Economic
Research
Working Paper
No. 90/2026

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The Technological Potential of Innovation Ecosystems

An Inter-Dimensional Network Approach

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Abstract

In developing countries' innovation activities, limited patenting suggests structural gaps that hinder technological progress. This paper investigates whether countries can leverage their scientific and productive capabilities to realize untapped technological potential. We analyze connections between trade, science, and technology across global innovation ecosystems and introduce an indicator to assess where countries are positioned to expand their technological capabilities. Our results show that the indicator predicts technological output growth, though growth slows when countries exceed their predicted potential, indicating diminishing returns. The indicator performs better in more complex ecosystems. These findings provide valuable insights for policymakers, offering a framework to address weaknesses in innovation ecosystems and foster balanced, sustainable technological development.

Keywords

innovation capabilities; complexity metrics; innovation ecosystems; science and technology policy; industrial policy; economic development; smart specialization

JEL Codes

O25; O31; O33; O30; O11; O14

Suggested citation

Moscatelli, F., C. Chacua, S. Gadgin Matha, H. Hartog, E. Hernández Rodriguez, J.D. Raffo and M.A. Yildirim (2025). Unveiling the Technological Potential of Innovation Ecosystems: An Inter-Dimensional Network Approach. WIPO Economic Research Working Paper No. 88. World Intellectual Property Organization.

Introduction

Most countries have the production capabilities to participate in trade, many engage in advanced scientific research, but far fewer contribute significantly to patenting (WIPO, 2024). Not surprisingly, the latter group contains the most industrialized and advanced economies. These economies also have consolidated well-functioning innovation ecosystems.

Innovation economics have long focused on how well-functioning innovation ecosystems establish strong technological linkages between its industrial and scientific bases (Edqvist, 1997; Nelson, 1993). Evidence indicates that firms in such ecosystems will generate technological innovations from existing scientific knowledge and industrial networks (Crepon et al, 1998; Thursby and Thursby, 2007; Malerba, 2012). Similarly, there is evidence of firms capable of transforming their exporting experience into technological innovations (Keller, 2006).

Yet, why is it that some economies manage to transform scientific and production capabilities into novel technologies while others strive? The absence of patenting in developing innovation ecosystems indicates the existence of structural gaps limiting an expected technological progression. Is there a latent technological potential in developing economies based on their existing productive and scientific capabilities that could be untapped?

This paper seeks to answer the latter question by developing a new metric of the technological innovation potential for innovation ecosystems. To do so, we make use of a novel dataset measuring the production of tradable goods, scientific publications and patented technologies of 160 economies for over 20 years to build a network of related capabilities (WIPO, 2024; Moscatelli et al, 2024). By examining how these dimensions interconnect in well-functioning innovation ecosystems, we identify patterns that drive successful technological development. Using data from international collections on exports, scientific publications, and patent families, we apply these insights to all countries globally, revealing not only where untapped technological potential exists, but also where the technological transformation exceeds its expected outcomes.

This study contributes to the growing body of research on innovation as a multidimensional process, moving beyond traditional intra-dimensional approaches (Pugliese et al, 2019; Catalán et al, 2022; Balland, and Boschma, 2022). By adopting an inter-dimensional network approach, this research provides a tool to identify structural breaks in innovation ecosystems. The findings offer valuable insights for policymakers, helping them understand where scientific or production activities fail to translate into technological development, unlike in more virtuous ecosystems.

The remainder of this paper is structured as follows: Section 1 motivates the paper by providing a review of the relevant literature and stating the main research questions. Section 2 outlines the data sources and estimation approach to test the hypotheses. Section 3 explains the methodological approach used to measure technological potential. Section 4 presents the results, highlighting key patterns and missing links in national innovation ecosystems. Section 5 discusses the implications of these findings and concludes with potential policy recommendations. Finally, additional details and supplementary analyses are provided in the annex.

1 A literature roadmap to measuring technological innovation potential

Innovation has become a central focus in economic development and policy, with numerous scholars examining the factors that drive a country's capacity to innovate. Innovation and creative destruction has long been recognized as a key driver of economic growth (Aghion and Howitt, 1990), and numerous theories have been proposed to explain how different factors contribute to a nation's innovative capacity.

One foundational concept in this field is the "principle of relatedness" which states that the current set of productive capabilities that allows a country to competitively produce a set of products predicts the country's likelihood to start producing a new product related to these skills (Hidalgo et al, 2007; Hidalgo and Hausmann, 2009).[1] The authors introduced the idea of product relatedness and economic complexity, arguing that the diversity and complexity of a country's productive capabilities are indicative of its potential for sustained economic growth. Building upon this, the relatedness-based approach posits that the extent to which a country's industries and technologies are interconnected plays a crucial role in its capacity to innovate and compete in the global market (Hidalgo et al., 2018).

Since this seminal work, a sizeable empirical economic literature kept testing the principle of relatedness by extending it to other units (e.g., regions or organizations) and other types of skills (e.g., scientific or technological skills). As a result, the positive relationship between a country's capabilities —ranging from scientific research to technological expertise— and its ability to generate new competitive outputs has been widely studied (See, for example, Boschma et al., 2015; Hidalgo et al., 2018; Balland et al., 2019; Deegan et al., 2021; Hidalgo, 2022; Rigby et al., 2022)

A significant body of scholar work has explored the relationship between relatedness and innovation output (Kogler et al., 2023; Boschma, 2017; Rigby, 2015; Boschma et al.,2015). Studies have shown that innovation tends to occur more efficiently in ecosystems where industries and technologies are closely related, as knowledge spillovers and synergies can emerge more easily in such contexts (Pinheiro et al., 2022). These studies emphasize that innovation ecosystems with a higher degree of relatedness facilitate the transfer and

[1] Other scholars, such as Tacchelia et al. (2012), have proposed similar approaches that have contributed to solidifying the concept of relatedness.

application of knowledge, which drives technological advancements and competitive advantage.

Another critical discussion in the literature concerns the correlation between innovation complexity and economic growth, as highlighted by Fagerberg et al. (2010) and Tushman and Anderson (1986). These studies have demonstrated that complex innovations – those that require diverse set of knowledge and capabilities – are often more likely to lead to significant economic development (Pintar and Scherngell, 2022; Mewes and Broekel, 2022; Fleming and Sorenson, 2001). Countries with highly complex and diverse innovation ecosystems tend to be more resilient to economic downturns and more capable of sustaining long-term growth (Steijn et al, 2023; Balland et al, 2015; Boschma, 2015). Conversely, less complex economies may struggle to innovate in competitive markets.

1.1 Is there a cross-dimensional link between technological outcomes and scientific or productive capabilities?

More recently, the relatedness and complexity strand of economic research has focused on understanding how these capabilities interact across different dimensions – such as science, technology, and production – extending the principle of relatedness across different types of skills (Pugliese et al., 2019; Catalán et al., 2022; Balland and Boschma, 2022; Castaldi and Drivas, 2023; Stojkoski et al., 2023; Moscatelli et al, 2024; Hausmann et al., 2024; Zhou et al, 2025). These recent studies have extended the relatedness concept by allowing for several dimensions – such as scientific, product and technological fields – to interact with each other.

First, measuring science, technologies and products, Pugliese et al. (2019) identified not only which cross-dimensional capabilities are needed to be competitive in another given one, but they also measure how much time is needed to transform it. Hausmann et al. (2024) propose that scientific publications, patents, and international trade data offer complementary insights into how ideas evolve, combine, and are transformed into innovation capabilities. Moscatelli et al. (2024) propose to inform innovation policymaking by analyzing the innovation potential across science, technology, and production fields of a given innovation ecosystem. Similar to Pugliese et al. (2019), these two papers also show that diversification opportunities can be inferred across innovation domains

Focusing on the link between science and technology, Catalan et al. (2022) explore the scientific and technological cross-density finding that countries observe a higher entry probability on a given the technology the higher is their cross-dimensional scientific relatedness to it. Balland and Boschma (2022) extend the country-level scientific and technological cross-dimensional analysis to European NUTS-2 regions. They find that regional scientific capabilities are a strong predictor of related new technologies in the same region.

Castaldi and Drivas (2023) provide an original extension using three intellectual property (IP) rights by analyzing the cross-dimensional capabilities across patents, industrial designs, and trademarks for NUTS-2 European regions and metropolitan statistical areas (MSAs) in the US. They find that cross-relatedness played a significant role in the emergence of new regional specializations for all three IP dimensions. Stojkoski et al. (2023) combining the complexity metrics from science, technologies and products provides a better predictive power in understanding the inclusive growth of regions and countries. Zhou et al (2025) extend the cross-dimensional approach to capture the interaction between industries and occupations in China's cities. They find cross-relatedness are significantly associated with new regional specializations in the co-evolution of industries and occupations, particularly in larger cities.

1.2 Can scientific or productive capabilities predict technological outputs?

What explains the cross dimensional relatedness found in empirical literature? In regard to innovation economic literature, there are many paths explaining why the principle of relatedness works cross-dimensionally.

First, likely inspired by the seminal work by V. Bush (1945), many innovation economists consider that technological innovation happens in a big extent thanks to a "science push" (Godin, 2006). At the macro level, economies that invest and produce more science are expected to produce more technologies (Rosenberg, 1974).

At the public organization level, many economists and social scientists have looked at how universities transfer knowledge to the private sector (Thursby and Thursby, 2007). This has inspired science and innovation policies -- such as the Bayh-Dole Act -- seeking to stimulate academic patenting to facilitate public to private technological transfer (Mowery et al. 2001, 2015). Similarly, defense related research also found to be influencing downstream civil use innovation (Gross and Sampat, 2020a, 2020b).

