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The Geography of Blockchain Innovations

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The geography of blockchain innovations[⋆]

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Abstract

We employ patent data to unravel the spatial dynamics and determinants of recent blockchain technological advancements. Our findings reveal four pivotal insights: (1) Lower-income countries exhibit a surprisingly robust propensity for blockchain innovation, diverging from traditional technology development patterns. (2) The 2017 cryptocurrency bubble served as a catalyst, driving heightened enthusiasm and research in blockchain advancements. (3) There are heterogeneous spillover effects in blockchain innovation, with a few leading innovators influencing both peer nations and the broader global landscape. (4) Regulatory environments play a decisive role; countries with lenient cryptocurrency regulations are more inclined to foster blockchain innovations compared to nations imposing strict bans.

Keywords: Blockchain, PATSTAT, Specialization, Diversification, Patent
JEL codes:

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1. Introduction

Since the introduction of Bitcoin and the underpinning distributed ledger technology (DLT) in Nakamoto (2008), Blockchain has emerged as an important technological innovation with the potential to transform several industries. Studies find that blockchain technology's wide-ranging implications can help add USD 1.76 trillion to the global GDP by 2030 (PWC, 2020). Given the transformative potential, it is important to understand the geographic patterns and driving factors behind blockchain technology evolution.

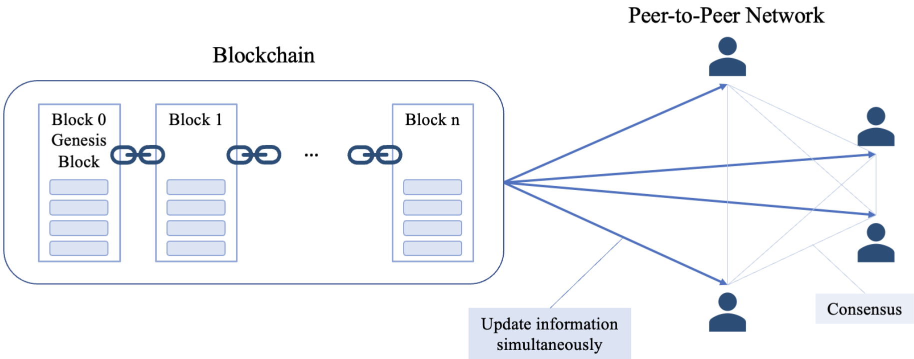


Figure 1: The basic structure of blockchain

Applying blockchain technology benefits businesses across multiple sectors as the decentralised network of blockchain operations ensures trust among the network participants and eliminates the need for a central authority or intermediary. The DLT functions as a shared and secure database where up-to-date information is simultaneously available to all participants (Zhang and Jacobsen, 2018; Zheng et al., 2018; Nofer et al., 2017). As illustrated in Fig. 1, data is structured into "blocks," each block permanently "chained" together through cryptographic and immutable signatures known as "hashes," referencing previous blocks. Notably, any alteration or access to blockchain data is recorded in these hashes. This unique characteristic allows blockchain to increase trust, security, and transparency (Aste et al., 2017). The advantages of blockchain technology applications can transform the future of several traditional industries, including banking, government, and healthcare, through improved data security and operational efficiency.

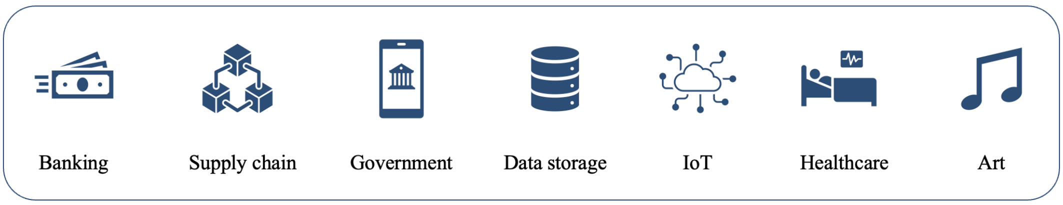


Figure 2: Application of blockchain technology

Originally conceived as the foundational infrastructure for cryptocurrencies, blockchain technology has transcended beyond its initial purpose to applications in other fields. For example, banks use self-executing "smart contracts" with contract terms directly computer-coded onto a blockchain to increase security and convenience in banking-related registrations and transactions (Podmurnyi, 2023). Another example is the integration of blockchain technology in traditional data storage solutions to enhance traceability and digitalization in fields like taxation, resource management, and healthcare (Chakraborty et al., 2017; Setyowati et al., 2020; Tapscott and Tapscott, 2020; Collosa, 2021). The fields with prospective applications of blockchain technology are shown in Fig. 2. In addition, blockchain has paved the way for novel technologies and economic activities, exemplified by the rise of the Internet of Things (IoT) and non-fungible tokens (NFTs) (Borri et al., 2022).

