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Innovation Convergence

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Abstract

This paper sheds light on convergence of innovation (patenting) using data from two-digit manufacturing industries in 32 countries over the period of 1976-2006. It shows that patenting rates tend to converge over time (patenting growth is faster when initial patents are lower), including within countries (across industries) and within industries (across countries). Notably, the quality (citations and citations per patent) and efficiency (patents per worker) of innovation also exhibit convergence. Convergence is widespread across all countries and industries in our sample, and in all time periods. Country-level data confirms patent convergence continued through 2020. Patent convergence is stronger where financial development, international financial integration, and institutional quality are higher, and under the presence of financial policies supportive of financial liberalization. These factors contribute to both within country (across industries) and within industry (across countries) convergence. The results highlight the importance of financial and institutional environment for the growth of patenting, and ultimately for economic growth and productivity.

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Keywords: Innovation, patents, citations, convergence, financial development, financial openness, institutional quality

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1 Introduction

Economic convergence - the idea that less developed countries should grow faster and catch up with more developed ones - is predicted by many basic models of growth and has been a central empirical question in the growth literature for decades. Innovation and improvement in productivity are essential for sustained long-term growth. Thus, bridging the innovation gap between countries is in principle crucial for convergence. Whether innovative outcomes exhibit convergence, and what contributes to it, remains an unexplored empirical question.

This paper addresses that question. We focus on empirically patenting at a country-industry level, and test for convergence in patenting rates both within and across countries and industries. We proxy innovative outcomes with patent data using the NBER patent database, which covers patents filed in the United States (by applicants worldwide). Our data covers 20 two-digit manufacturing industries from 32 countries over 1976-2006. Thus, convergence in our data implies that country-industry pairs with initially low rates of patenting experience faster growth in patenting. We study both convergence in patenting rates, as well as convergence in patent quality (citations) and efficiency (patents per worker). We also explore the heterogeneity in patent convergence rates based on countries' financial and institutional environment.

We find robust evidence for convergence in patenting. Patent rates converge in general, across industries within a country, and across countries for a given industry. We find evidence of unconditional and conditional convergence. We further show evidence for convergence in patent citations (a measure of aggregate quality of innovation), citations per patent (a measure of the average patent quality), and patents per worker (a measure of efficiency of innovative production). Patent convergence is broad based across all countries and industries in our sample and is robust to various alternative specifications. It is possibly driven both by increasing patenting rates at the low end and by declining patenting rates at the high end. Convergence is also observed in all time periods and is possibly increasing over time. Country-level data confirm that patent convergence has continued up through 2020.

Additionally, we show that patenting convergence is faster with greater levels of financial and institutional development. Higher levels of bank credit, market capitalization, and institutional quality are also associated with higher convergence rates in patenting. Likewise, greater international financial integration and foreign investment predict a higher speed of convergence. Further, policies supportive of financial liberalization seem to be associated with stronger patent convergence. These effects are pronounced both within countries across industries and across countries within industries.

These findings and analysis are novel. We study convergence with country-sector level data, which enables us to simultaneously demonstrate patterns of convergence both across and within countries. This granularity also allows us to control for period-specific shocks to certain countries or certain industries which may impact patenting but be unrelated to long-term convergence. Further, we are the first to study convergence in patenting outcomes. We document a number of important findings related to these, highlighting the heterogeneity in convergence across countries and across industries, as well as the importance of financial and institutional environment to create conditions conducive for increased innovation.

Our findings have important implications for understanding the convergence process. Convergence in patenting implies more than just technological transfer. Patents are necessarily innovations over existing work, so the fact that patent volumes, quality, and efficiency are all converging suggests that low patenting countries are increasingly contributing to the global stock of innovation. Further, convergence within countries indicates that this is not solely driven by, for instance, innovation in advanced countries being off-shored to cheaper labor markets. Indeed, we show that higher patenting rates at the country-industry level are associated with a persistent increase in value added for that country-industry pair. Thus, while frontier patenting seem be to be declining, there is a reason to be optimistic that innovation in the emerging world is yielding new technological advances that may be uniquely produced there, thereby adding to the global stock of knowledge and enhancing global growth.

There is a long literature on convergence to which this paper contributes, both theoretical and empirical. The theoretical literature[1] has expanded to directly consider technological development and the role of technological transfer (Aghion, 2015). Our paper reinforces the need to incorporate an innovation channel in order to better understand the convergence process, but we demonstrate that convergence in innovation goes well beyond technological transfer, as new and higher quality patents are increasingly produced in (initially) lower patenting countries. Aghion, Howitt, and Mayer-Foulkes (2005) incorporates financial development and shows theoretically and empirically that convergence occurs after sufficient financial development. We show that financial development boosts patenting outcomes for low patent countries and industries, providing additional empirical evidence for a link between financial development and productivity/growth.[2]

For the empirical literature, we provide evidence for this innovation channel as an important driver of convergence in growth rates. Rodrik (2013) shows that labor productivity in manufacturing has been unconditionally converging.[3] We add to this showing that

[1] Among many others, see Barro (1997, 2003); Islam (1995); Sala-i Martin (1996); Solow (1956).

[2] Hardy and Sever (2021) show that financial crises have a strong and lasting negative impact on patenting, working through firms' access to finance.

[3] The paper also notes that less developed countries don't exhibit strong convergence in part due to the low share of manufacturing in the economy. Klein and Crafts (2023) similarly finds unconditional convergence in manufacturing labor productivity within the U.S. over 1880-2007, with manufacturing driving overall productivity convergence. In contrast to those papers, Bernard and Jones (1996) find evidence for convergence in services but not manufacturing, using less granular and less recent data.

convergence in patenting rates could explain this pattern, and that research productivity (patents per worker) has also converged. Kremer, Willis, and You (2021) show that more recent data reveal a clear trend towards unconditional convergence, emphasizing the role of convergence in human capital and institutions. Our findings support the importance of strong institutions. Pascual and Westermann (2002) emphasize the importance of evaluating convergence within the same industry in order to have clear comparisons. We provide more depth and insight into a mechanism for the manufacturing convergence picture by uniquely showing converge in innovative activity, documenting this both across sectors and across countries over three decades, and highlighting the convergence in patent volume, quality, and efficiency.

A number of papers examine theoretically and empirically the role of technological diffusion in explaining productivity and growth (Comin & Hobijn, 2010; Eaton & Kortum, 1999; Keller, 2002). Evidence from Xu (2000), Perez-Trujillo and Lacalle-Calderon (2020), and Benhabib and Spiegel (2005) indicates that sufficient human capital and/or institutional development is needed to see technological diffusion lead to productivity growth. Our paper corroborates this by showing that better institutions speed up the patenting convergence process. In congruence with Kugler (2006), which shows that FDI linkages produce productivity spillovers to up or downstream sectors, we find that greater FDI links amplify the patent convergence process. In general, our paper deepens this literature by utilizing more granular industry level data, showing that diffusion alone does not drive patenting convergence, and pointing to the possibility that diffusion may help increase the aggregate stock of ideas and not just the usage of existing ideas.

This paper also contributes to the extant literature on cross-country convergence (as mentioned above) by providing evidence on a potential a channel (i.e. patent convergence) for the observed patterns of income and productivity convergence. The two closest studies to this are Rodrik (2013) and Madsen and Timol (2011). Rodrik (2013) shows that labor productivity in manufacturing industries converges across countries over time. Patent convergence, as shown by this study, provides an underlying mechanism which can give rise to productivity convergence in manufacturing industries, considering the role of innovation in productivity. Madsen and Timol (2011) shows in a long sample of OECD countries that manufacturing productivity has been (unconditionally converging), and is boosted by both domestic R&D (patenting) and international R&D spillovers. Our paper examines specifically the process of patent convergence in order to better understand how patenting is evolving across countries and industries and establish that convergence is occurring beyond what technological transfer would imply.

Finally, several of these papers examine the factors affecting cross-country convergence. In particular, institutions (Acemoglu & Molina, 2021) and financial development (Aghion et al., 2005) have been shown to foster convergence in economic growth. Our findings reinforce those points, and show the role they play for fostering patenting outcomes. We go further to examine more tangible financial policy measures which can support convergence in innovation and thus convergence in productivity and growth.

The rest of this paper is organized as follows. Section 2 explains the data. Section 3 illustrates the stylized facts. Section 4 introduces the empirical methodology. Section 5 documents and discusses the findings. Section 6 concludes.

2 Data

This sections explains the data and the variables. See the Appendix (Table A1) for a brief description.

2.1 Industry level variables

The literature on innovation uses data on patents as a measure of cross-country innovative outcomes (e.g. Acharya and Subramanian (2009); Griffith, Harrison, and Van Reenen (2006); Hardy and Sever (2021); Hsu, Tian, and Xu (2014)). Due to the territorial principle in patenting laws in the US, any company claiming exclusive rights for an invention needs to file the corresponding patent in the US. Since the US has been the largest technology consumption market in the world since decades, the literature assumes that potentially important inventions from countries across the globe have been patented in the US. In this study, we follow this standard assumption, and use the data on patent application filings in the US to proxy for innovative outcomes in a cross-country setting.

Due to the nature of the US Patent and Trademark Office (USPTO) patent data, any patent filed is in principle unique. Thus, if that patent is filed in a country, say, with a low patenting activities, it represents a genuine improvement in technology rather than a mere transfer of existing technology from abroad. That said, as patents build on each other, technological transfer may still play a role in boosting new patents in low patenting countries.