This has also been largely studied from the private sector perspective. Several firm level studies have explored how public academic institutions are a significant source for the firm's technological innovation (Crepon et al, 1998; Raffo et al, 2008).

Second, innovation economists have also indicated that innovation is not a linear cognitive process that only moves from public scientific output to private technological innovation (Kline, 1985). Indeed, core concepts of the innovation economic literature indicate multiple paths from industrial production to technological innovation.

Arrow's (1962) famous "learning by doing" concept points to the fact that the more a company produces a given product the more likely it will develop a deeper understanding of the related industrial process, opening opportunities to develop more efficient techniques (process innovation) or improve the product (product innovation).

Similarly, Cohen and Levinthal's (1989, 1990) seminal work on absorptive capacity offer support for several cross-dimensional relatedness paths. Companies operating in industries with active innovation environments are more likely to improve their scientific and technological skills so to better "absorb" the external available knowledge. Cohen and Levinthal propose several sources that provoke such an increase in scientific and technological capacities to firms. In addition to active public scientific systems, companies operating in industries with technology active competitors or in markets with unsatisfied demand for technologies are expected to invest more in research and development activities. There is a vast firm level empirical literature inspired by Cohen and Levinthal and applying the CDM empirical approach [2] consistently finding that public academic institutions, competitors and demand are significant source for the firm's technological innovation (e.g., Cohen and Levinthal, 1989, 1990; Crepon et al, 1998; Raffo et al, 2008). Moreover, innovation scholars have also found that this absorptive capacity mechanism can lead to innovative companies – especially the large ones – to increasingly publish peer-reviewed scientific articles (Simeth and Raffo, 2013; Simeth and Cincera, 2016).

In the trade related literature prompted among others by Bernard and Jensen (1999), the concept of "learning by exporting" suggests that the participation in competitive markets induces technological innovation (Keller, 2004; Fernandes and Isgut, 2005; Salomon and Shaver, 2005; Harris and Li, 2007; Loecker, 2010). The intuition is not far from the absorptive capacity concept. Firms operating in highly competitive markets – such as international trade – face increasing pressure to deliver products of a higher quality and a lower price. Both elements induce firms to develop new products and processes, leading to technological innovation. Likewise, the literature on sectoral innovation ecosystems (Malerba and Orsenigo, 1993; Breschi and Malerba, 1997; Malerba, 2002) or global supply chains (Gereffi et al., 2005; Pietrobelli and Rabellotti, 2011) indicate that substantial technical knowledge is transferred within an industry's supply chain. For instance, highly specialized suppliers of the automotive or aerospace industries often innovate through collaboration with the main assembly clients.

1.3 Using network approaches to connect across innovation dimensions

Both the empirical cross-dimensional economics literature and vast innovation economics literature agree that in that the principle of relatedness applies across dimensions, which

[2] The CDM approach stems from the seminal work by Crépon, Duguet and Mairesse (1998) where technological innovation is modeled as the output of absorptive capacity (R&D intensity), which in turn is modeled as the output of several sources for information such as public academic institutions, competitors and demand, amongst other variables.

indicates that past related scientific and production capabilities can predict the development of new technological capabilities (entry) and output. Following the exploratory work in Moscatelli et al (2024), we propose in this paper to extend these results to develop a metric of potential technological output. In other words, the resulting relatedness network connecting scientific and productive capabilities with technological ones allows us to impute a future technological output.

While the details of how we implement the indicator are discussed in the following section, we now turn to what should be expected of such an indicator. First, if the indicator is well conceived, we should expect that the potential technological output should positively predict future observed technological output (H1). Second, and reciprocally, innovation ecosystems should converge to their expected potential (H2). Indeed, innovation ecosystems will likely also reduce their technological output if their potential is below the observed output.

Following the product and technological complexity literature, we could also expect that the potential technological output cannot be transformed equally into future observed one depending on its complexity. Two contradicting effects may operate here. First, we can expect that firms, entrepreneurs or research labs are more likely to transform scientific or productive capabilities into technological ones the higher the reward there is for the new technological capability. As a result, rational economic agents will have more incentives to make the effort to transform the more complex the resulting technological output is (H3a). Conversely, the potential output in more complex technological fields is harder to achieve than in less complex ones. In this case, the higher cost of learning may operate against selecting the more complex fields (H3b).

From an innovation ecosystem perspective, we can expect that countries or regions with better functioning innovation institutions and policies are more likely to be prepared to leverage their technological potential. Indeed, due to their higher absorptive capacity, we can also expect that more complex innovation ecosystems are more likely to fulfill their potential (H4).

The main hypotheses to be tested are listed as follows:

H1: Potential technological output positively predicts future observed technological output

H2: Innovation ecosystems converge to their expected potential

H3a: Potential output is more likely to be achieved in more complex technological fields than in less complex ones (incentives effect)

H3b: Potential output is more likely to be achieved in less complex technological fields than in more complex ones (learning costs effect)

H4: Innovation ecosystems with higher absorptive capacity are more likely to fulfill their potential

2 Data and empirical strategy

This paper intends to contribute to the intersection of these critical debates in the literature from the previous section by offering a new framework to measure innovation potential. Our suggested measure integrates the concept of latent technological capabilities with the dynamic interrelationships of science, technology, and production.

In order to do so, we analyze a dataset that includes 626 distinct fields of innovation in the period 2001-2020, sourced from PATSTAT and WIPO, Web of Science, and UN COMTRADE. These data sources provide comprehensive coverage of scientific progress, technological advancement, and production across countries, enabling a deeper understanding of national innovation ecosystems.

For scientific articles, we utilize data from the Web of Science, specifically the Science Citation Index Expanded collection, which encompasses scholarly articles published in internationally recognized academic journals grouped in 169 scientific fields. The publications are assigned to countries based on author affiliations, ensuring accurate attribution of scientific output to the respective national innovation ecosystems. As our focus is on the academic fields that may affect technological potential, social sciences and humanities fields were excluded from this analysis. We proxy technological output using patent data sourced from PATSTAT and WIPO databases. We focus on foreign-oriented patent families, which represent inventions for which patent protection has been sought beyond the applicant's country (Miguelez et al., 2019) and grouped in 172 technological fields. Finally, we make use of the export flows in the UN COMTRADE database for 285 distinct goods and services fields.[3]

Finally, we group the yearly data in five 4-year periods (2001-2004, 2005-2008, 2009-2012, 2013-2016, 2017-2020). This aggregation helps mitigate the high volatility of innovation outputs, particularly in the scientific and productive dimensions, ensuring a more stable representation of capabilities over time. Shorter timeframes, such as single-year periods, have proven to be too sensitive to annual fluctuations, making it difficult to capture consistent and meaningful patterns in national innovation ecosystems. By using four-year windows, we smooth out temporary spikes or dips while still preserving the dynamism of innovation trends.

The initial dataset contains 513,320 observations representing the outputs for 626 fields of innovation –i.e. scientific, technological and production fields – in 164 countries for the period 2001-2020 (grouped into five 4-year periods). The number of observations is then reduced when focusing on the 172 technological fields and removing countries without innovation capabilities.

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[3] The focus on international outputs across these three domains is intentional. By analyzing internationally recognized measures of innovation, we can ensure a level of comparability across countries and avoid domestic biases and lack of coverage.

2.1 Empirical strategy

We analyze the evolution of the potential of technological outcome over time to test if innovation ecosystems converge to their expected outputs, particularly for the case of technologies using both science and production.

In order to address the hypotheses mentioned in the previous section, we formulate a baseline model that captures the growth of innovation outputs as a function of the past innovation outputs and idiosyncratic country and innovation field determinants. To test the predictive power of technological potential (H1), we add our main variable of interest to the baseline model. We also then introduce interactions to account for the convergence (H2), the field complexity (H3) and the innovation ecosystem complexity (H4).

Formally, the main model is expressed as follows:

$$asinh(Output_{c,f,t}/Output_{c,f,t-1}) = \theta\, asinh(Output_{c,f\in T,t-1}) + \beta_1\, asinh\left(POT^{d}_{f\in T,c,t-1}\right) + \beta_2\, asinh(POT^{d}_{f\in Tc,t-1}) \times untapped_{c,f\in T,t-1} + \beta_3\, asinh(POT^{d}_{f\in T,c,t-1}) \times PCI^{*}_{f\in T,t-1} + \beta_4\, asinh(POT^{d}_{f\in T,ct-1}) \times ECI^{*}_{c,t-1} + RD_{c,f\in T,t-1} + \alpha_t + \alpha_c + \alpha_{f\in T} + \varepsilon_{c,f\in T,t} \quad (1)$$

Where:

- $Output_{c,f\in T,t}$ is the number of outputs of innovations for country c in technological fields $f \in T$ and period t.
- T is the set of technological fields.
- $POT^{\mathrm{D_n}}_{f\in T,c,t-1}$ is the expected number of technological innovations (T) for country c in field f and period t that are based on outputs from dimension $d \in D$.
- D is the set of dimensions of innovation (technologies, science, and production).
- $untapped^{*}_{c,f\in T,t-1}$ is a binary variable that identifies when potential is greater than outputs for country c in technological field f and period $t-1$.
- $RD_{c,f\in T,t}$ is the relatedness density of country c in technological field f and period $t-1$.
- $ECI^{*}_{c,t-1}$ is the economic complexity index for country c and period $t-1$
- $PCI^{*}_{f,t-1}$ is the product complexity index for technological field f and period $t-1$.
- $\alpha_t + \alpha_c + \alpha_{f\in T}$ are the time, country and technological field effects.

