is to identify technological niches where windows of opportunities can open up more frequently. Park and Lee (2006) show that these opportunities usu-

ally emerge in technologies with short life cycle, where barriers of entry are lower and latecomers are less at disadvantage with advanced economies. In these niches, as shown by the experience of Korea, leapfrogging can occur (Lee and Lim, 2001). However, the latter is true only if latecomers have accumulated enough technological capabilities, otherwise rapid technological change becomes an additional barrier for latecomers (Lee, 2013: 98).

An important caveat of this paper is that we focus exclusively on patents. Patents are praised as the only systematic measure of invention, but also criticized because they only capture some specific types of innovation and technologies. Many generic forms of innovation, especially in developing countries, won't show up in patent data. Similarly, patents don't capture the innovation outcomes that are generated by the imitative activities of firms. These activities can range from pure imitation of existing technologies to creative design of novel processes and products, whose innovative content can be regarded as relevant as that in patents (Bell, 2009). It is important to bear these critiques in mind while interpreting the results and critically assessing the policy implications we are drawing. Also, it is not clear whether the results we report will also hold true for non-manufacturing sectors, or for sectors relying less on patenting activity. This could be addressed in future research combining patents with innovation surveys, both in the manufacturing and service industry. An interesting question here is whether service sectors can also serve as catalyzers, enhancing technological diversification possibilities, as they generally span over different types of productive activities.

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Appendix A.

A. *Test for Sample Selection*

As mentioned in the methodological section, one appropriate concern is that the sample we have used to estimate our econometric model may not be an unbiased representation of the world production of patents and its distribution over countries. We address this issue by including a sample selection test to identify whether the particular selection of countries we use in the analysis, those who had activity in all periods, may have influenced our results. This test, proposed by Wooldridge (1995), does not require imposing any restriction on distribution of the error term in the regression equation, and allows for arbitrary serial dependence. In order to carry it out we need to calculate the likelihood any given country was included in our sample at any period of time, and according to different country-level characteristics, to later obtain the Inverse Mills Ratio (IMR) and include it the regression equation. The IMR is computed after estimating a separate probit model at each period. A significance *t*-test on the additional variable will then be used to detect the presence of sample selection. The purpose of this Appendix A is to describe the construction of this test, which involves defining and describing a whole new set of country-level variables.

We use the World Bank's World Development Indicators (WDI) database; which provides a diverse collection of development indicators compiled from officially-recognized international sources. Additionally, data on bilateral trade flows and distances were obtained from the BACI database developed by the CEPII.

Table A1 below provides a short description of all country-level variables. These variables aim at capturing whether the inclusion in

Table A1
Country-Level Variables.

Variable Name	Description	Source
Distance	Thousands of km to US (using capital cities)	CEPII
Language	Whether or not English is an official language	CEPII
Population	Population in millions	WDI
GDP per capita	GDP per capita in thousands of 2005 US dollars	WDI
Outward Orientation	Share of total exports to GDP	WDI
Trade	Share of exports oriented to the US market	BACI

Table A2
Main Country-Level Descriptive Statistics.

	Mean	SD	Min	Max
Distance	8.51	3.57	0.55	16.1
Language	0.31	0.46	0	1
Population	33.54	129.7	0.02	1311
	Mean	SD	Min	Max
GDP per cap	8.91	13.30	0.09	84.07
Outward O.	0.89	0.53	0.16	4.79
Trade	0.15	0.19	0	0.91

Number of Countries: 169.
Coverage: 1993–2007 (5 intervals of 3 years each).

Table A3
Results of the Probit Models.