We adopt the NBER patent database which contains detailed information of all patent applications with the USPTO over the period of 1976-2006.[4] Unfortunately, the data is not available for more recent years, restricting the sample period. It includes a number of details for each patent, such as the patent application year, the identity of assignee(s), a three-digit technology class, the number of citations, and a weighting factor for citations (to be described in detail below).[5] The database covers the patents that were eventually granted, but does not contain information on the patents that were filed but not granted afterwards. This

[4]The NBER patent database is available online at `https://sites.google.com/site/patentdataproject/Home`.

[5]Following the literature (e.g. Bravo-Biosca (2007); Hardy and Sever (2021); Hsu et al. (2014)), we do not include patent applications by governments. However, we note that patents by governments are a tiny share of overall patents, and all the results throughout this paper are robust to not excluding them.

measure is useful for our question, as we are interested in examining actual developments in innovation (i.e. output) rather than investment.

In the analysis, we adopt four measures of patenting outcomes, namely the number of (i) patents, (ii) patents per worker, (iii) citations, and (iv) citations per patent. The number of (granted) patent applications provide a proxy for the quantity of innovative outcomes. As with the literature, we calculate the number of country-industry level patents, using the application year instead of the grant year. The reasoning behind this is that the application year is the actual time of innovation, whereas the grant year is subject to procedural delays. As a measure of efficiency, or productivity, of the patent production process, in a separate test, we normalize the number of patents with the number of employees in an industry.

Although the number of patents is a straightforward and intuitive measure, one concern is that it is not able capture the importance, or relevance, of the inventions. To address this issue, our next measure is based on the information on total citations received by all filed patents in a given country-industry submitted in a given year. This is widely accepted as a proxy for the value of the patents by the literature (e.g. Aghion, Van Reenen, and Zingales (2013); Harhoff, Narin, Scherer, and Vopel (1999); Trajtenberg (1990)). Higher number of citations indicates greater market value of the innovative output, considering that many other inventions (i.e. patents) benefit from and make reference to it. Using citation numbers without any adjustment would be problematic though, since patents can receive citations beyond 2006 (the year when the data ends). Therefore, a simple count of citations is subject to truncation bias for patents, particularly for the ones that were filed later in the sample. To correct for this bias, we adjust the number of citations by obtaining the weighting factor in the NBER patent database following the literature. This weighting factor was proposed by Hall, Jaffe, and Trajtenberg (2005) based on the estimation of the shape of the citation-lag distribution. In addition to the total number of citations, the ratio of citations to patents at the country-industry level (i.e. the average citations per patent), is used as a proxy for the average patent quality.

For the purpose of our study, the patenting and citation outcomes are aggregated at the industry level for two-digit manufacturing industries (SIC 20-39). Assigning the individual patents in the NBER Patent database to industries is not straightforward, since the USPTO does not require patent applicants, or examiners, to provide industry (SIC) codes in the documentation of filings. Instead, the USPTO adopts a three-digit technology class system that assigns patents to a technology classification (together with Compustat identifiers for listed firms). To overcome this problem, Hsu et al. (2014) propose a comprehensive approach, based on Kortum and Putnam (1997) and Silverman (2002), by leveraging the distribution of the US listed firms' patent classes. The authors identify patents that were owned by the listed firms in the Compustat database, and then link the each patent's technology class to firms' SIC codes in the database using a weighting scheme. We follow the same procedure to map patents in the NBER database to two-digit SIC codes.[6] This makes it possible to recover the number of patents in each two-digit manufacturing industry (as listed in the Appendix).

The final sample consists of 32 countries with 20 manufacturing industries (SIC 20-39) each, spanning 30 years. Since the use of patenting data in a cross-country cross-industry setting is limited, we highlight a few empirical regularities. Patenting outcomes vary considerably across both countries and industries (Table 1 and Table 2). Advanced economies have relatively large number of patents compared to emerging markets, with the US as the natural outlier. Chemicals, machinery, electronics, transportation, and measuring instrument industries filed the highest number of patents. Tobacco, textile, apparel, wood, and leather industries on the contrary filed little. To mitigate any concerns on the distribution of patents across countries and industries, we examine convergence about different subsamples as robustness. In the analysis, we use the logarithm of one plus the patenting measures,

[6] We thank Xuan Tian for providing the weights on his website.

and calculate annual growth rates as the log difference.

Table 1: *The number of patents per country (thousands)*

Country	Number	Country	Number
Argentina	0.1	Korea	38.8
Australia	9.2	Luxembourg	1.3
Austria	5.7	Malaysia	0.2
Belgium	7.1	Mexico	0.4
Brazil	0.8	Netherlands	19.9
Canada	33.9	New Zealand	1.1
Denmark	5.7	Norway	2.8
Finland	10.5	Poland	0.3
France	64.1	Russia	0.4
Germany	181.0	Singapore	2.2
Hungary	1.7	South Africa	1.1
India	1.5	Spain	2.2
Ireland	1.2	Sweden	21.5
Israel	7.3	Switzerland	30.8
Italy	25.2	UK	49.3
Japan	580.3	USA	1244.6

Notes: The data is from the NBER Patent database. The number of patents is assigned to countries by using the weights as proposed by Hsu et al. (2014).

Table 2: *The number of patents per industry (thousands)*

Industry SIC	Number	Industry SIC	Number
Food (20)	24.7	Rubber Products (30)	31.9
Tobacco (21)	2.0	Leather (31)	0.9
Textile (22)	5.1	Stone Products (32)	34.8
Apparel (23)	2.2	Primary Metal (33)	29.8
Wood Products (24)	4.1	Fabricated Metal (34)	44.1
Furniture (25)	13.0	Machinery (35)	490.3
Paper (26)	68.3	Electronic (36)	531.3
Printing (27)	8.1	Transportation (37)	288.7
Chemicals (28)	419.6	Measuring Products (38)	272.3
Petroleum (29)	62.0	Miscellaneous Manufacturing (39)	18.7

Notes: The data is from the NBER Patent database. The number of patents is assigned to industries by using the weights as proposed by Hsu et al. (2014). Industries are listed with their SIC code in parentheses. For the full industry names, see the Appendix.

In a separate test, we control for the role of for industry size (value added share) in convergence in robustness. Industry value added and worker data are obtained from the UNIDO database.[7]

[7] UNIDO database represents ISIC codes. The concordance table to map those to SIC codes is available at http://unstats.un.org/unsd/cr/registry/regdnld.asp?Lg=1.

2.2 Country level variables

We examine the role of various country-specific variables in patent convergence. We start with various macroeconomic outcome variables and institutional quality. We use bank credit and stock market capitalization as share of GDP from the World Bank's Financial Development and Structure Dataset (FDSD) as proxies for financial sector development. Trade as share of GDP (a proxy for trade openness) and inflation rate (deflator-based) are taken from the WDI database. Finally, a measure of institutional quality, namely the polity score, is adopted from the Polity V dataset by the Center for Systemic Peace. It is the difference between the indexes on institutionalized democracy and autocracy. The polity score is between -10 and 10, higher values indicating stronger institutions.

We next switch to the role of international financial integration in patent convergence. We adopt several proxies for international financial integration from the comprehensive database by Lane and Milesi-Ferretti (2017). The authors compile information on total external liabilities, FDI, portfolio equity, portfolio debt, other foreign investment. These measures indicate the level of financial integration in a de facto manner. We use those variables as shares of GDP.

Finally, we test the role of financial policies in innovation convergence by adopting various measures of financial policy from Abiad, Detragiache, and Tressel (2008). The database focuses an the multifaceted nature of financial policy and provides information on several dimensions (i.e. credit controls, interest rate controls, entry barriers, banking supervision, privatization, international capital controls, and securities markets), as well as a composite index. Credit controls examine directed credit, credit ceilings, and reserve requirements. In the case of interest rate controls, the database assesses, for both lending and deposit rates, whether rates are administratively set, and there are floors, ceilings, or bands for those rates. Regarding entry barriers, it evaluates the restrictions on banks' activities and licensing, the participation of foreign banks, and the geographic area where banks can operate. On banking supervision, the operationalization of the Basel I capital accord, the power and independence of supervisory agency, exemption of some financial institutions from supervisory oversight, and the effectiveness of examinations of banks are covered. For privatization, state-ownership in the banking sector is considered. On international capital controls, restrictions on international financial transactions are evaluated. Finally, for securities markets, the database compile information on the auctioning of government securities, establishment of debt and equity markets, and policies to boost development of these markets, and openness of securities markets to foreign investors. Each of those individual indexes varies between 0 and 3. The overall financial regulation index, which is the sum of the individual indexes, ranges from 0 to 21. Lower values of the indexes indicate greater degree of repression, and higher values represent more liberalization.

As an alternative to the capital flow restrictions, we also gauge the level of financial openness using the index by Chinn and Ito (2006). It is a de jure (regulatory) measure of capital account openness, scaled between -2 and 2, higher values indicating more open financial systems.

In separate analysis, we examine patent convergence at the country level based on the aggregate numbers of patents adopted from the World Bank WDI dataset. These data allows the analysis to extend through 2020. The dataset reports the number of patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office. Similar to the industry-level analysis, we use the logarithm of one plus the patenting. The analysis in this test covers the same countries and the period of 1980-2020, restricted by the availability of data.