We use a fixed-effects OLS estimator model to account for the country (α_c), field (α_f) and period (α_t) idiosyncratic effects. Additionally, we use as a dependent variable the change in technological outputs of the past period. We use growth rates since time series and panel data to avoid any unit root problems frequently arising in non-stationary data, which can lead to spurious correlations.

We also apply the inverse hyperbolic function transformation to outputs and potentials instead of natural logarithms to avoid dropping the negative and zero values.[4]and perform a z-score normalization to these variables to be able to compare the coefficients between the variables in standard deviation units.

To capture the persistence and potential feedback effects of technological outputs over time, we keep a lagged version of how past levels of technological outputs influence future growth.

$ECI^*_{c,t}$ is computed at country-period level. This treats each country-period observation as a different country. This allows to compare the ecosystem complexity over time, under the assumption that field capabilities do not change over this time. Indexes are then max min normalized.

$PCI^*_{f,t}$ is computed at field-period level. This treats each field-period observation as a different field. This allows to compare the capability complexity over time. This allows to compare the ecosystem complexity over time, under the assumption that country capabilities do not change over this time. Indexes are then max min normalized.

Finally, we include a dummy variable to identify cases of untapped potential (where potential is higher than actual outputs), the relatedness density ($RD_{c,f,t}$) to control for its effect in output growth (principle of relatedness) plus fixed effects for time (α_t) country (α_c), field (α_f) and dimension from where the potential estimation comes from (α_n).

We now turn to how we construct our innovation potential indicator.

3 Defining technological innovation potential

Based on this dataset, we build a technological innovation potential indicator seeking to identify how a country's outputs in one scientific or production field can predict the outputs in a technological field. Our goal is to allow policymakers and researchers to better understand and support the untapped potential within innovation ecosystems.

Following Moscatelli et al (2024), we build this indicator by (1) defining multidimensional innovation capabilities, (2) establishing a benchmark of high-performing innovation ecosystems, and (3) setting a vector of weights based on the network of cross-dimensionally relatedness between these capabilities in the high-performing group. We describe these as follows.

[4] The inverse hyperbolic sine ($\text{asinh}(x) = \ln(x + \sqrt{x^2+1})$) transformation is used to handle small and zero values in the growth rate data, as it allows for smooth handling of such values, unlike the logarithm. This transformation is commonly used in economics, particularly when dealing with skewed data or small values.

3.1 Innovation capabilities

This study follows Moscatelli et al (2024), by merging absolute and relative advantage capability algorithms to capture the ability of innovation ecosystems to generate competitive outputs. Capabilities are then assigned to countries based on the origin of their scientific publications, patents, and product exports. Scientific capabilities are linked to the country of the university affiliation address of the authors. Patent capabilities are attributed to the inventors' country addresses, while production capabilities are assigned based on the country of origin of the manufactured products and services.

Much like most of the literature on this topic, to systematically analyze innovation capabilities, we first binarize the capabilities assigned to each country. A country is considered to have a capability in a specific field if its presence surpasses a given threshold.

$$Capability_{c,f,p}^{inno} = \begin{cases} 1 \quad if\ RCA_{c,p,f} \geq 1\ or\ HHI_{p,f}^{-1} \geq Rank_{c,p,f} \geq 3 * HHI_{p,f}^{-1} \\ \quad 0 \quad if\ RCA_{c,p,f} < 1\ or\ 3 * HHI_{p,f}^{-1} \leq Rank_{c,p,f} \end{cases} \tag{2}$$

Where:

- $RCA_{c,p,f}$ is the revealed comparative advantage (Balassa, 1965) for country c in period p in field f
- $HHI_{p,f}^{-1}$ is the inverse Herfindalh-Hirshmann index in period p for field f that captures the number of effective countries that represent the field in each period.
- $Rank_{c,p,f}$ is the ranking for country c in period p for the total number of outputs in field f, where the highest producer of each field in each period is assigned 1.

Transforming the data into a matrix of 1s and 0s allows us to measure relatedness between fields by analyzing how often they co-occur in the same national ecosystems. These relatedness patterns, in turn, enable us to derive complexity indicators, which assess the sophistication of a country's innovation capabilities and its ability to engage in competitive, high-value activities.

This assignment of capabilities aligns with established findings in the literature, particularly with respect to the principle of relatedness — the idea that countries tend to develop new capabilities in fields that are closely related to their existing strengths (Hidalgo et al., 2007). Furthermore, the approach builds on prior work demonstrating that capability complexity is strongly correlated with economic growth (Hausmann et al., 2014; Tacchella et al., 2012).

3.2 High-performing innovation ecosystems

Having established a systematic framework for measuring innovation capabilities across countries, the next critical step involves identifying which ecosystems demonstrate superior performance that could serve as benchmarks for others. Rather than relying on predetermined assumptions about which countries should be considered innovation leaders, we adopt a bottom-up, data-driven approach that allows the empirical evidence to reveal the ecosystems with the most robust innovation capabilities.

This methodology is particularly crucial given that innovation activities are highly concentrated globally, with a small number of ecosystems accounting for a disproportionate share of technological advancement and knowledge creation (WIPO, 2024). By employing this data-driven identification process, we enable the capability patterns themselves to identify those ecosystems that have successfully developed and maintained high-performing innovation portfolios—ecosystems that other countries might realistically aspire to emulate. This approach ensures that our benchmark selection is grounded in observable innovation outcomes rather than preconceived notions, providing a more objective foundation for understanding what constitutes excellence in innovation ecosystem performance.

We define as high-performing innovation ecosystems as the set of countries that are at the frontier of technological, scientific, and productive capabilities. These countries are characterized by their ability to drive innovation across all dimensions, pushing the boundaries of what is technologically and economically possible.

In this work, the countries are selected using a bottom-up approach that clusters countries based on the similarities of the innovation capabilities using a K-means clustering method. The first step is to create a proximity matrix $P_{c,c}$ that pairs countries based on the similarity of their capabilities. We use the capability matrix $M_{c,f}$ (commonly referred as $M_{\mathrm{c,p}}$ in the literature) to compute it. If M_c and $M_{c'}$ represent the binary capability vectors (rows from the M_{cf} matrix) for countries c amd c' then their proximity is computed as:

$$P_{c,c'} = \frac{M_c \, M_{c'}}{||M_c|| \, ||M_{c'}||} \quad (3)$$

The algorithm minimizes the sum of squared distances between each data point and the centroid of its assigned cluster:

$$\min_{C_1 \dots C_K} \sum_{i=1}^{K} \sum_{c \in C_i} \left|\left| P_{c,:} - \mu_i \right|\right|^2 \quad (4)$$

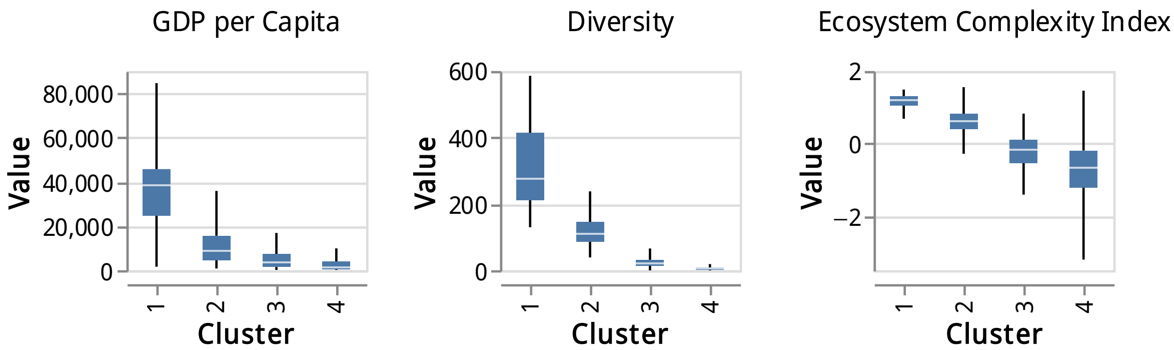
Where:

- k is the number of clusters.
- C_i is the set of countries in cluster i.
- μ_i is the centroid of cluster i, computed as the mean proximity vector of countries in C_i.

Finally, one the clustering is finished, we evaluate the groups to find significant differences between them. The selection criteria for determining which cluster represents the frontier of well-functioning ecosystems are grounded in established findings in the literature, where higher capability diversity, capability complexity, and output competitiveness are positively correlated with higher levels of economic development and innovation performance.

To differentiate countries based on the performance of their innovation ecosystems, we applied a K-means clustering algorithm using the proximity matrix. We selected $k = 4$, aligning with the World Bank income classifications: low, lower-middle, upper-middle, and high income. While our clustering is data-driven and based on innovation metrics rather than income levels, the resulting groups roughly mirror these traditional classifications.

Figure 1. Distribution of GDP per capita, diversity, and complexity across innovation capability clusters, 2001-2020.



Within this grouping, Figure 1. Distribution of GDP per capita, diversity, and complexity across innovation capability clusters, 2001-2020. shows how cluster 1 stands out in terms of income levels, complexity, and diversity across all periods. It is the one with the highest GDP per capita, the most diverse, and the most complex. Throughout the 5 periods of this work, 32 different national innovation ecosystems belong to it.