	Period 2	Period 3	Period 4	Period 5
Intercept	−0.794***	−0.941***	−0.972***	−1.053***
	(0.021)	(0.0201)	(0.019)	(0.019)
Distance	−0.00006***	−0.00006***	−0.00007***	−0.00007***
	(0.000)	(0.000)	(0.000)	(0.000)
Language	−0.818***	−0.901***	−0.938***	−0.917***
	(0.0147)	(0.015)	(0.015)	(0.016)
Border	3.982***	3.709***	3.89***	4.184***
	(0.040)	(0.04)	(0.039)	(0.04)
Trade	−1.552***	−1.235***	−1.38***	−1.65***
	(0.0453)	(0.038)	(0.037)	(0.041)
GDP pc	0.094***	0.094***	0.087***	0.08***
	(0.0011)	(0.001)	(0.001)	(0.001)
Population	0.030***	0.028***	0.027***	0.0266***
	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Outward Orientation	0.203***	0.307***	0.441***	0.519***
	(0.0096)	(0.011)	(0.011)	(0.012)

Significance levels: 0.001 '***', 0.01 '**', 0.05 '*'.

the final sample can be explained by country-specific characteristics, which may have an impact on our estimated coefficients if the country-level fixed effects cannot appropriately control for them in the regression equation.

Distance to the US market, as well as language barriers, directly shift up barriers to entry, therefore affecting the likelihood that firms within a country will regularly patent at the USPTO. Additionally, countries' outward orientation and the importance of the US market as a commercial partner may increase the likelihood of participation in the US 'technological market'. The former by reflecting the need of technological upgrading to compete in international markets, while the later by capturing the effect that strong trade relationships have on the orientation of patenting activity. Lastly, population and GDP per capita aim at capturing size effects and remaining factors that could be related to countries' level of development. Table A2 shows descriptive statistics of the variables.

Table A3 below shows the results of estimating the likelihood any given country was included in our sample at any period of time (a separate probit model for each period, first period is dropped as we use lagged values in the main equation). All country-level variables are highly significant, consistent over time, and in line with what we could expect; the likelihood increases with population, the degree of outward orientation, and the level of development of the country. Additionally, border and distance effects have the expected signs. Sharing language impacts negatively given the substantial proportion of developing countries, in number, where English is an official language. There is a negative relationship between the proportion of exports directed to the US and the likelihood of a country being included in the sample, this looks somehow unintuitive, as you would expect that strong trade relationships may increase the amount of patenting activity between countries. However, this is mainly due to the fact that most of this US oriented exporters are from developing economies, and mostly exporting low-end goods.

It may be the case that these relationships are non-linear, or that interaction effects are important. We included all possible interactions, and third-degree polynomials of each variable in the version used for estimation; however, as results don't change in any significant way, and because we wanted to provide a parsimonious description, we decided to report this summarized version. Additional results are available upon request.

B. ***Robustness of the Results: Dividing Countries into Developed and Developing Economies using World Bank's Classification.***

In our baseline model (see Section 4), we interacted the variable *GDP per capita* with the main variables of interest in order to evaluate whether effects are different as countries develop. This implies imposing a linear relationship in the way our variables of interest are affected as *GDP per capita* increases. If this assumption does not hold, coefficient estimates could be biased.

An alternative option is to divide countries according to their stage of development using a dummy variable based on the categories created by the World Bank. We can then evaluate whether we observe a similar pattern with respect to the baseline model.

Therefore we perform a new estimation dividing countries into **High-Income** and **Low-Middle-Income** economies. This classification is taken directly from the World Bank, and is based on *GDP per capita*.[8] Table 4 below provides the list of countries that fall in each category.

Table 4
List of Countries by Income Levels.

Low-Middle Income Countries	High-Income Countries
Argentina	Australia
Belarus	Austria
Brazil	Bahamas
Bulgaria	Belgium
China	Canada
Colombia	Chile
Costa Rica	Croatia
Cuba	Czech Republic
Egypt	Denmark
India	Estonia
Jordan	Finland
Lebanon	France
Malaysia	Germany
Mexico	Greece
Morocco	Hong Kong
Pakistan	Hungary
Philippines	Iceland
Russia	Ireland
South Africa	Israel
Sri Lanka	Italy
Thailand	Japan
Turkey	Korea
Ukraine	Latvia
Venezuela	Lithuania
Vietnam	Luxembourg
	Netherlands
	New Zealand
	Norway
	Poland
	Portugal
	Slovakia
	Slovenia
	Spain
	Singapore
	Sweden
	Switzerland
	United Kingdom

Table 5 below shows the result of estimating the same econometric model than in the baseline case but interacting the variables with a dummy identifying *High Income* countries. In columns 1 and 2 we test the likelihood that a country will diversify its technological activities, by patenting in a new technological class in which it had no patenting activity before. As in the baseline model, we identify instances of diversification by restricting to cases in which countries show a RTA value below 0.1 at the starting point of our sample, and in the previous period.