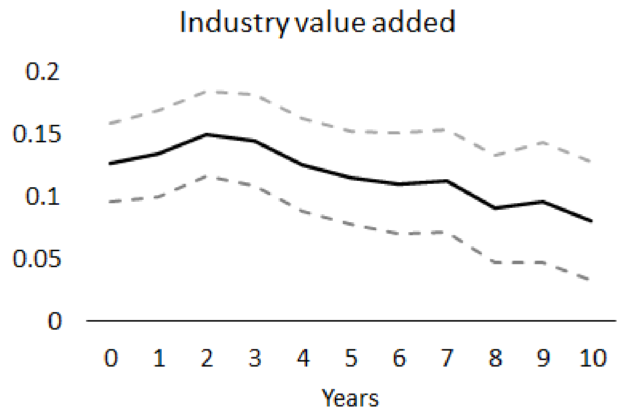
2.3 Sample

The sample covers 20 two-digit manufacturing industries in 32 countries, as listed in Table 1 and Table 2. It consists of 10 emerging markets and 22 advanced economies (as classified by the UN) spanning different geographic regions. The period of the analysis is from 1976 to 2006, restricted by the availability of the patent data, aforementioned. The annual data is transformed into six non-overlapping 5-year periods, i.e. 1977-1981, 1982-1986,... and 2002-2006. The average changes of the innovative outcomes are calculated within each 5-year period. All country-industry-period observations are included in the sample.

3 Stylized Facts

We document whether (i) higher industry's patenting outcomes are associated with industry growth, and whether (ii) there seems to be a convergence pattern in innovative outcomes in the data. Regarding the former, Figure 1 illustrates the relationship between the number of patents and (value added based) industry growth using the local projections methodology Jordà (2005). The positive and statistically significant coefficient estimates suggest that higher patenting outcomes are associated with growth, and this relationship is long-lasting. The coefficient estimate at year 10 (which is 0.08) implies that industry value added remains 0.8 percent higher for upwards of 10 years following a 10% increase in the number of patents. We conclude that greater patenting rates are associated with a persistently higher value added at the industry level.

Figure 1: *Innovation and indsutry value added*



Notes: The results are based on the local projections regressions. The y-axis represent the coefficient estimates (solid lines) and the 90% confidence interval (dashed lines). The x-axis is the years. For more details on the estimation see the Appendix.

Next, we examine whether patent convergence is apparent at first blush in the data. To do so, we compare patent growth in low patenting country-industries (below the median) vs high patenting country-industries (above the median).[8] Higher growth in initially low patenting country-industries implies β-convergence.

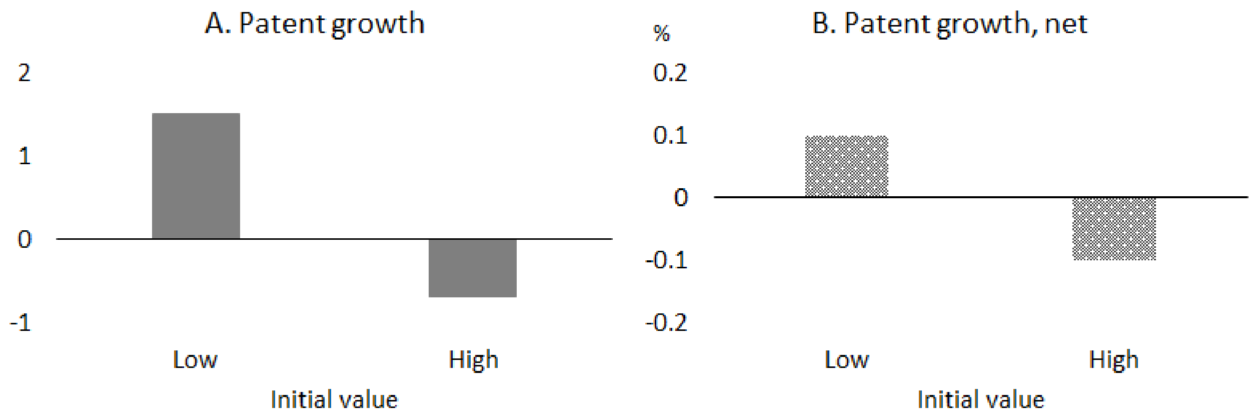
Chart **A** in Figure 2 shows that this is the case. The average growth rate of patenting at the country-industry level is 1.5% per annum for low patenting observations, whereas it is -0.7% for high patenting ones.

In Chart **B**, we document the same, but first remove the average patent growth rate of each industry, each country, and in each year. The negative association between the beginning-of-period patents and its rate of change in the following period remains similar. These indicate that patents grow more rapidly in countries, industries, and periods, where they are low to start with, pointing to convergence across countries and industries

[8]We transform the data into non-overlapping 5-year periods in line with the regression analysis below. Then, we divide the sample into two equal subsamples based on the beginning-of-period value of the number of patents being above or below the median value at the country-industry level. In each subsample, we report the average growth rate of industry patents during the subsequent 5-year periods.

over time. Also note that convergence appears to be driven by both slower growth at the frontier and faster growth at the bottom. Motivated by these, the next section introduces the empirical methodology to examine this phenomenon more formally.

Figure 2: *Innovation convergence*



Notes: **A.** *Non-overlapping 5-year periods are used in line with the regression analysis. The sample is divided into two subsamples based on the median value of the beginning-of-period values of the number of patents. The average growth rate of patents is reported for both subsamples where the initial number of patents is low versus high, based on the median value.* **B.** *The same procedure is applied, but the average growth rate of patents are net of country, industry and year fixed effects.*

4 Methodology

4.1 Industry-level analysis

The goal is to examine whether patenting outcomes converge across countries and industries over time. The annual data is transformed into non-overlapping 5-year periods in line with the standard practice in the convergence literature.[9] The specification is as follows:

$$\Delta\ Patent_{c,i,t} = \beta\ Patent_{c,i,t}\ +\ \theta^1_{c,t}\ +\ \theta^2_{i,t}\ +\ \theta^3_{c,i}\ +\ \epsilon_{c,i,t} \quad (1)$$

where c, i and t stand for country, industry, and period, respectively. *Patent* represents the number of patents. The dependent variable $\Delta\ Patent_{c,i,t}$ is the average annual change

[9]The literature on cross-country convergence adopted this approach, Barro (1997, 2003). It maintains the within-country variation while smoothing out annual variations. It also captures the medium-run dynamics of the outcome variable. As mentioned before, the results are robust to using annual frequency, or non-overlapping 10-year periods, as we show later on.

of the number of patents in each period (i.e. the average of the annual changes between years $t+1$ and $t+5$). $Patent_{c,i,t}$ is the beginning-of-period value (adopted from year t for a period that starts at year t). We also adopt three other measures of innovative outcomes (i.e. the number of patents per worker, citations, and citations per patent). These measures capture distinct aspects of innovation: the volume of innovation (patents), the efficiency of innovation production (patents per worker), the quality of innovation (citations), and the average quality of each innovation (citations per patent).

The specification controls for the effects of three sets of shocks on patenting outcomes. First, country-time shocks that are common across all industries, such as the changes in demand in a given period, can affect patenting. Next, industry-time shocks, such as a shift in global opportunities, can influence incentives for innovation in an industry. Finally, there can be time-invariant factors that are specific to a given industry in a country, which can impact patenting activities. The specification in equation 1 absorbs the influence of all possible combinations of such effects with the inclusion of country-time ($\theta^1_{c,t}$), industry-time ($\theta^2_{i,t}$), and country-industry ($\theta^3_{c,i}$) fixed effects. We also show the results without the fixed effects (i.e. unconditional β-convergence). Standard errors are clustered at the country-industry level. We note that the significance of the results throughout the paper stay virtually the same, if standard errors are clustered at different levels.

In the current setup, convergence in patenting outcomes is captured by β. If there exists convergence, β must be negative, suggesting that patenting tends to grow faster in countries, industries, and periods where it is initially lower (i.e. β-convergence). On the other side, $\beta \approx 0$ means that differences in patenting outcomes do not narrow across countries and industries over time, and $\beta > 0$ indicates divergence (widening gaps across industries and countries).

Since our data is at the country-industry level, convergence could be driven by different countries converging to each other, different industries converging to each other, or both. We adopt two versions of the specification in equation 1 in order to test convergence (i) across industries within each country (equation 2), and (ii) across countries within each industry (equation 3). For the former (latter), we examine cross-industry (cross-country) convergence for each country (industry) separately. The specifications are as follows:

$$\Delta\ Patent^{c}_{i,t} = \beta^{c}\ Patent^{c}_{i,t}\ +\ \theta^{1,c}_{i}\ +\ \theta^{2,c}_{t}\ +\ \epsilon^{c}_{i,t}\ \ \forall c \tag{2}$$

$$\Delta\ Patent^{i}_{c,t} = \beta^{i}\ Patent^{i}_{c,t}\ +\ \theta^{1,i}_{c}\ +\ \theta^{2,i}_{t}\ +\ \epsilon^{i}_{c,t}\ \ \forall i \tag{3}$$

To test cross-industry convergence within each country, we run the specification in equation 2 for 32 countries in the sample. This provides us the estimates regarding the convergence in innovative outcomes across two-digit manufacturing industries for a given country (β^{c}).