Only 18 ecosystems belong to cluster 1 in all five periods. These are: Australia, Austria, Belgium, Canada, Switzerland, China, Germany, Denmark, Spain, Finland, France, United Kingdom, Italy, Japan, Republic of Korea, Netherlands, Sweden, and the United States.

Some ecosystems only appear once (Singapore and Hungary), while others twice (India, Mexico, New Zealand, Poland, and Portugal), and thrice (Brazil, Czechia, Israel, Norway, Russia, and Turkey). None appears four times.

This work will treat any country that has managed to get into this select cluster as a well-functioning innovation ecosystem.

3.3 Inter-dimensional connections and weights

The interplay between the three dimensions in the innovation frontier can provide valuable insights into the latent capabilities of countries, particularly for developing ecosystems that may have unbalanced participation in these dimensions. By analyzing the co-occurrence of capabilities in developed ecosystems, we aim to identify the proximity between different pairs of dimensions—science vs. technology, science vs. production, and technology vs. production—that are statistically significant (Pugliese et al., 2019).

To begin our computation of connections by using subsets of the capability matrix $M_{c,\mathrm{f}}$ for each period. These binary matrices have 164 rows (number of countries), and 626 columns (number of fields) and are populated with 0s and 1s based on the presence of a capability in any field-country combination. For every period, we define $O_{i,j}^{obs}$ as the observed overlap between field i_m in dimension m and field j_n in dimension n, where both fields belong to ecosystems that are part of the frontier $\hat{C}$. Formally:

$$O_{i_m,j_n}^{obs} = \sum_{\hat{c}} M_{\hat{c},i_m} M_{\hat{c},j_n} \qquad \text{where: } i_m \in D_m\ ,\ j_n \in D_n\ , \hat{c} \in \hat{\mathrm{C}} \tag{5}$$

In parallel, we calculate the expected cooccurrence O_{i_m,j_n}^{exp} in a randomized scenario and keep significant connections to achieve O_{i_m,j_n}^{*}. For this exercise we use 95% as the threshold of significance. Formally:

$$O_{i_m,j_n}^{exp} = \frac{\sum_{\hat{c}} M_{\hat{c},i_m} \sum_{\hat{c}} M_{\hat{c},j_n}}{N_{\hat{\mathrm{C}}}} \qquad \text{where: } N_{\hat{C}} = number\ of\ countries\ in\ frontier \tag{6}$$

Finally, we filter out the overlaps that do not meet the significance threshold as follows:

$$O_{i_m,j_n}^{*} = \begin{cases} \sum_{\hat{c}} M_{\hat{c},i_m} M_{\hat{c},j_n} & if\ \ O_{i_m,j_n}^{obs} > O_{i_m,j_n}^{exp} + 1.96\sigma_{i_m,j_n} \\ 0 & otherwise \end{cases} \tag{7}$$

The O_{i_m,j_n}^{*} matrix captures only the statistically significant proximities between fields, filtering out co-occurrences that could arise by chance. By doing so, it highlights the structural relationships within well-functioning ecosystems, revealing how capabilities in one dimension (e.g., science) tend to be systematically associated with capabilities in another (e.g., technology or production).

The filtered network of connections offers a refined map of interdependencies. The significance threshold ensures that only robust and meaningful linkages remain, distinguishing genuine capability connections from incidental ones. Building on this framework, we now turn to estimating technological potential by leveraging these interdimensional proximities to predict innovation outputs across fields.

This subsection examines the significant edges connecting different fields of innovation across science, technology, and production in well-functioning national innovation ecosystems. In total, the analysis covers 626 capabilities across five time periods, resulting in a proximity matrix of 626 × 626 field pairs for each period. Each pair of fields is assigned a proximity value ranging from 0 to 1, reflecting the strength of their co-occurrence within the national innovation ecosystems at the frontier. However, not all observed proximities are statistically significant—many may arise by chance rather than reflecting meaningful innovation linkages.

To focus on robust and meaningful relationships, we filter out non-significant connections using a 95% significance threshold. After this filtering process, we retain a total of 33,318 significant edges across periods (1.7% of all connections) that connect 613 nodes (98% of all fields). These edges represent the strongest and most reliable connections between fields of innovation and form the backbone of the network we analyze, highlighting where relatedness between scientific, technological, and productive capabilities are most consistently found in the world's leading innovation ecosystems.

Figure 2. Innovation capability space with most significant connections, 2017-2020.

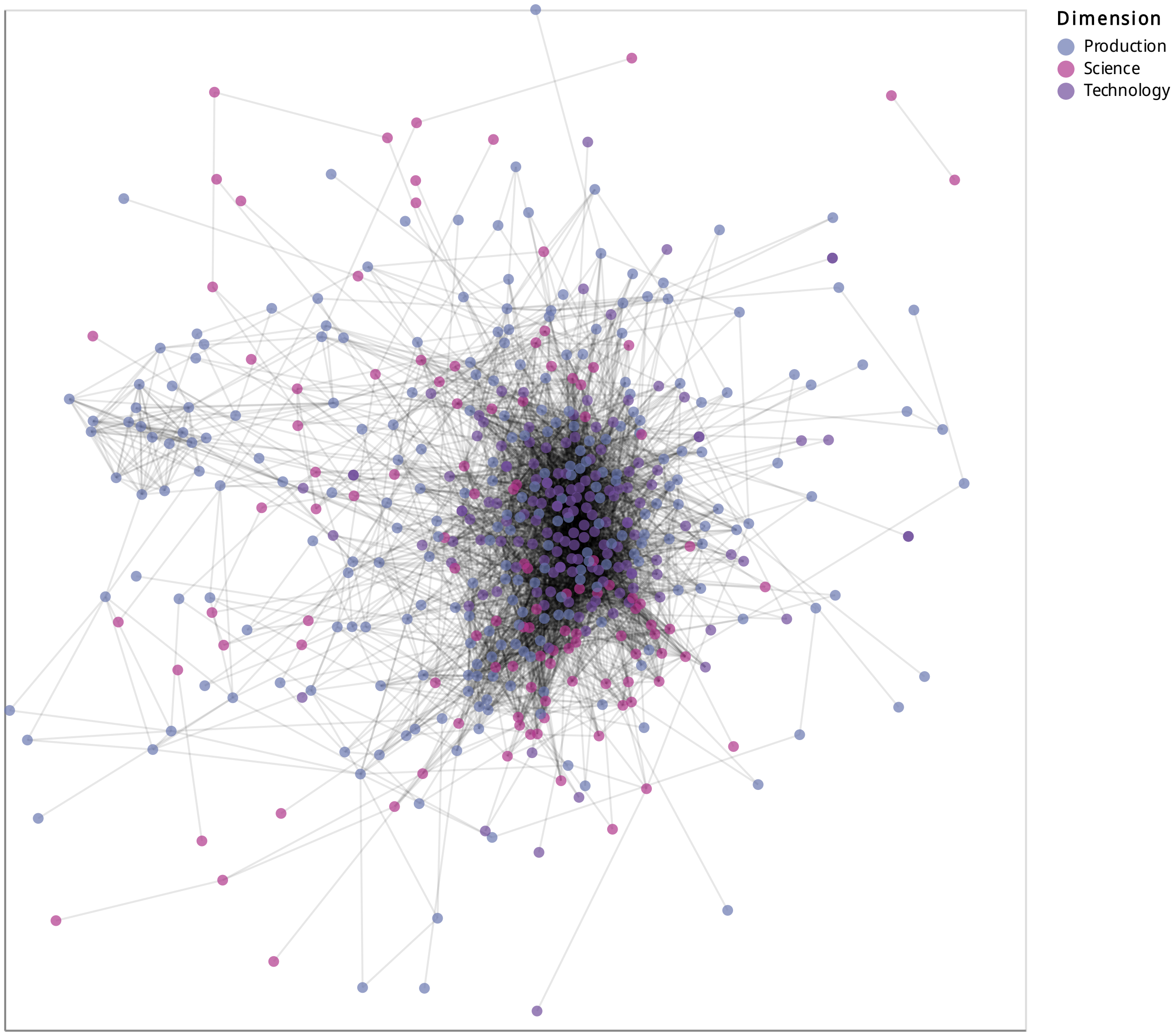
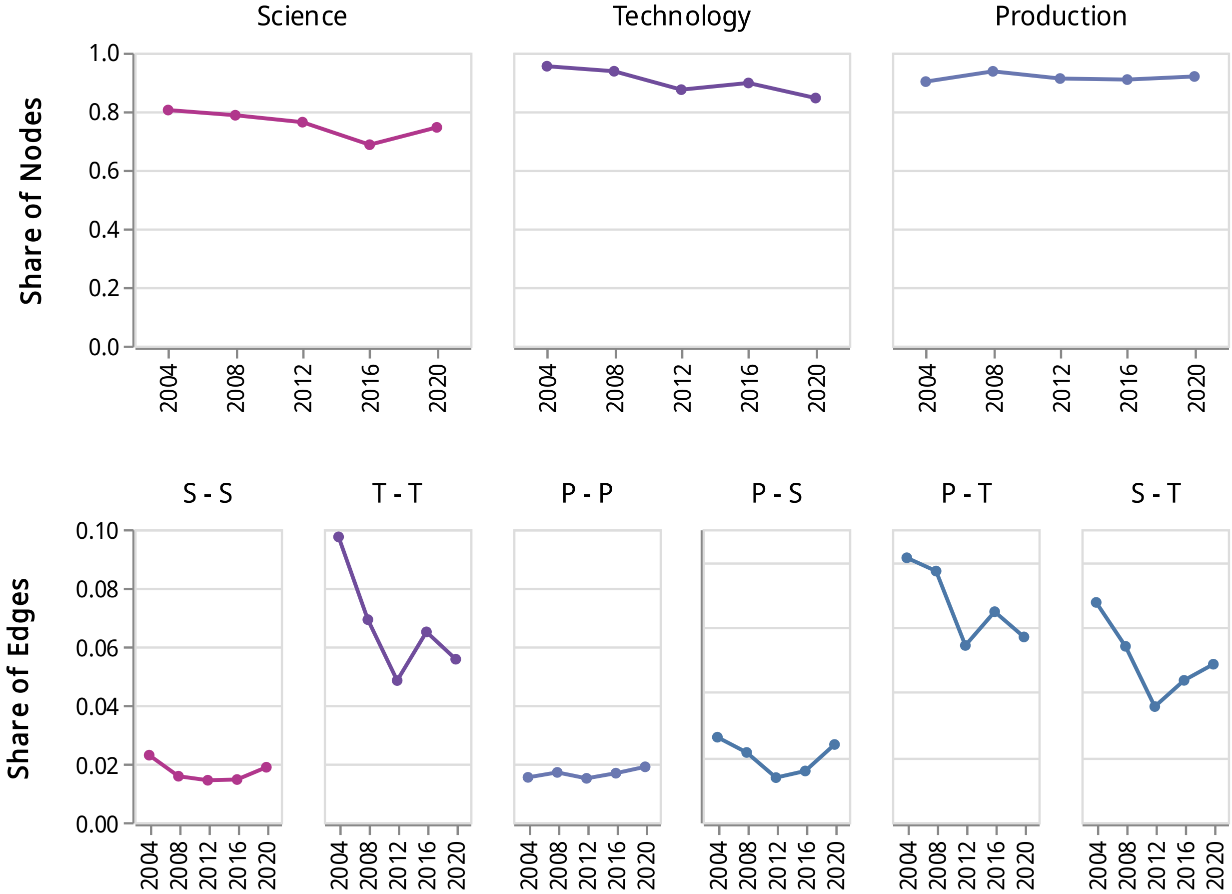