The results reported in Table 5 shows that having capabilities in related technologies is important when entering into a new technological domain, as reflected by the positive and significant coefficient of the *density* variable in all the specifications of the model. The above finding confirms what we obtained in the baseline model: the likelihood that a new technological capability will emerge in a country is higher the closer a technology is to its existing capabilities. And this latter effect is stronger in developing economies (i.e lower for **High-Income countries**).[9] Similarly, we confirm that is less likely to find diversification into more complex and valuable technologies, as shown by the negative coefficients of the *ITC* and *Value Added* variables.

Column 3 summarizes the results of the specialization equation. As in the baseline model, we find a significant and positive reinforcement of having developed related capabilities, as captured by the *density* coefficient. Additionally, these findings confirm that

[8] see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups

[9] Note, however, that this is not true for the first column, in which we subset the sample keeping those cases where RTA < 0.1 in the previous period. This is partly explained because we end up with a very limited and highly unbalanced panel for the High-Income group.

Table 5
Results of the Econometric Model.

	Diversification Equation (RTA < 0.1 in the previous period)	Diversification Equation (RTA < 0.1 at the beginning of the sample)	Specialization Equation
Density	0.21***	0.338 ***	0.87***
	(0.024)	(0.037)	(0.037)
Density * GDP	−0.038	−0.095 **	
	(0.030)	(0.0412)	
Tech-Level Variables			
Value Added	−0.0008***	−0.0007 ***	−0.0005 *
	(0.00021)	(0.00023)	(0.00017)
Log Size	0.014**	0.026 ***	0.028 ***
	(0.0075)	(0.0061)	(0.005)
Herfindahl Index	−0.153***	−0.208 ***	−0.232 ***
	(0.041)	(0.036)	(0.0463)
ITC	−0.026***	−0.0245 ***	−0.026 ***
	(0.0049)	(0.0048)	(0.004)
Value Added * GDP			0.00017 *
			(0.00009)
Log Size * GDP			−0.00064
			(0.006)
Herfindahl Index * GDP			− 0.186 **
			(0.0611)
ITC * GDP			0.022 **
			(0.00029)
Sample Selection Test (Wooldridge 1995)	0.008 (0.0153)	0.0073 (0.0139)	0.014 (0.018)
Adjusted R-Squared	0.081	0.081	0.27
Tech Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes
Number of observations	54370	58808	89440

Significance levels: 0.001 '***', 0.01 '**', 0.05 '*'. Standard errors were clustered by country, technology, and time according to Cameron et al. (2011).

High-Income countries tend to specialize into more complex, more valuable, and less concentrated technologies.

Overall, the above results confirm our previous findings; which point towards the fact that developed countries tend to show a distribution of their technological production biased towards the production of less concentrated, more valuable, and more complex technologies. Additionally, note that the coefficient of the sample selection test is not significant in all three specifications and that the *log size* variable is always positive and significant as expected.

C. *Technologies' Life Cycles and Barriers to Entry.*

As mentioned in section four, we show here that independently of their proximity to existing competences, complexity, and value, technologies may have different barriers to entry, which are captured in our econometric regressions by technology fixed effects, as illustrated in Fig. A1 below.