Next, to explore whether patent convergence exists across countries within a given industry, we employ the specification in equation 3 for 20 two-digit manufacturing industries separately. This provides us the estimates measuring the extent of convergence in innovative outcomes across countries within each industry (β^{i}).

We also examine whether cross-country cross-industry convergence has been changing over time. For this purpose, we run the specification in equation 4 for each of six non-overlapping 5-year periods separately.

$$\Delta\ Patent^{t}_{c,i} = \beta^{t}\ Patent^{t}_{c,i}\ +\ \theta^{1,t}_{c}\ +\ \theta^{2,t}_{i}\ +\ \epsilon^{t}_{c,i}\ \ \forall t \tag{4}$$

Next, we extend the specification in equation 1 to examine the role of country-specific factors in patent convergence. Although the direct average effect of country level time-varying variables on patenting outcomes are soaked by country-time fixed effects above, those factors may still shape convergence. To capture any such impacts, we add an interaction between the initial number of patents and the beginning-of-period values of several country-specific factors ($X_{c,t}$).[10] These include measures of financial development and other macroeconomic/institutional variables (bank credit to GDP, stock market capitalization to GDP, trade to GDP, inflation, and institutional quality); international financial integration (total external liabilities, FDI, portfolio equity, portfolio debt, other foreign investment); and financial regulation (credit controls, interest rate controls, entry barriers, banking supervision, privatization, capital account restrictions, stock market controls). Those variables help determine what environment and policies facilitate foster convergence in patenting. The specification is as follows:

$$\Delta\ Patent_{c,i,t} = \beta_1\ Patent_{c,i,t}\ +\ \beta_2\ Patent_{c,i,t}\ \times\ X_{c,t}\ +\ \theta^1_{c,t}\ +\ \theta^2_{i,t}\ +\ \theta^3_{c,i}\ +\ \epsilon_{c,i,t} \tag{5}$$

In this setup, the existence and the pace of patent convergence would be determined by a country-specific time-variant convergence parameter $\lambda_{c,t}\ =\ \beta_1\ +\ \beta_2\ X_{c,t}$, discussed in more depth with the results.

Finally, we include this interaction term in the specification in equation 2 and equation 3 to explore the role of country-specific factors in within country (across industries) and within industry (across countries) convergence patterns, respectively. The specifications are as follows:[11]

$$\Delta\ Patent^c_{i,t} = \beta^c_1\ Patent^c_{i,t}\ +\ \beta^c_2\ Patent^c_{i,t}\ \times\ X_{c,t}\ +\ \theta^{1,c}_i\ +\ \theta^{2,c}_t\ +\ \epsilon^c_{i,t}\ \ \forall c \tag{6}$$

$$\Delta\ Patent^i_{c,t} = \beta^i_1\ Patent^i_{c,t}\ +\ \beta^i_2\ Patent^i_{c,t}\ \times\ X_{c,t}\ +\ +\ \alpha^i\ X_{c,t}\ +\ \theta^{1,i}_c\ +\ \theta^{2,i}_t\ +\ \epsilon^i_{c,t}\ \ \forall i \tag{7}$$

4.2 Country-level analysis

We also explore patent convergence at the country-level. The annual data is similarly transformed into non-overlapping 5-year periods. The specification is as follows:

$$\Delta\ Patent_{c,t} = \beta\ Patent_{c,t}\ +\ \theta^1_c\ +\ \theta^2_t\ +\ \epsilon_{c,t} \tag{8}$$

[10] Note that $X_{c,t}$ cannot be included in this estimation separately due to collinearity given the country-period fixed effects.

[11] Note that $X_{c,t}$ cannot be included in equation 6 due to collinearity given the period fixed effects. We note that equation 6 cannot be run for the countries in which the country-specific factor does not have any variation over time. Finally, we note that we add $X_{c,t}$ in equation 7 to avoid omitted variable bias.

where c and t stand for country and period, respectively. $Patent$ represents the number of patents from the World Bank WDI database covering the period of 1980-2020. The dependent variable $\Delta\ Patent_{c,t}$ is the average annual change of the number of patents in a country in each period, and $Patent_{c,t}$ is the beginning-of-period value.

The specification controls for the effects of country-specific time-invariant factors and common period shocks on patent growth by including country (θ_c^1) and period (θ_t^2) fixed effects, respectively. Standard errors are robust to heteroskedasticity.

5 Results

5.1 Main results

Our baseline results are shown in Table 3.[12] Column 1 adopts the number of patents as a proxy for innovative outcome in an industry. Column 2 uses the number of patents per worker to gauge the productivity/efficiency of innovative production. The third column captures the overall quality of innovative output with the number of total citations. And the last column uses citations per patent as a proxy for average patent quality.

The coefficient estimates (β) across these columns are negative and statistically significant at the 1% level, meaning that patenting outcomes tend to grow at a higher pace in countries, industries and periods where they are initially lower. This implies that innovative outcomes tend to converge across countries and industries over time (i.e. β-convergence). This is true for both the quantity (patent), the quality (citations) measures of innovation. The coefficient estimates suggest that convergence is economically significant. The convergence rate of about 12.5% (in the first column) implies that an industry with initially half the number of patents relative to a peer experiences a convergence boost in patents of 8.6 percentage points per annum for the subsequent period ($0.125 \times ln(2)$).

[12] The analysis is based on the data from 20 manufacturing industries from 32 countries, and non-overlapping 5-year periods.

Convergence across each of these measures provides a comprehensive picture of conditional convergence. Country-industry observations have been converging in both quantity and quality of patenting outcomes over the period of our data. Additionally, they have been converging in patents per worker, meaning that low patenting industries are converging not necessarily because they have put more resources into R&D, but because they are getting better at producing new innovations. Further, since all of these patents are registered with the USPTO, each represents an innovation on the existing stock of technology, not (only) a transfer of technology.

Table 3: *Main results*

Variable	Patents	Patents per worker	Citations	Citations per patent
Patent	-0.125***	-0.180***	-0.134***	-0.131***
	(0.017)	(0.060)	(0.014)	(0.015)
Country-time F.E.	Yes	Yes	Yes	Yes
Industry-time F.E.	Yes	Yes	Yes	Yes
Country-industry F.E.	Yes	Yes	Yes	Yes
Countries	32	32	32	32
Observations	3840	2996	3840	3840
R^2	0.936	0.394	0.872	0.755

Notes: The results are based on equation 1. Columns 1-4 use the number of patents, patents per worker, citations, and citations per patent, respectively. The analysis is done at non-overlapping 5-year periods. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Throughput the paper, we use non-overlapping 5-year periods (in line with Table 3), but the results stay similar when the analysis is done using non-overlapping 10-year periods, and at the annual frequency (see Appendix Table A2).

5.2 The set of fixed effects

The analysis above tests convergence by including three sets of fixed effects, i.e. convergence conditional on country-period, industry-period and country-industry factors. This section examines unconditional convergence and which conditions (i.e. which fixed effects) have the biggest impact on measured convergence in patenting. Table 4 illustrates the findings based on the number of patents. Column 1 examines unconditional convergence (no fixed effects). The coefficient estimate is still negative and statistically significant at the 1% level, but its magnitude is smaller. Industries that initially have half of the number of patents relative to their peers see a convergence boost in patents of 1.9 percentage points per year during the subsequent 5-year period ($0.027 \times ln(2)$). This is around $1/4$ of the initial effect found in Table 3, but is still economically important, particularly considering that the median annual growth rate of patenting is 0.8 percent in the sample.

Country-industry fixed effects have the largest impact on the pace of convergence. These fixed effects account for time-invariant factors specific to each country-industry which may affect the growth of patenting and productivity improvements. This means that individual country-industries show marked convergence to their own individual growth path, convergence conditional on their unique context. Therefore, including such unit fixed effects can be important to gauge economically meaningful convergence in a comparable way Acemoglu and Molina (2021). We explore some aspects of the role of this context in section 5.7.

Country-time and industry-time fixed effects, which account for shocks to patenting common to all industries in each country in a given period and to the same industry across all countries in the same year, do not have a large impact on measured convergence. Overall, across columns 2-7, the coefficients imply an economically important convergence boost ranging from 1.4 to 14.3 percentage points.

Table 4: *Different sets of fixed effects*

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patent	-0.027***	-0.206***	-0.018***	-0.019***	-0.123***	-0.170***	-0.023***
	(0.008)	(0.030)	(0.005)	(0.005)	(0.022)	(0.022)	(0.005)
Country-time F.E.	No	No	No	Yes	No	Yes	Yes
Industry-time F.E.	No	No	Yes	No	Yes	No	Yes
Country-industry F.E.	No	Yes	No	No	Yes	Yes	No
Countries	32	32	32	32	32	32	32
Observations	3840	3840	3840	3840	3840	3840	3840
R^2	0.069	0.371	0.719	0.790	0.786	0.860	0.908

Notes: The results are based on equation 1. Columns 1-7 include the corresponding sets of fixed effects. The number of patents are adopted for all regressions. The analysis is done at non-overlapping 5-year periods. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5 documents unconditional convergence for the other three innovation measures. As with the number of patents, the magnitudes decline, however, even in this somewhat "unfair" specification, ignoring country- and industry-specific context, we still observe convergence for patents per worker and total citations.