Figure 2. Innovation capability space with most significant connections, 2017-2020. shows the results of this exercise for the 2017-2020 period in which dots represent the fields of innovation that are connected by the filtered edges. In total, 536 fields out of 626 (86%) have at least one significant connection with any other field of innovation. Production is the most

connected dimension, with 92% of its nodes connected, followed by technologies (85%) and science (75%).

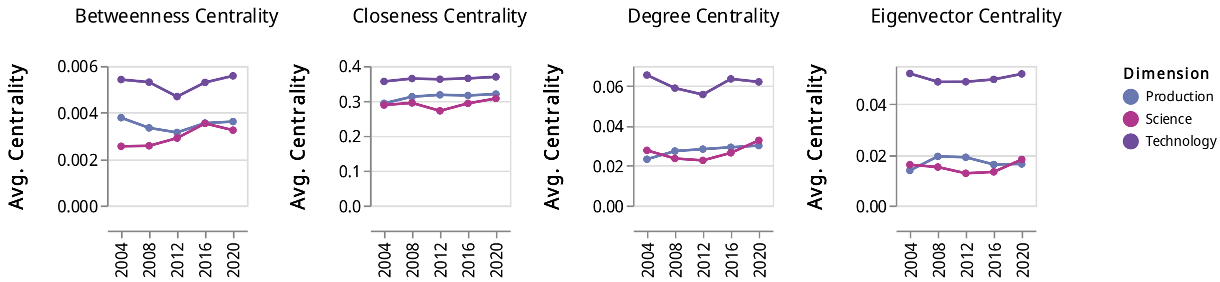
Significant connections show a prevalence of connections within the same dimensions (58% of all edges), led by technology, and followed by science and production. Technology is also the most connected in interdimensional connections, as they are present in 78% of all these types of connections.

Figure 3. Evolution of connected nodes and significant edges, 2001-2020.



The distribution of nodes and edges can be found in Figure 3, with the additional insight that significant connections and nodes vary over time. The Figure shows the evolution of the share of active nodes by dimension, and the share of active edges over all possible combinations of each type of edge. Our results show that technological connections are becoming less common, both within its dimension and with the other two.

Figure 4. Evolution of centrality indicators, 2001-2020.



Despite this downward trend in connectivity, technologies remain at the center of the network. Figure 4 shows that between 2004 and 2020, the network structure remained remarkably stable across all centrality indicators. The technological dimension consistently demonstrated the highest average centrality across degree, closeness, betweenness, and eigenvector measures[5], indicating its role as the core hub of connectivity and influence within the network. In contrast, the production and scientific dimensions maintained lower but increasing centrality values, suggesting their peripheral positioning. The persistence of these patterns highlights a mature and well-defined network structure, with technologies acting as the primary conduit for interaction and influence.

These findings underscore the dynamic nature of innovation ecosystems at the frontier, where the interplay between scientific, technological, and productive capabilities has become increasingly structured and selective over time. While technological connections have declined in relative prevalence, they remain central to the network. The overall network of significant complementarities remains robust, providing a clear map of the most consistent and meaningful linkages between fields. Building on this network, we leverage these proximities to estimate countries' technological potential and explore how well this indicator captures the opportunities and constraints that shape their innovation outputs.

3.4 Defining technological potential

The matrix of pairwise significant proximities between the fields of innovation that result from the previous step is then used to build the bridge between the different dimensions of innovation. These proximities will then allow us to use the innovative outputs of one dimension (science, for instance) to predict the output in another (technologies).

To calibrate the concordance between innovation outputs of different dimensions, we assume that for all the ecosystems in the innovation frontier, the predictions will equal the actual

[5] Degree centrality indicators measure the number of direct connections a node has relative to the network. Closeness, how quickly a node can reach all other nodes. Betweenness, how often a node sits on the shortest path between two other nodes. Eigenvector centrality measures how connected the node's neighbors are—important nodes connected to other important nodes have higher scores.

outputs of every field. The weight factor that corrects the volumes between dimensions is named $\Gamma_{i_m}^{D_n \to D_m}$, which indicates the number of units of D_n that equals one unit of $i_m \epsilon D_m$. Formally:

$$\Gamma_{i_m}^{D_n \to D_m} \sum_{j_n} Output_{j_n}^{D_n} O_{i_m j_n}^{*} = Output_{i_m}^{D_m}, \ \forall j_n \epsilon D_n, \forall i_m \epsilon D_m \quad (8)$$

$$\Rightarrow \Gamma_{i_m}^{D_n \to D_m} = \frac{Output_{i_m}^{D_m}}{\sum_j Output_{j_n}^{D_n} O_{i_m j_n}^{*}} \quad (9)$$

This assumption, by definition, will have, for every field, some ecosystems in the frontier group that are better at transforming their innovative outputs than the average, and others that are worse at doing so. When extending these conversion rates to all countries, the potential number of outputs of a field based on the total innovation outputs of a country in any dimension, for any given ecosystem, can be written as:

$$POT_{i_m,c,t}^{D_n} = E\left(Output_{i_m,c}^{D_m} | Output_c^{D_n}\right) = \Gamma_{i_m}^{D_n \to D_m} \sum_{j_n} Output_{j_n,c} O_{i_m j_n}^{*}, \ \forall c \epsilon C \quad (10)$$

Finally, we use the innovation potential indicator to build two other indicators, expressed as the difference between the potential outputs and the actual outputs of a country in any field of innovation based on its outputs on any other field. When the difference is positive, we name the indicator untapped potential. When its negative, we call it over-realized potential. Formally:

$$UTP_{i_m,c,t}^{D_n} = POT_{i_m,c,t}^{D_n} - Output_{i_m,c,t} \quad if \quad POT_{i_m,c,t}^{D_n} - Output_{i_m,c,t} > 0, \ else \ 0 \quad (11)$$

$$ORP_{i_m,c,t}^{D_n} = POT_{i_m,c,t}^{D_n} - Output_{i_m,c,t} \quad if \quad POT_{i_m,c,t}^{D_n} - Output_{i_m,c,t} < 0, \ else \ 0 \quad (12)$$

These measures leverage the interconnections across scientific, technological, and productive domains to estimate where a country has untapped opportunities—or where it may be exceeding expectations. A positive potential value suggests that a country has the capabilities to expand into a field but has not yet fully realized them (untapped potential), while a negative value indicates that the country is overperforming relative to expectations (over-realized potential).

With this, we establish a systematic approach to identifying both underutilized and exceptionally strong innovation capabilities.

The following section presents the results of this analysis and illustrates how different countries position themselves within the innovation landscape.

4 Results

We examine the relevance and validity of the technological potential indicator by testing three hypotheses related to the relationship between scientific, production-based, and technological outputs. These hypotheses are designed to explore how innovation capabilities in scientific and production dimensions affect technological achievements, how complexity influences these outcomes, and whether more complex ecosystems can better fulfill their technological potential.

Table 1. Panel regression results for technological output growth, using potentials based on science, technology, and production.