Fig. A1 plots the coefficient estimates of the technology fixed effects across different technological sectors. All technologies are

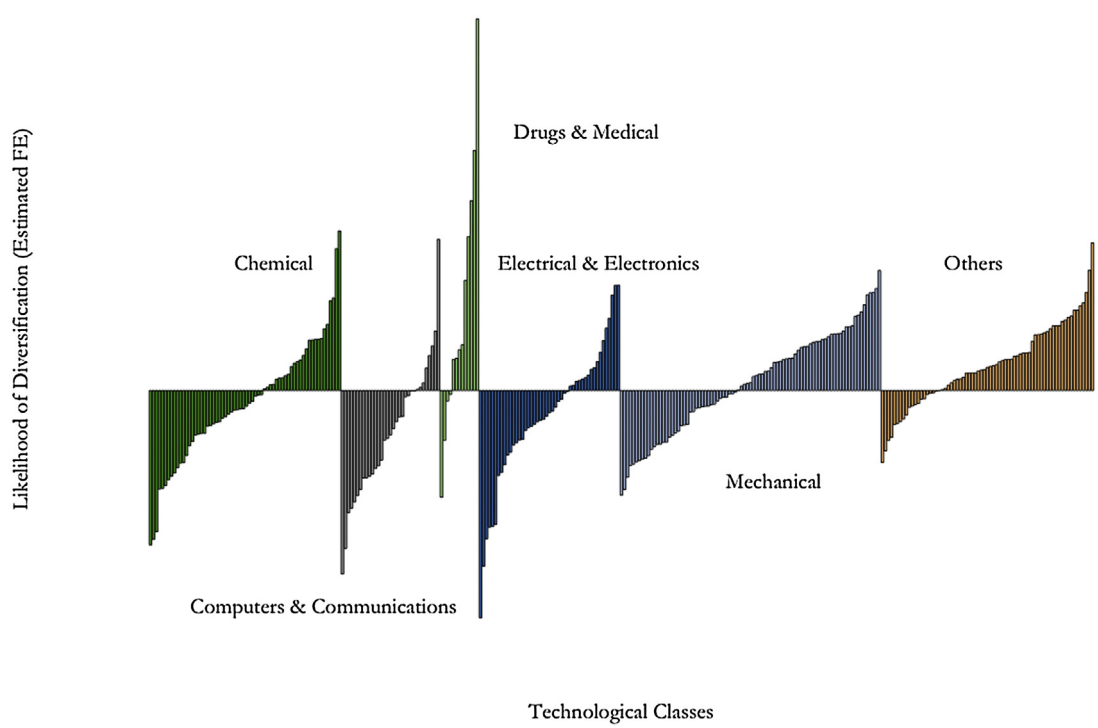

Fig. A1. Differences in Entry Barriers Across Technologies.

Table 6
Replication of Park and Lee (2006).

	Likelihood of Entry (Tech-Level FE Estimation in Model)
Tech-Regime Variables in Park and Lee (2006)	
OPPORTUN	−0.004
	(0.019)
CUMUL1	−0.257***
	(0.018)
APPRO	0.066**
	(0.032)
INITIAL	0.067***
	(0.009)
CYCLETIME	−0.092***
	(0.007)
Adjusted R-Squared	0.82
Number of observations	315

Significance levels: 0.001 '***', 0.01 '**', 0.05 '*'.

grouped according to their main economic classification (Chemical, Computers and Communications, Drugs and Medical, Electrical and Electronic, Mechanical, and Others) and are ordered by their estimated coefficient. Higher values indicate a higher likelihood of diversification in that particular technology (or lower barriers to entry). All values are centered with respect to the average. This graph clearly portrays how disparate technologies are in terms of entry barriers, both within and between categories.

Moreover, we show in Table 6 that these coefficient estimates strongly correlate with the determinants of entry used in Park and Lee (2006).[10] We replicate the model of Park and Lee (2006, Table 4, first column), but differently from them, in our econometric specification the dependent variable is given by the fixed-effect estimated coefficients, which proxy the likelihood of technological diversification (i.e. the inverse of barriers to entry). We find that all main variables keep the same direction, including the variable called CYCLETIME, which means that technologies with a shorter-life cycle evidence lower barriers to entry.

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