For the remainder of this analysis, we focus on specifications using the number of patents as our innovative proxy and include all sets of fixed effects, unless otherwise indicated.

Table 5: *Convergence in other proxies in the absence of fixed effects*

Variable	Patents per worker	Citations	Citations per patent
Patent	-0.110***	-0.024***	-0.009
	(0.032)	(0.006)	(0.019)
Country-time F.E.	No	No	No
Industry-time F.E.	No	No	No
Country-industry F.E.	No	No	No
Countries	32	32	32
Observations	2996	3840	3840
R^2	0.104	0.063	0.001

Notes: The results are based on equation 1. The estimation excludes all three sets of fixed effects. Columns 1-3 adopt the corresponding proxy for innovative outcomes. The analysis is done at non-overlapping 5-year periods. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3 Robustness

In the Appendix, we provide a large set of robustness checks to our main results. First, we focus on the industry composition. Table A3 shows that industry outliers patenting intensity, or size, do not drive the results.

Next, Table A4 in the Appendix focuses on the model specification, outcome variables, and industry level controls. It shows that the results are robust to adopting a dummy variable for initially high patenting, using a linear probability model, and allowing for a non-linearities in the response via a squared term. It also demonstrates robustness to defining patent growth and level in terms of distance to the frontier (ie the US growth and level), interacting patent level with the frontier patent level, and interacting the initial number of patents with the initial value added share for that industry.

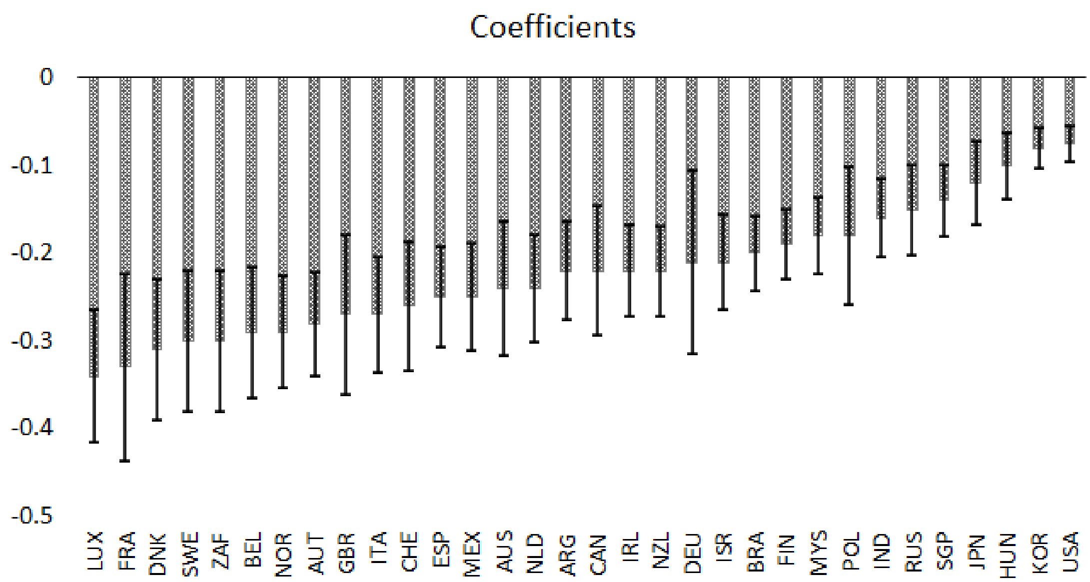
We then run the analysis by excluding either the early periods or the last period of the analysis. The former may be sensible, since some countries have started to apply for patents more heavily in later years of the analysis. The latter is also important, since a patent must be granted to be recorded in the patent database, thereby possibly generating a bias in the last few years of the sample due to the lags between application and granted years (Cornaggia, Mao, Tian, and Wolfe (2015)). Table A5 in the Appendix shows that the results stay similar. We note that the concerns about different periods in the analysis are also explicitly addressed in Section 5.6.

Lastly, Table A6 in the Appendix we examine robustness to different country groups. These results are robust to examining only Europe or excluding Europe (since Europe is a major patenting location), examining just advanced economies or emerging markets, focusing on just Asia or Latin America, and excluding the US.

5.4 Cross-industry convergence within countries

In this section, we explore convergence across industries within each country based on the specification in equation 2. Figure 3 illustrates the coefficient estimates for β together with the 90% confidence intervals from those country-specific regressions. It shows that convergence is statistically significant in all countries in the sample, meaning that within-country convergence across industries is wide-spread. However, the rate of convergence varies considerably across countries. The US, Korea and Hungary have quite low rates of within-country convergence, while Luxembourg and France have higher rates, though measured with some imprecision.

Figure 3: *Convergence across industries within different countries*

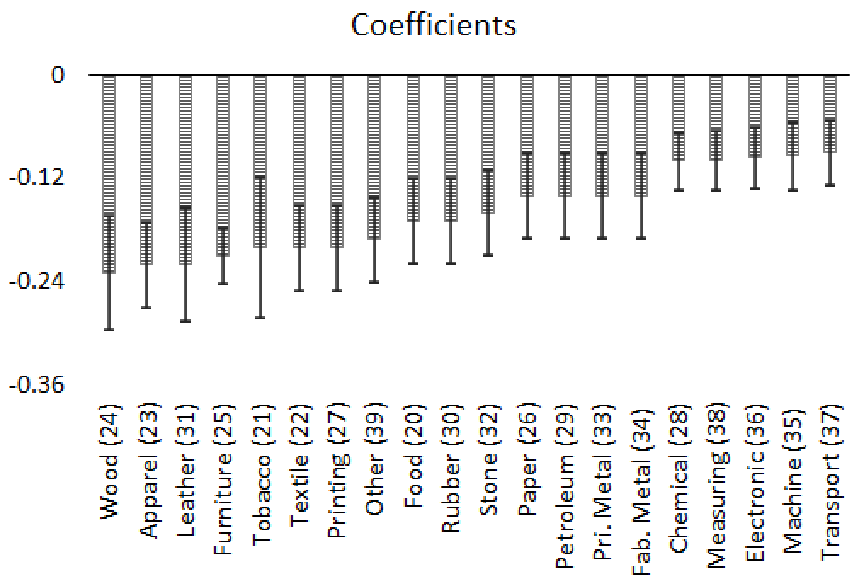


Notes: The figure represents the coefficient estimates for different countries based on the specification in equation 2. All regressions adopt the number of patents. The 90% confidence bands are added. Standard errors in parentheses are robust.

5.5 Cross-country convergence within industries

This section examines convergence across countries within each industry based on the specification in equation 3. Figure 4 documents the coefficient estimates from each regression together with the 90% confidence intervals. The results show that within-industry convergence across countries is also broad-based, and not driven by specific industries. The strength of convergence shows some variation across industries though. In particular, the coefficient estimates in the regressions with transportation, machinery, electronic, measuring products, and chemicals industries seem to be lower compared to the rest of industries.

Figure 4: *Convergence across countries within different industries*

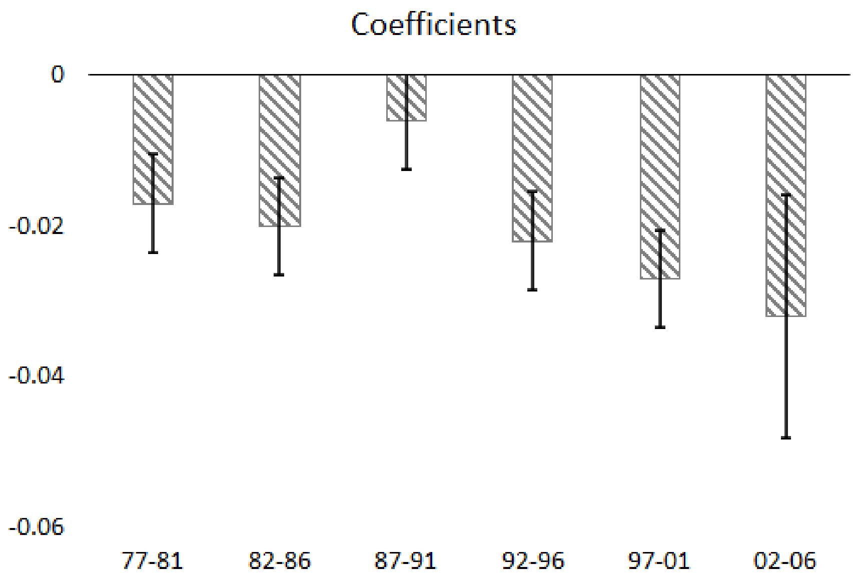


Notes: The figure represents the coefficient estimates for different industries (with SIC codes in parentheses) based on the specification in equation 3. All regressions adopt the number of patents. The 90% confidence bands are added. Standard errors in parentheses are robust.

5.6 Convergence in different periods

In this section, we explore if patent convergence remains similar over the periods of the analysis based on the specification in equation 4. Figure 5 illustrates the coefficient estimates and the 90% confidence intervals. Focusing on the estimates and the confidence intervals, patent convergence is statistically significant for all periods, but is relatively weaker in the third 5-year period (1987-1991). We conclude that there is no specific period in the sample driving our results, and convergence stays pronounced in each period. Further, if one abstracts from the abnormally low convergence in 1987-1991, there seems to be a trend increase in the rate of convergence over time, though not measured with sufficient precision to confirm.