	$\Delta_t patents_{c,f}$				
Model	(1)	(2)	(3)	(4)	(5)
$patents_{c,ft-1}$	-2.630 *** (0.011)	-2.649 *** (0.011)	-2.650 *** (0.011)	-2.688 *** (0.011)	-2.575*** (0.013)
β_1 : $potential_{c,f,t-1}$		0.126 *** (0.006)	0.137 *** (0.006)	0.110 *** (0.007)	
$potential_{c,f,t-1}$ x from prod.			-0.015 *** (0.003)	-0.013 *** (0.003)	-0.013 *** (0.003)
$potential_{c,f,t-1}$ x from science			-0.010 *** (0.003)	-0.008 *** (0.003)	-0.008 *** (0.003)
$relatedness\ density_{c,f,t-1}$				0.608 *** (0.014)	0.607 *** (0.014)
β_{1a} : $untapped\ potential_{c,f,t-1}$					0.104 *** (0.009)
β_{1b} : $over\text{-}realized\ potential_{c,f,t-1}$					-0.120 *** (0.012)
time FE / country-field FE	yes / yes	yes / yes	yes / yes	yes / yes	yes / yes
observations	225’848	225’848	225’848	225’848	225’848
R^2	0.479	0.481	0. 481	0.485	0.485

Before testing the first hypothesis, we run a baseline regression OLS model (model 1 in Table 1) where the only independent variable is the lagged logarithm outputs.

The regression results indicate that the coefficient on lagged “log” outputs is significantly negative. This negative relationship reflects diminishing returns to technological output or convergence effects, where countries with initially high output levels experience slower growth, while those starting from lower levels catch up. In addition, a significant negative coefficient is a strong indication of a stationary series, thus avoiding unit root issues[6].

Our first hypothesis suggests that higher scientific and production-based potential leads to improved technological outcomes. To test this, we employed a series of regressions (2 to 4 in Table 1) examining the relationship between scientific and production outputs and technological outcomes, controlling for other variables, such as the relatedness density.

Results show that the potential indicator is a significant contributor to technological output growth. However, its impact is lower when using the predictions that do not come from other technological outputs (variables in rows 3 and 4).

Additionally, the indicator remains significant and with a similar coefficient even when adding other predictors of entry and output growth such as the relatedness density indicator. Relatedness shows a much larger impact (5 times larger), but the potential indicator effect is still informative and does not get absorbed by it.

These results are consistent across innovation ecosystems, whether they belong to the frontier or not (see Annex B). However, the effect of the potential indicator is halved for non-frontier ecosystems and is compensated by a higher importance of the relatedness density indicator.

Model 5 aims to answer the second hypothesis. By splitting the potential between the observations that have untapped potential and over-realized potential, the potential indicator shows how untapped potential tends to affect positively the future outputs, while having an over realized potential has the opposite effect.

Table 2. Panel regression results for technological output growth, and its relation to complexity indicators.

	$\Delta_t patents_{c,f}$			
Model	(6)	(7)	(8)	(9)
$patents_{c,f,t-1}$	-2.688 *** (0.011)	-2.584 *** (0.013)	-2.697 *** (0.011)	-2.567 *** (0.013)
β_1 : $potential_{c,f,t-1}$	-0.011 (0.015)		-0.662 *** (0.043)	
β_{1a} : $untapped\ potential_{c,f,t-1}$		-0.017 (0.048)		-0.195 *** (0.062)
β_{1b} : $over\text{-}realized\ potential_{c,f,t-1}$		0.155 ** (0.064)		-0.723 *** (0.086)

[6] Unit root tests, such as the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP), typically require a larger number of time periods to produce reliable results. With only five time periods available, these tests lack sufficient power, increasing the risk of incorrect inferences (e.g., failing to detect non-stationarity). As a result, alternative diagnostic methods—such as examining autoregressive coefficients or model residuals—were considered more appropriate for assessing stationarity in this context.

relatedness density $_{c,f,t-1}$	0.631 *** (0.014)	0.621 *** (0.014)	0.522 *** (0.015)	0.595 *** (0.014)
capability complexity $_{c,t-1}$	0.268 *** (0.024)	0.286 *** (0.028)		
β_2: *pot* $_{c,f,t-1}$ *x cap complexity* $_{c,t-1}$	0.161 *** (0.020)			
β_{2a}: *cap complexity* $_{c,t-1}$ *x ut pot* $_{c,f,t-1}$		0.158 ** (0.068)		
β_{2b}: *cap complexity* $_{c,t-1}$ *x or pot* $_{c,f,t-1}$		-0.388 *** (0.091)		
ecosystem complexity $_{c,t-1}$			0.871 *** (0.062)	-0.025 (0.045)
β_3: *pot* $_{c,f,t-1}$ *x eco complexity* $_{c,t-1}$			0.993 *** (0.055)	
β_{3a}: *eco comp* $_{c,t-1}$ *x ut pot.* $_{c,f,t-1}$				0.382 *** (0.082)
β_{3b}: *eco comp* $_{c,t-1}$ *x or pot.* $_{c,f,t-1}$				0.784 *** (0.106)
time FE / country-field FE	yes / yes	yes / yes	yes / yes	yes / yes
observations	225848	225848	225848	225848
R^2	0.486	0. 486	0.487	0.486

The third hypothesis suggests that potential in more complex technological outputs is more difficult to achieve. Using the complexity of technological outputs as a measure, we performed regressions (6 and 7 in Table 2) to determine if higher capability complexity affects the effect of the potential indicator.

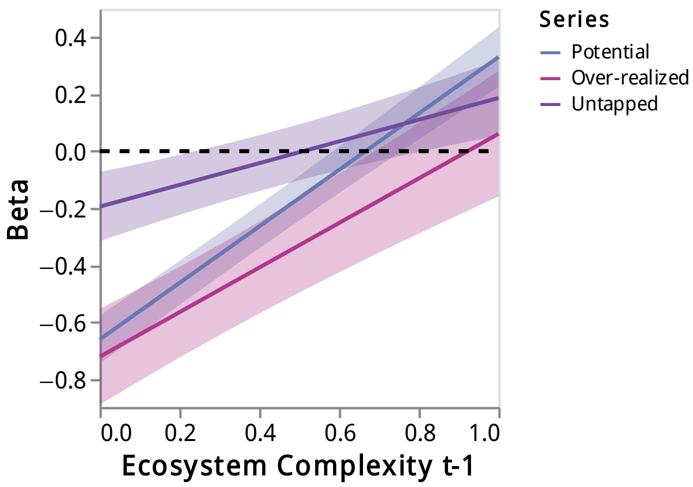
The results of these experiments do not support this hypothesis. The effects of capability complexity over the potential indicator is unchanged from the previous models. It remains positive both for the indicator and for the interaction with capability complexity in model 6, indicating that the overall effect of potential stays positive. In addition, the capability complexity indicator has a positive coefficient, indicating that as complexity of capabilities is higher, so does output growth. This stands also for model 7, but only where potential is untapped, as when there is overachieved potential, the overall effect is negative.

The final hypothesis examines whether more complex ecosystems are better at fulfilling their technological potential. Using the complexity of innovation ecosystems as a measure, we performed regressions (8 and 9 in Table 2) to determine if higher ecosystem complexity affects the effect of the potential indicator.

Results from regressions 8 and 9 support the hypothesis. Model 8 shows that, despite the change in sign on the potential indicator (from positive to negative), the overall effect of potential is reverted for ecosystems on higher complexity levels. Model 9 extends this by slicing the data between untapped and over-realized potentials and shows that for those ecosystems that have untapped potential, the indicator has a positive effect on output growth for more ecosystems, while for those that are over-realizing it, the effect is negative for most.

Figure 5 shows the effect of complexity for these three cases, with a 95% confidence interval. When potential is not discriminated against untapped and over-realized, ecosystems with complexities above 0.597 have a positive effect on their potential. This involves virtually all developed ecosystems and most developing economies (130 of 139). The exception are some African countries (Burkina Faso, Benin, Gabon, The Gambia, Guinea, Madagascar, Mali and Niger) plus Afghanistan. The list of exceptions gets small when considering only untapped potential (Gabon, Gambia, Guinea, Madagascar, Mali and Niger). For those ecosystems that are over-realizing it, the threshold is much higher, as only nine ecosystems (Austria, Finland, Israel, Japan, Republic of Korea, Singapore, Sweden, Switzerland and the United Kingdom) meet the requirement for a small positive effect, although statistically unsignificant.

Figure 5. Impact of Ecosystem complexity on technological potential



In summary, the results confirm the relevance and explanatory power of the technological potential indicator in capturing the dynamics of innovation across countries and sectors. The patterns observed underscore how differences in capability complementarities and ecosystem complexity shape innovation outcomes. Countries that effectively mobilize their scientific and productive strengths tend to realize or exceed their technological potential, while others leave significant opportunities untapped. These findings set the stage for the following discussion, where we interpret these results in greater depth and explore their implications for policymakers, practitioners, and future research. We also outline potential applications of the indicator for identifying strategic priorities and guiding innovation policy.

5 Discussion

This section interprets the key findings presented in the results, highlighting their implications for understanding innovation dynamics across countries and dimensions. By examining the role of technological potential our analysis sheds light on how ecosystems leverage their scientific and productive capabilities to drive technological advancement. We discuss how the strength of relatedness between different fields of innovation, as well as ecosystem complexity, influence a country's ability to fulfill or exceed its potential. Finally, we explore how these insights can inform strategic decision-making and policy interventions aimed at fostering more effective innovation ecosystems.

5.1 The interconnectedness of capabilities

The increasing interdependence of innovation fields observed over time can be attributed to several factors that influence the evolution of well-functioning national ecosystems. As the results show, both the number of significant connections and the number of connected nodes has grown significantly across the 20 years analyzed. This growing interdependence is reflective of several dynamics that shape innovation ecosystems.