Figure 5: *Convergence in different periods*



Notes: The figure represents the coefficient estimates for different periods based on the specification in equation 4. All regressions adopt the number of patents. The 90% confidence bands are added. Standard errors in parentheses are robust.

5.7 The role of country-specific factors

We now shed light on the role of various country-specific factors ($X_{c,t}$) in patent convergence. We examine them in three sets: macro-financial development, international financial integration, and financial regulation.

In the this set of analysis, convergence is captured by a country-specific time-variant convergence parameter $\lambda_{c,t} = \beta_1 + \beta_2 X_{c,t}$, as mentioned above. Patents exhibit convergence across countries and industries over time, if and only if $\lambda_{c,t}$ is negative. Therefore, for the case where $\beta_1 < 0$, if β_2 is found to be negative, there exists convergence for all levels of the country-specific factor $X_{c,t}$, and the pace of convergence increases as $X_{c,t}$ increases. In other words, higher values of $X_{c,t}$ promotes patent convergence in that case. If β_2 is around zero, this indicates that convergence is not much affected by $X_{c,t}$. Finally, whenever β_2 is positive, both the presence and the rate of convergence depends on the value of $X_{c,t}$. In this case, depending on the relative size of the coefficient estimates (β_1 and β_2), patent convergence can still be pronounced at lower levels of $X_{c,t}$ (as long as $\lambda_{c,t} < 0$). As $X_{c,t}$ becomes larger, convergence becomes negligible (i.e. $\lambda_{c,t} \approx 0$); and eventually turns out to be divergence (i.e. $\lambda_{c,t} > 0$), meaning widening patenting gaps across countries and industries over time.

Table 6 presents the results for macro-financial development, covering bank credit, stock market capitalization, trade, inflation, and institutional quality. The results in the first and second columns in show that more developed financial systems, in terms of the banking sector and stock market size, are associated with faster patent convergence. Trade openness (column 3) and inflation (column 4) do not appear to play a role in patent convergence. The lack of a role for trade is particularly notable, since one may hypothesize that greater trade helps facilitate technological transfer across countries, which would help industries in low patenting countries to improve productivity and progress technologically to a point where it is easier to make patentable improvements. Finally, higher institutional quality is found to predict a stronger convergence process (column 5). These findings imply that as countries take steps to deepen financial markets and strengthen institutions, this can help industries catch up with the innovative activities in more advanced economies.

Table 6 also reports the change in the convergence parameter λ as one moves from the 25th percentile to the 75th percentile of the sample in the corresponding country-specific factor ($\Delta\lambda^{75th-25th}$).[13] It is a useful measure to gauge the size of the impact on convergence of changing each country-specific variable. In the table, positive values indicate higher patenting growth from low initial patents. For instance in column 1, for a country-industry that patents half as much as another, the relative growth of this country-industry's patents relative to that peer would increase by 1.3 percentage points ($0.019 \times ln(2)$) if bank credit to GDP moves from the 25th percentile to the 75th in both countries (i.e. bank lending has a greater impact on patenting growth in low patenting country-industry observations than

[13] It is equal to β_2 multiplied by the gap between the values of the country specific factor $X_{c,t}$ between the 75th and 25th percentiles of the sample.

high patenting ones).

Table 6: *The role of macro-financial and institutional environment in convergence*

Variable	Bank credit	Market capitalization	Trade	Inflation	Institutional quality
Patent	-0.110***	-0.155***	-0.142***	-0.132***	-0.105***
	(0.019)	(0.02)	(0.019)	(0.019)	(0.018)
Patent $\times$ *X*	-0.040***	-0.018**	0.008	-0.005	-0.005***
	(0.011)	(0.009)	(0.011)	(0.005)	(0.001)
Country-time F.E.	Yes	Yes	Yes	Yes	Yes
Industry-time F.E.	Yes	Yes	Yes	Yes	Yes
Country-industry F.E.	Yes	Yes	Yes	Yes	Yes
Countries	32	32	32	32	32
R^2	0.941	0.952	0.940	0.940	0.920
Observations	3680	3120	3640	3640	3760
$\Delta\lambda^{75th-25th}$	0.019***	0.010**	-0.003	0.000	0.013***
	(0.005)	(0.005)	(0.005)	(0.001)	(0.004)

Notes: The results are based on equation 5. Columns 1-5 include the interaction between the beginning-of-period value of the number of patents and the corresponding macroeconomic outcome variable (X). All columns adopt the number of patents. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We dig deeper into the role of financial factors by examining the role of international financial integration and financial policy measures. Financial investment from abroad could boost patenting activity both by increasing financing generally (as shown above in Table 6) as well as by creating incentives for investors to boost returns by facilitating technological transfer or investment in R&D. Arms length lending, such as portfolio or other investment, would favor more the former channel. Table 7 shows that greater overall financial integration, as proxied by total external liabilities as share of GDP, is associated with faster patent convergence (column 1). Column 2 shows the direct investment, which would contribute also to the latter channel, has a significant role in convergence. Columns 3 and 4 suggest that arms length lending in the form of portfolio equity and debt also predict faster patent convergence.

Table 7: *The role of international financial integration in convergence*

Variable	Total external liabilities	FDI	Portfolio equity	Debt	Other investment
Patent	-0.128***	-0.129***	-0.129***	-0.123***	-0.150***
	(0.015)	(0.018)	(0.018)	(0.018)	(0.021)
Patent × *X*	-0.002*	-0.003**	-0.003*	-0.008**	-0.005
	(0.001)	(0.001)	(0.002)	(0.004)	(0.005)
Country-time F.E.	Yes	Yes	Yes	Yes	Yes
Industry-time F.E.	Yes	Yes	Yes	Yes	Yes
Country-industry F.E.	Yes	Yes	Yes	Yes	Yes
Countries	32	32	32	32	32
R^2	0.940	0.940	0.940	0.940	0.955
Observations	3660	3660	3660	3660	2680
$\Delta\lambda^{75th-25th}$	0.001*	0.001**	0.001*	0.004**	0.001
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)

Notes: The results are based on equation 5. Columns 1-5 include the interaction between the beginning-of-period value of the number of patents and the corresponding aspect of international financial integration (X). All columns adopt the number of patents. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

While broader factors like institutional quality of financial market development are difficult for policy makers to shift in the shorter term, more tangible financial policy measures may still impact convergence, opening the door for policy action to spur innovation and development. Table 8 shows that convergence is stronger when at lower levels of financial repression (column 1). The negative and statistically significant coefficient estimates in the rest of the columns offer specific windows of opportunity for policy makers: As countries take policy actions to liberalize their banking sector, securities markets, and international capital movements, patent convergence becomes stronger.

Table 8: *The role of financial regulation in convergence*

Variable	Overall index	Credit controls	Interest rate controls	Entry barriers	Banking supervision	Privatization	Securities markets	Capital controls	Chinn-Ito index
Patent	-0.091***	-0.118***	-0.113***	-0.117***	-0.130***	-0.120***	-0.097***	-0.105***	-0.132***
	(0.023)	(0.019)	(0.022)	(0.021)	(0.018)	(0.019)	(0.026)	(0.021)	(0.017)
Patent × *X*	-0.004***	-0.006**	-0.009**	-0.011***	-0.012***	-0.010***	-0.015***	-0.013***	-0.012***
	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.006)	(0.003)	(0.003)
Country-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countries	31	31	31	31	31	31	31	31	31
R^2	3520	3520	3520	3520	3520	3520	3520	3520	3460
Observations	0.924	0.941	0.942	0.942	0.943	0.942	0.942	0.942	0.943
$\Delta\lambda^{75th-25th}$	0.033***	0.013**	0.009**	0.022***	0.024***	0.020***	0.015***	0.027***	0.025***
	(0.007)	(0.005)	(0.003)	(0.009)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)

Notes: The results are based on equation 5. Columns 1-9 include the interaction between the beginning-of-period value of the number of patents and the corresponding measure of financial regulation (X). All columns adopt the number of patents. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We next take the country-specific factors as shown in Table 6, Table 7 and Table 8, and include them in within-country and within-industry regressions (equations 6 and 7). Table 9, Table 10, and Table 11 summarize the results for each set of factors.[14] In row 1, we report the percentage of countries for which the coefficient estimate of the interaction (β_2^c) is negative and statistically significant at least at the 10% level, i.e. the countries in which the corresponding factor is associated with stronger patent convergence (across industries). Likewise, in row 2, we report the percentage of industries, i.e. the industries in which the specific factor predicts stronger patent convergence (across countries).

The results show that most of those factors catalyze both (i) cross-industry convergence within countries; and (ii) cross-country convergence within industries for a large portion of countries and industries, respectively. There are, however, important patterns to mention. The findings of the analyses as shown in Table 9 suggest that financial development

[14]In particular, to explore the role of each of 19 country-specific factors (as represented in Table 6, Table 7 and Table 8) in patent convergence within country (within industry), we run equation 6 (equation 7) for each country (industry) separately. Therefore, the results represented in Table 9, Table 10, and Table 11 are based on $(20 + 32) \times 19 = 988$ regressions.

(both in the form of bank credit and stock market) and stronger institutions facilitate both within country and within industry patent convergence in the majority of cases. Interestingly, although higher trade does not seem to foster cross-country patent convergence within industry, it has a positive in patent convergence across industries within countries. Table 10 illustrates that degree of international financial integration has wide-spread role in patent convergence within country and within industry, particularly for FDI. Finally, Table 11 shows that various policies supportive of financial liberalization have a positive role on patent convergence across countries for a given industry, whereas its role in facilitating within-country convergence seems less broad-based.

Table 9: *The role of macro-financial and institutional environment in convergence within industries and countries*

Explanation	Bank credit	Market capitalization	Trade	Inflation	Institutional quality
Countries (%)	50	72	88	0	69
Industries (%)	75	90	0	0	80

Notes: In row 1, the results are based on equation 6. Columns 1-5 present the share of the countries in the sample for which the interaction term (between the initial number of patents and the corresponding factor) is negative and statistically significant at least at the 10% level. In row 2, the results are based on equation 7. Columns 1-5 documents the share of the industries in the sample for which the interaction term (between the initial number of patents and the corresponding factor) is negative and statistically significant at least at the 10% level. Standard errors are robust.

Table 10: *The role of international financial integration in convergence within industries and countries*

Explanation	Total external liabilities	FDI	Portfolio equity	Debt	Other investment
Countries (%)	78	81	78	53	69
Industries (%)	100	100	85	75	95

Notes: In row 1, the results are based on equation 6. Columns 1-5 present the share of the countries in the sample for which the interaction term (between the initial number of patents and the corresponding factor) is negative and statistically significant at least at the 10% level. In row 2, the results are based on equation 7. Columns 1-5 documents the share of the industries in the sample for which the interaction term (between the initial number of patents and the corresponding factor) is negative and statistically significant at least at the 10% level. Standard errors are robust.

Table 11: *The role of financial regulation in convergence within industries and countries*

Explanation	Overall index	Credit controls	Interest rate controls	Entry barriers	Banking supervision	Privatization	Securities markets	Capital controls	Chinn-Ito index
Countries (%)	42	25	13	65	40	50	22	28	38
Industries (%)	100	100	55	100	100	95	90	85	100

Notes: In row 1, the results are based on equation 6. Columns 1-9 present the share of the countries in the sample for which the interaction term (between the initial number of patents and the corresponding factor) is negative and statistically significant at least at the 10% level. In row 2, the results are based on equation 7. Columns 1-9 documents the share of the industries in the sample for which the interaction term (between the initial number of patents and the corresponding factor) is negative and statistically significant at least at the 10% level. Standard errors are robust.

5.8 Country-level analysis

In this section, we examine patent convergence based on aggregate data from the World Bank. The main advantage of this analysis are (i) to observe whether the results represented in manufacturing industries hold looking at aggregate data, and (ii) to extend the period of the analysis until 2020.[15] Table 12 shows the results for different combinations of fixed effects.

Column 1 shows that patents exhibit convergence conditional on country-specific time-invariant characteristics and common period shocks. However, there is less evidence for unconditional convergence at the country level (column 2). Columns 3 and 4 isolate which conditionality matters by including either country or time fixed effects. We observe that period-specific shocks that are common across countries do not play much role in cross-country patent convergence, but country-specific factors are important to control for to see patent convergence at the country level. There results echo the ones presented in Table 4 regarding the important role of country-specific factors in patent convergence.

An important question is whether convergence continued beyond the 2006 end-date of our industry-level data. Columns 5 and 6 split this regression into pre- and post-2005. Con-

[15] It is, however, worth noting that the coverage of patent applications are different regarding the source. In the NBER data, we cover the patents filed with USPTO, whereas the WDI database provides information on the applications filed through the Patent Cooperation Treaty procedure or with a national patent office, as noted above.

vergence is observed in both periods, confirming that the patent convergence documented thus has continued in recent decades. Further, the rate of convergence appears to be increasing. This evidence thus corroborates that from Figure 5, confirming that convergence has not only continued but may be increasing over time.

Table 12: *Country-level convergence*

Variable	(1)	(2)	(3)	(4)	(5) 1980-2004	(6) 2005-2020
Patent	-0.041***	-0.005	-0.043***	-0.005	-0.041**	-0.107***
	(0.014)	(0.004)	(0.013)	(0.004)	(0.019)	(0.028)
Country F.E.	Yes	No	Yes	No	Yes	Yes
Time F.E.	Yes	No	No	Yes	Yes	Yes
Countries	31	31	31	31	31	31
Observations	234	234	234	234	144	90
R^2	0.439	0.017	0.412	0.060	0.532	0.701

Notes: The results are based on equation 8. Columns 1-4 include the corresponding sets of fixed effects. The number of patents are adopted for all regressions. The analysis is done at non-overlapping 5-year periods. Standard errors in parentheses are robust to heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Conclusion

This paper has documented clear patterns of convergence in patenting outcomes for the manufacturing sector. Convergence in patenting outcomes is broad based, is observed within all countries and industries, and holds both conditionally and unconditionally. Convergence occurs in aggregate patents, in aggregate patent value (citations), and average quality of patents (citations per patent), and in the efficiency of patent production (patents per worker). Better financial development, greater international financial integration, and stronger institutions appear to support the convergence process both within and across countries and industries. We also provide evidence that financial policy can have a role in the speed of the convergence process for patenting.

Our results provide an important view into the ongoing convergence process. Innovation is important for increasing productivity, which is a key element for economic growth (and thus convergence in real output). The fact that convergence occurs within countries is encouraging, as industries previously not known for innovating are doing so at higher rates. However the role of finance and institutions (e.g. rule of law) again has shown to be crucial to support innovation. Research leading to innovative outcomes requires long term investment which often must be financed externally (including by foreign investors), and requires strong support of property rights to ensure a payoff to the effort will be received. Many low patenting countries (i.e. emerging markets) have benefited substantially from improvements in institutions and development of the domestic financial system, and this shows itself also in the evolution of patenting outcomes.

These results are encouraging from a global growth perspective, as this suggests that low patent countries and industries are securing more patents at a high pace, which will allow them to benefit from their investment for a time, and because the additional patenting done adds to the global stock of knowledge and technology. However, there may be some reasons for concern. For instance, our results, while encouraging, could be consistent in part with offshoring of R&D from the rich world to cheaper labor markets, which does not necessarily increase the aggregate productivity stock.

Nevertheless, we show that our results hold within countries as well as across them, so more than offshoring drives this convergence. And finally, convergence in patents per worker means that the R&D process is becoming more efficient in previously low-patenting areas, which could be important for boosting global output and resource efficiency.

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Appendix

Data

Table A1 provides a brief description of the data and the variables. For more details see Section 2.

Table A1: *Variables*

Variable	Explanation	Source
Patents	Number of patents	NBER Patent Database
Patents per worker	Number of patents	NBER Patent Database (and UNIDO)
Citations	Number of total citations	NBER Patent Database
Citations per patent	Number of citations per patent	NBER Patent Database
Value added	Value added share in manufacturing	UNIDO
Employees	Number of employees	UNIDO
Patents (country-level)	Number of patents	WDI
Bank credit	As share of GDP	FDSD
Stock market capitalization	As share of GDP	FDSD
Trade	As share of GDP	WDI
Inflation	Based on GDP deflator	WDI
Polity score	Proxy for institutional quality	Polity V
Total external liabilities	A proxy for international financial integration	Lane and Milesi-Ferretti (2017)
FDI	A proxy for international financial integration	Lane and Milesi-Ferretti (2017)
Portfolio equity	A proxy for international financial integration	Lane and Milesi-Ferretti (2017)
Portfolio debt	A proxy for international financial integration	Lane and Milesi-Ferretti (2017)
Other foreign investment	A proxy for international financial integration	Lane and Milesi-Ferretti (2017)
Overall financial regulation	A proxy for financial regulation	Abiad et al. (2008)
Credit controls	A proxy for financial regulation	Abiad et al. (2008)
Interest rate controls	A proxy for financial regulation	Abiad et al. (2008)
Entry barriers	A proxy for financial regulation	Abiad et al. (2008)
Banking supervision	A proxy for financial regulation	Abiad et al. (2008)
Privatization	A proxy for financial regulation	Abiad et al. (2008)
International capital controls	A proxy for financial regulation	Abiad et al. (2008)
Capital account openness	A proxy for capital account openness	Chinn and Ito (2006)

Manufacturing industries in the sample

The long explanation of manufacturing industries (with two-digit SIC codes in parentheses) is as follows: Food and Kindred Products (20), Tobacco Products (21) Textile Mill Products (22), Apparel and Other Finished Products Made from Fabrics and Similar Materials (23), Lumber and Wood Products, Except Furniture (24), Furniture and Fixtures (25), Paper and Allied Products (26), Printing, Publishing, and Allied Industries (27), Chemicals and Allied Products (28), Petroleum Refining and Related Industries (29), Rubber and Miscellaneous Plastics Products (30), Leather and Leather Products (31), Stone, Clay, Glass, and Concrete Products (32), Primary Metal Industries (33), Fabricated Metal Products, Except Machinery and Transportation Equipment (34), Industrial and Commercial Machinery and Computer Equipment (35), Electronic and Other Electrical Equipment and Components, except Computer Equipment (36), Transportation Equipment (37), Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks (38), Miscellaneous Manufacturing Industries (39).