First, as global challenges become more complex, solutions often require the integration of capabilities across various domains—science, technology, and production. The increasing number of connections indicates that these capabilities are no longer isolated but rather work in tandem to drive innovation. Over time, the boundary between what constitutes 'scientific,' 'technological,' or 'productive' fields becomes more fluid, as more innovations span multiple dimensions. This convergence is reflected in the greater number of cross-dimensional connections observed in the results, particularly between production and technology, which together form the strongest linkages across ecosystems.

Second, the growth in connections highlights the role of multidisciplinary approaches in modern innovation. Fields that were previously separate, such as those in science and technology, now collaborate more often, facilitating a more integrated and efficient innovation process. As ecosystems mature, their innovation capabilities are increasingly interconnected, fostering the sharing of knowledge and resources across domains. Consequently, the increasing interdependence seen in the data suggests that leading ecosystems are creating networks of innovation that leverage complementary capabilities across dimensions, driving enhanced productivity and technological advancement.

In essence, this evolution points to the growing complexity and synergy within innovation ecosystems, where capabilities are increasingly interdependent, enabling a more efficient and expansive ecosystem of innovation.

5.2 Global patterns of innovation potential

This subsection explores the global distribution and patterns of innovation potential across countries and sectors, as measured by our indicator. By examining both national and sectoral cases, we highlight how different innovation ecosystems convert their scientific and productive capabilities into technological outputs. The analysis uncovers varying degrees of untapped and overachieved potential, illustrating how countries at different stages of development and specialization leverage their existing capabilities. We present key examples that demonstrate how the technological potential indicator captures meaningful differences in innovation trajectories and strategic positioning across the globe.

Figure 6. Technological outputs and potential of Canada by domain, 2017-2020

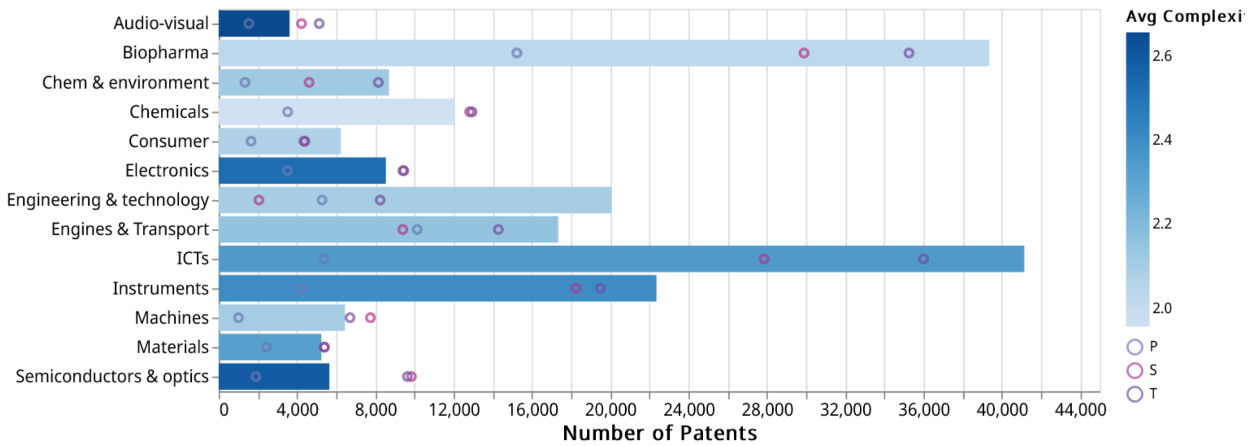
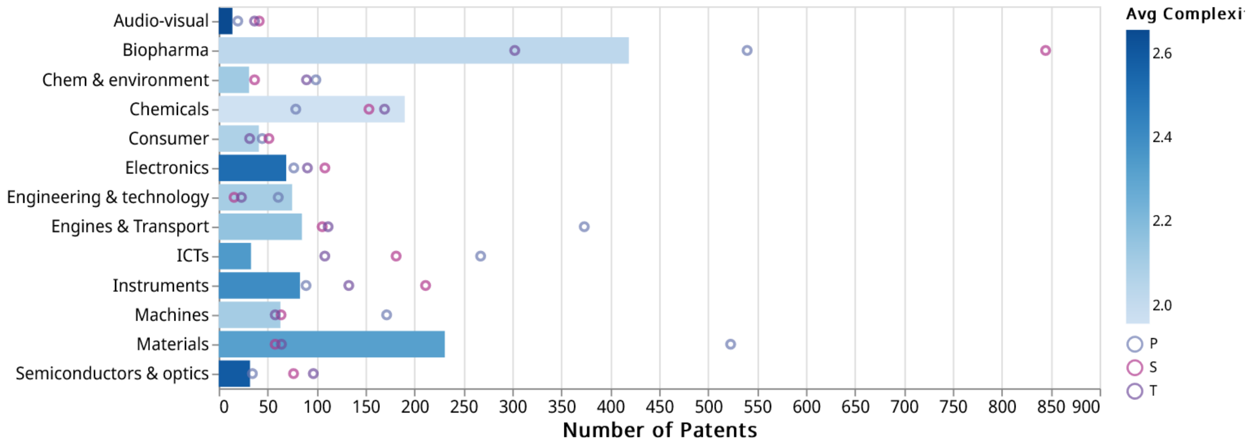


Figure 6 shows the Canadian technological outputs (expressed in bars) alongside its potential (circles) based on its respective scientific publications, exports in goods and services, and patents. As many other medium-sized high-income ecosystems, Canada has untapped potential in many sectors.

For example, given its scientific production, Canada produces half as many patents in audiovisual technologies and two-thirds as many in chemical technologies compared to the average frontier economy. In other sectors, with the same scientific output, Canada produces 16 percent more patents in civil engineering technologies than the average well-functioning national innovation ecosystem.

This insight can be powerful when it comes to identifying missing links between the stakeholders in an innovation ecosystem. By looking into how these dimensions interact in a well-functioning ecosystem policymakers can prioritize between domains and zoom into the relations between academic institutions, industry and the IP system, to identify the particular constraints that are stopping the economy from reaching its full potential.

Figure 7. Technological outputs and potential of Colombia by domain, 2017-2020



Both countries have domains where, based on their scientific outputs, there is untapped technological potential. For Canada, there is room for improvement in three of the most complex domains – audiovisual, electronics, and semiconductors and optics. The average well-functioning national innovation ecosystem would produce more patents if it had the same scientific outputs as Canada. For example, given its scientific production, Canada produces half as many patents in audiovisual technologies and two-thirds as many in chemical technologies compared to the average cluster 1 economy. In contrast, with the same scientific output, Canada produces 16 percent more patents in civil engineering technologies than the average well-functioning national innovation ecosystem.

This insight can be powerful when it comes to identifying missing links between the stakeholders in an innovation ecosystem. By looking into how these dimensions interact in a well-functioning ecosystem policymakers can prioritize between domains and zoom into the relations between academic institutions, industry and the IP system, to identify the constraints that are stopping the economy from reaching its full potential. For less diversified economies such as Colombia technological capabilities are less present at the international scale, and its observed patents are far from reaching their potential. Indeed, Colombia's transformation of scientific publications into international patents is in all fields less than 50 percent of that of the average cluster 1 economy. This is particularly relevant for biopharma and ICTs where Colombia produces a considerable related scientific output but realizes no more than 18 percent and six percent, respectively, of the technological transformation potential.

Figure 8. Technological outputs and potential in engineering and technology by sub-continent, 2017-2020

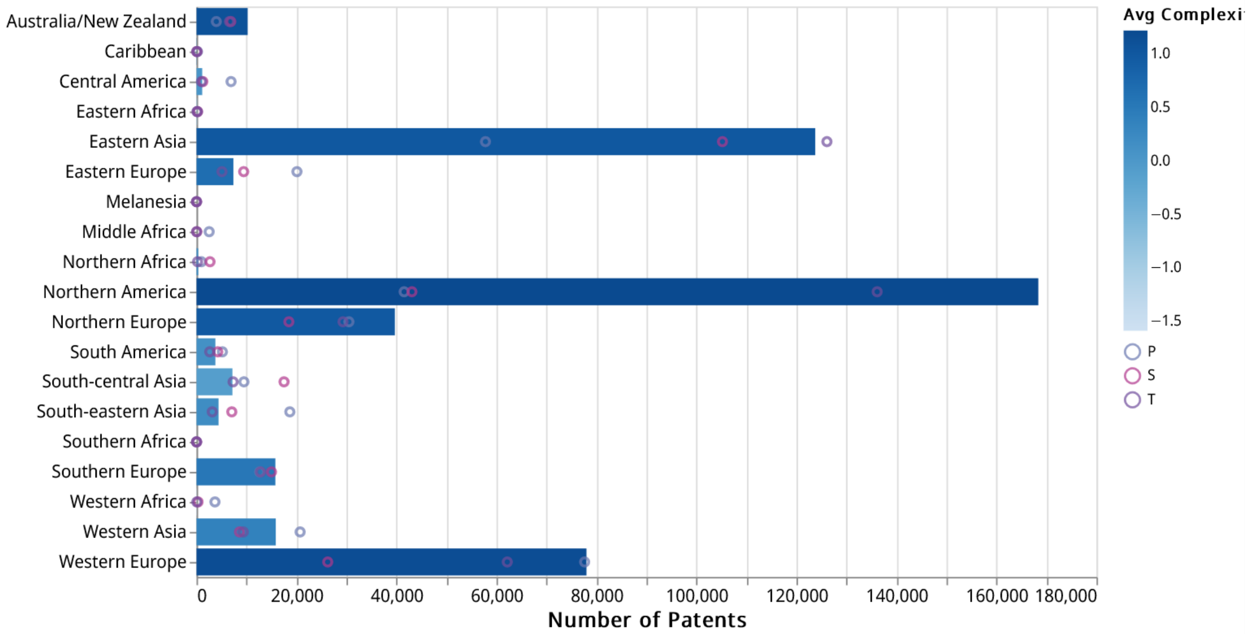


Figure 8 presents the distribution of actual outputs and untapped potential across global regions within the engineering and technology sector. The results highlight significant untapped potential in South Central Asia, Southeastern Asia, and Eastern Europe, where expected technological outputs, based on scientific and productive capabilities, exceed current performance levels. This suggests that these regions possess the underlying capacity to generate more technological outputs but are not yet fully translating their capabilities into tangible technological outputs.