Local projections regressions

This section explains the local projections methodology used to obtain the association between industry value added and the number of patents, as illustrated by Figure 1. The specification is as follows:

$$VA_{c,i,t+p} = \gamma_p \; Patent_{c,i,t} \; + \; \theta^1_{c,t+p} \; + \; \theta^2_{i,t+p} \; + \; \theta^3_{c,i,p} \; + \; \epsilon_{c,i,t+p}$$

where c, i and t stand for country, industry, and year, respectively. $VA_{c,i,t+p}$ represents the logarithm of industry value added for year $t+p$. The right-hand side variable $Patent_{c,i,t}$ is the logarithm of the number of patents. We include country-year ($\theta^1_{c,t+p}$), industry-year ($\theta^2_{i,t+p}$), and country-industry ($\theta^3_{c,i,p}$) fixed effects. Standard errors are clustered at the country-industry level. Figure 1 report the coefficient estimates for γ_p for the subsequent 10 years (for $p = 0, ..., 10$ with year 0 being the current year), and the 90% confidence interval.

Convergence tested at different frequencies

This section employs the analysis on patent convergence using non-overlapping 10-year periods, and at the annual frequency. Table A2 presents the results. Convergence stays similar when tested at different frequencies.

Table A2: *Convergence at different frequencies*

Variable	10-year periods Patents	Patents per worker	Citations	Citations per patent	Annual frequency Patents	Patents per worker	Citations	Citations per patent
Patent	-0.09***	-0.19***	-0.10***	-0.08***	-0.27***	-0.96***	-0.43***	-0.69***
	(0.01)	(0.06)	(0.01)	(0.01)	(0.02)	(0.09)	(0.02)	(0.02)
Country-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countries	32	32	32	32	32	32	32	32
Observations	1920	1420	19220	1920	18910	14660	18870	18870
R^2	0.96	0.55	0.93	0.85	0.66	0.56	0.56	0.63

Notes: The results are based on equation 1. Columns 1-4 (Columns 5-8) do the analysis using non-overlapping 10-year periods (at the annual frequency). Columns 1-8 use the corresponding proxy for innovative outcomes. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Robustness to industry composition

This section employs robustness checks related to the industry composition. Table A3 illustrates the findings. Column 1 runs a weighted regression where weights are the average number of patents in each country-industry (over the sample period). This approach decreases the influence of industries with lower number of patents in order to mitigate a concern about whether those industries drive the previous results. Relatedly, the second column excludes the 25th percent of industries that have the least number of patents during this period (i.e. five industries with SIC 21, 22, 23, 24, 31). Another potential issue may be that convergence may be driven by the industries that generally apply for lots of patents. To address that, the third column excludes the 25th percent of industries with the highest number of patents during the period of the analysis (i.e. five industries with SIC 28, 35, 36, 27, 38). The results indicate that industries with very high or low number of patents are not the ones driving convergence.

Columns 4 and 5 run the test based on the data from the smaller and larger half of the industries in each country. The reasoning behind this is that large industries may have more resources for innovation, which can boost their patenting outcomes. Moreover, their activities can affect overall productivity in the country, which can in turn influence patenting performance. The results show that convergence is specific to neither larger nor smaller industries.

The last column employs the analysis by winsorizing the growth rate of patents at the 5th and 95th percentile to make sure that several outliers do not drive the findings. The result remains similar.

Table A3: *Industry-related tests*

Variable	Weighted regression	Excluding low patents	Excluding high patents	Smaller industries	Larger industries	Winsorized
Patent	-0.12***	-0.13***	-0.17***	-0.14***	-0.12***	-0.11***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Country-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Countries	32	32	32	32	32	32
Observations	3840	2880	2880	1890	1860	3840
R^2	0.97	0.95	0.94	0.94	0.95	0.93

Notes: The results are based on equation 1. Column 1 runs a weighted regression where the weights are the total number of patents over the sample period. Column 2 (column 3) drops the five industries with the largest (lowest) number of patents over the sample period. Column 4 (column 5) runs the test using the smaller (larger) half of industries in each country, where those are the ones which have average value added share below (above) the country median over the sample period. The last column winsorizes the growth rate of patents at the 5th-95th percentile levels. All columns adopt the number of patents. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Robustness to model specification

We now focus on the model specification, outcome variables, and industry level controls. Table A4 illustrates the results. The first column assigns a dummy variable 1 for the cases in which the beginning-of-period value of patents is high (above the sample median), and 0 otherwise. Column 2, instead, runs a linear probability model, where the dummy variable for the growth rate of patents takes 1 whenever it is above the sample median. The findings still point to convergence.

In the third column, convergence is tested relative to the US, since it is viewed as the technology leader of the world. The dependent variable is the difference between growth rates of patenting in an industry relative to that of the same industry in the US. The initial patenting is also defined in the same way. Hence, this test aims ti explore a slightly different question, namely whether patents in industries that initially have lower patents relative to the frontier tend to grow faster than the patenting in the same industry in the frontier(i.e. the US). Patent convergence stays unchanged.

In the fourth column, we explore, if any, non-linearity in convergence, by adding the squared value of the number of patents into the estimation, and do not find any evidence on that.

In column 5, we account for the role of global patenting trends in convergence. If global shifts, as observed in an industry on the frontier, increase innovative activities of the same industry in other countries that initially have lower number of patents, it can influence convergence. This test also related to the idea of technology transfer. If some industries in the frontier innovate heavily, this can facilitate the knowledge transfer into other countries during the following period, thereby spurring innovation in those, and possibly affecting convergence. To test these phenomena empirically, we proxy for the global patenting using the number of patents in the US industries (and drop the US from the sample). We do not find such evidence.

Finally, the role of industry size in convergence is explored. As mentioned above, larger industries can have more resources for R&D activities, which can let them generate more patents. If an industry is large but has less patents at the first place, such a size effect, rather than low initial patenting, can explain the previous findings. To eliminate this alternative explanation, we include the beginning-of-period value added share of an industry (in total manufacturing), as well as an interaction between this variable and the initial patents. The result in the last column illustrates that this is not the case. Convergence remains similar, even after industry size is accounted for, and size does not seem to play a role in patenting outcomes (neither directly nor through convergence).

Table A4: *Other checks*

Variable	Dummy variable	Linear probability	Distance to the US	Non-linearity	Global patenting	VA share
Patent	-0.03***	-0.36***	-0.12***	-0.13***	-0.16***	-0.13***
	(0.01)	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)
Patent squared				-0.00		
				(0.00)		
Patent × US patents					0.05	
					(0.04)	
Patent × VA share						0.04
						(0.04)
VA share						(0.15)
						(0.10)
Country-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Countries	31	32	31	32	31	32
Observations	3840	3840	3720	3840	3720	3028
R^2	0.91	0.62	0.90	0.94	0.93	0.94

Notes: The results are based on equation 1. Column 1 uses a dummy variable indicating high number of patents on the right-hand side, which takes 1 when the number of patents is above the sample median. Column 2 runs a linear probability model, where the growth rate of patents on the left-hand side takes 1 when it is above the sample median. Column 3 calculates the growth rate and the number of patents as distance to the US. Column 4 adds the squared value of the number of patents. Column 5 includes the interaction between the beginning-of period value of the number of patents in the US and in each industry. Column 6 includes the interaction between the initial value added share and the number of patents, as well as the value added share itself. All columns adopt the number of patents. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Robustness to time-period of sample

This section employs two robustness tests related to the period of the analysis by excluding the pre-1990 period (column 1) and dropping the last 5-year period (column 2). Table A5 shows that the results stay similar.

Table A5: *Robustness to different periods*

Variable	From the 1990s	Excluding the last period
Patent	-0.25***	-0.11***
	(0.02)	(0.02)
Country-time F.E.	Yes	Yes
Industry-time F.E.	Yes	Yes
Country-industry F.E.	Yes	Yes
Countries	32	32
R^2	0.97	0.74
Observations	1920	3200

Notes: The results are based on equation 1. Columns 1-2 run the tests in the corresponding subsamples. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Convergence in different country groups

In this section, we explore convergence in various country groups. Table A6 shows the results. First, one concern is that for European firms, applying for patents at the USPTO may not be as important, since Europe is also a large technology consumption market with its own major patenting office. In columns 1 and 2, we test if such an issue may influence the results, by running the tests in two subsamples consisting of European and non-European countries, respectively.

Next, we examine convergence only in advanced economies (column 3) and emerging markets (column 4). Focusing on regions, columns 5 and 6 employ the analysis using data from Asian and Latin American countries in the sample, respectively. Finally, we drop the USA from the sample, since it is an outlier. The results illustrate that convergence is pronounced within different income and geographical groups, and not driven by the high number of patents in the US. We also note that convergence remains unchanged when we drop a country at a time and use data from the remaining 31 countries.

Table A6: *Convergence in different country groups*

Variable	Europe	Excluding Europe	Advanced economies	Emerging markets	Asia	Latin America	Excluding the US
Patent	-0.17***	-0.12***	-0.17***	-0.11***	-0.11***	-0.22***	-0.12***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	(0.02)
Country-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countries	17	15	22	10	5	3	31
Observations	2040	1800	2640	1200	600	360	3720
R^2	0.96	0.92	0.96	0.89	0.93	0.90	0.94

Notes: The results are based on equation 1. Columns 1-7 run the analysis is the corresponding subsamples. All columns adopt the number of patents. Standard errors in parentheses are clustered at the country-industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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