For the private sector and industry stakeholders, this analysis highlights promising regions for investment and collaboration. Companies seeking to expand their R&D footprint or establish partnerships can view these areas as underutilized innovation ecosystems with strong underlying capabilities. By entering these markets early—through joint ventures, research partnerships, or technology licensing agreements—firms can tap into a wealth of scientific knowledge and production expertise that has not yet been fully leveraged. Moreover, identifying regions with high untapped potential allows businesses to anticipate emerging hubs of technological innovation, positioning themselves ahead of competitors in accessing new technologies, talent pools, and market opportunities.

5.3 Implications for developing ecosystems

This section explores how the findings of the study can inform strategies for developing and emerging innovation ecosystems. The insights from the innovation potential indicator, the significant connections across fields, and the global patterns of untapped potential offer practical lessons for policymakers, industry leaders, and ecosystem stakeholders in these contexts.

1. Recognizing and Leveraging Existing Capabilities Through Complementary Linkages

Developing innovation ecosystems often underestimate their existing scientific and production strengths. The innovation potential indicator highlights where countries already have the foundations to expand technological outputs, guiding national strategies toward sectors with the greatest opportunity rather than diluting efforts across too many fields. However, realizing this potential depends on building strong complementarities between science, technology, and production. Encouraging public-private partnerships, innovation hubs, and joint R&D initiatives can foster these cross-sectoral linkages. By bringing together academia, industry, and government, these collaborative platforms accelerate knowledge exchange, bridge institutional gaps, and help translate scientific and technological capabilities into productive outcomes. This integrated approach is especially critical for developing countries aiming to strengthen their innovation systems and move towards more complex, high-value activities.

2. Focusing on Complexity and Coordination

The study shows that ecosystems with higher complexity and better coordination are more successful in fulfilling their potential. Developing ecosystems should focus not only on increasing output volume but also on diversifying and upgrading their technological capabilities.

An important actionable insight is the need to invest in capability-building programs that strengthen the skills base and infrastructure of local industries. Such investments are critical for enabling firms and sectors in developing ecosystems to move into more complex and high-value technological activities. Building human capital through targeted education and training programs ensures a workforce capable of engaging with advanced technologies, while upgrading infrastructure—such as research facilities, digital connectivity, and manufacturing capabilities—provides the necessary foundation for innovation to thrive. These efforts not only enhance a country's ability to develop sophisticated technologies but also improve its position in global value chains, fostering long-term economic growth and competitiveness.

3. Attracting Investment and Industry Engagement

By identifying areas of untapped potential, developing ecosystems can attract foreign direct investment (FDI) and multinational corporations interested in tapping into underutilized knowledge and production bases. Clear evidence of potential can help make the case for investment incentives, technology parks, and incubators.

6 Conclusions

This study sets out to examine whether countries can leverage their existing scientific and productive capabilities to expand their technological outputs and close gaps in their innovation ecosystems. By developing and applying a Technological Potential Indicator grounded in relatedness and complexity metrics, we offer new insights into the global dynamics of innovation. Our analysis shows that the indicator successfully predicts technological output growth and highlights the significance of capability complementarities and ecosystem complexity in determining innovation performance.

One of the key findings is that while countries with untapped potential tend to experience stronger growth in technological outputs, exceeding predicted potential is associated with diminishing returns. This suggests that sustainable innovation growth requires balancing ambition with the underlying capacity of the ecosystem. Moreover, our results show that complex ecosystems—those that combine diverse and sophisticated capabilities—are more effective at realizing their technological potential. This reinforces the importance of building strong linkages between science, technology, and production sectors.

For policymakers, these findings offer a practical framework to identify sectors with high potential for technological advancement, prioritize investments in complementary capabilities, and design policies that foster ecosystem complexity. For industry practitioners, the indicator provides actionable insights into where collaborative efforts, capability-building, and technology transfer initiatives can deliver the highest impact. The indicator can also serve as a tool for targeting public-private partnerships and guiding foreign direct investment toward underutilized innovation opportunities.

In closing, this research contributes to the understanding of how innovation potential can be measured and harnessed to foster balanced and sustainable technological development. Future work can extend this framework by integrating firm-level data or exploring case studies that illustrate successful strategies in bridging gaps between potential and performance.

6.1 Limitations

While this study provides valuable insights into global patterns of innovation potential and technological progression, several limitations should be acknowledged.

First, our analysis focuses exclusively on internationally visible innovation outputs, including exports, scientific publications, and international patent families. While these indicators provide a robust basis for cross-country comparisons and help avoid domestic biases, they do not capture the full extent of innovation activities occurring within national borders. As a result, important domestic innovations, informal technological developments, and regionally significant outputs that are not internationally registered may be overlooked. This limitation is particularly relevant for developing ecosystems, where innovation can take forms that are less visible in global datasets but are nonetheless critical for local development.

Second, the study concentrates on specific types of innovation outputs, primarily those associated with formal scientific and technological activities. This approach excludes other important forms of innovation, such as social innovations, grassroots technological adaptations, and process improvements that may not lead to patents or international exports but significantly impact societal and economic progress. Consequently, the Technological Potential Indicator does not capture the full diversity of innovation processes and outcomes.

Finally, while the use of relatedness and complexity metrics allows us to map innovation capabilities across countries and sectors, these methods rely on the quality and availability of existing data. Data limitations may influence the accuracy of complexity measures and the identification of capability complementarities, especially in countries with less comprehensive reporting systems.

Addressing these limitations in future research—by incorporating domestic innovation data, expanding the range of innovation outputs considered, and improving data coverage—could provide a more comprehensive understanding of innovation potential and its drivers.

6.2 Further research

Building on the findings of this study, several avenues for further research could enhance the methodology and broaden the scope of analysis.

First, future work could extend the analysis to the subnational level, examining regional innovation ecosystems within countries. Many important innovation dynamics occur at the local or regional scale and analyzing these patterns could reveal hidden capabilities and potential that national-level data may obscure. A subnational approach would also allow for more tailored policy recommendations and a deeper understanding of territorial innovation strategies.

Second, methodological improvements can help test the robustness of the Technological Potential Indicator. One avenue is to explore different lag structures in the regression models, which would allow for a better understanding of the time horizons over which scientific and production capabilities translate into technological outcomes. Varying the lags could help determine whether different sectors or regions require more time to realize their innovation potential.

Third, expanding the range of innovation outputs could provide a more comprehensive picture of technological development. Incorporating trademark data as an additional dimension of innovation would complement the existing indicators of exports, scientific publications, and patents. Trademarks capture aspects of innovation related to branding, commercialization, and market differentiation—elements that are especially relevant in sectors like consumer goods and services, which may not be fully reflected in scientific or patent activity.

Finally, future studies could explore alternative complexity and relatedness measures or employ dynamic panel data models to further validate and refine the conclusions presented here. These extensions would strengthen the reliability and policy relevance of the Technological Potential Indicator as a tool for strategic decision-making in innovation policy.

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Annexes

A. Correlation matrix of main variables

	Outputs Change ASINH	Potential LAG1 ASINH	Relatedness LAG1	Capability Complexity LAG1	Ecosystem Complexity LAG1	Untapped Potential LAG1 ASINH	Over-realized Potential LAG1 ASINH
Outputs Change ASINH	1.000	-0.016	0.000	0.018	0.013	0.259	-0.300
Potential LAG1 ASINH	-0.016	1.000	0.739	0.183	0.610	0.293	0.007
Relatedness LAG1	0.000	0.739	1.000	-0.031	0.626	-0.058	0.066
Capability Complexity LAG1	0.018	0.183	-0.031	1.000	-0.003	0.141	0.039
Ecosystem Complexity LAG1	0.013	0.610	0.626	-0.003	1.000	0.093	0.078
Untapped Potential LAG1 ASINH	0.259	0.293	-0.058	0.141	0.093	1.000	-0.221
Over-realized Potential LAG1 ASINH	-0.300	0.007	0.066	0.039	0.078	-0.221	1.000

B. Regression results for high-performing vs non-high performing ecosystems

	$\Delta_t patents_{c,f}$	
Model	(frontier)	(non-frontier)
$patents_{c,f,t-1}$	-2.214 *** (0.023)	-2.802 *** (0.012)
$\beta_{1:}$ $potential_{c,f,t-1}$	0.254 *** (0.012)	0.069 *** (0.008)
$potential_{c,f,t-1}$ *x from production*	-0.011 *** (0.003)	-0.019 *** (0.005)
$potential_{c,f,t-1}$ *x from science*	-0.014 *** (0.003)	-0.010 * (0.006)
$rd_{c,f,t-1}$	0.31 *** (0.014)	0.759 *** (0.041)
time FE / country-field FE	yes / yes	yes / yes
observations	52’192	173’656
R^2	0.382	0.506