This paper examines the evolution of blockchain innovations across technology fields and geographies. Using patent data, we assess the impact of blockchain innovations across various fields and identify the underlying driving forces. Through a systematic examination of patent data and cross-field impact analysis, our research sheds light on the dynamic interactions between blockchain advancements and innovations in diverse industries, thereby deepening our understanding of the technological landscape and its potential implications for future research and policy-making.

We provide three main contributions to the literature on blockchain technology innovations. First, we use the patent data to study blockchain technology development. Being a nascent form of technology, blockchain is unclassified in most databases. We navigate the data constraint by identifying blockchain-related patents using the methodology in Clarke et al. (2020). We identify the key country players and technology fields in blockchain technology applications using patent data.

Second, we use the revealed technology framework to comprehensively analyse countries' specialisation in blockchain technology applications. Furthermore, we construct the technology space to examine the role of density and divergence of blockchain innovation in facilitating blockchain technology specialisation. Density pertains to the ability of new technological sectors to adopt blockchain technology, given other sectors' existing blockchain technological strengths. Diversity measures the scale of application of blockchain technology across multiple technical fields. While the potential for extensive application of blockchain technology across various domains is evident, a quantitative evaluation of blockchain technology specialisation among countries is missing in existing literature.

In terms of the third contribution, we examine the role of the 2017 cryptocurrency bubble event in enabling blockchain specialisation in the top innovator countries. The study also evaluates the importance of cryptocurrency regulation frameworks in blockchain technology applications.

The remainder of this paper is structured as follows: In Section 2, we discuss the data and outline the method for identifying blockchain patents. This section also encompasses a descriptive analysis of blockchain patenting activity, providing an overview of its evolution. Section 3 presents the construction of measures concerning blockchain technology specialisation, density and diversification, the empirical framework and results. Finally, Section 5 concludes.

2. Data and descriptive analysis

This paper employs the PATSTAT database, a backbone data set for patent statistics research, to conduct a comprehensive analysis of blockchain patents. Published by the European Patent Office (EPO) on behalf of the Organization for Economic Cooperation and Development (EPO, 2022), the PATSTAT database encompasses a vast collection of over 100 million patents from 196 patent offices spanning the years 1782 to 2022. This extensive dataset includes patent bibliographic data, citation information, legal events, inventor, and applicant data, among other crucial details.

However, it is essential to acknowledge that the complexity of data sources introduces challenges regarding data completeness, particularly regarding country codes and technical classifications of patents.

To mitigate the issue of missing information, we adopt the imputation method officially recommended by the EPO, as proposed by de Rassenfosse and Seliger (2021). This approach aids in inferring the absent data points, ensuring a more robust analysis. Moreover, for the Autumn 2022 edition (version 5.20) database version, we refer to the imputation method and results outlined in the technical note by Ge et al. (2022).

Given the ambiguity surrounding the definition of blockchain, it is imperative to accurately identify relevant patents within the PATSTAT database. Although a common practice involves filtering patent titles and abstracts using keywords such as “blockchain” and “bitcoin”, this approach can lead to the inclusion of less related technologies, potentially introducing noise in our analysis. To address this challenge and avoid false positives, we adopt a method proposed by Clarke et al. (2020). This approach combines specifically related patent classifications with carefully selected keywords, which were developed in collaboration with experts and patent examiners from the EPO. By incorporating domain expertise, this method enhances the precision of our patent identification process, ensuring that our analysis remains focused and robust.

Trends in blockchain patent applications:. Fig. 3 illustrates the rising trend in blockchain patent applications. The vertical axis represents the number of patent families by their earliest filing year. From the figure, the growth in blockchain patenting activity has been exponential since 2015, reaching its peak with over 8,000 blockchain patent families in 2020. It is important to note that the decrease in patent applications from 2021 onward is primarily due to low data coverage and does not necessarily imply a decline in blockchain technology advancements.

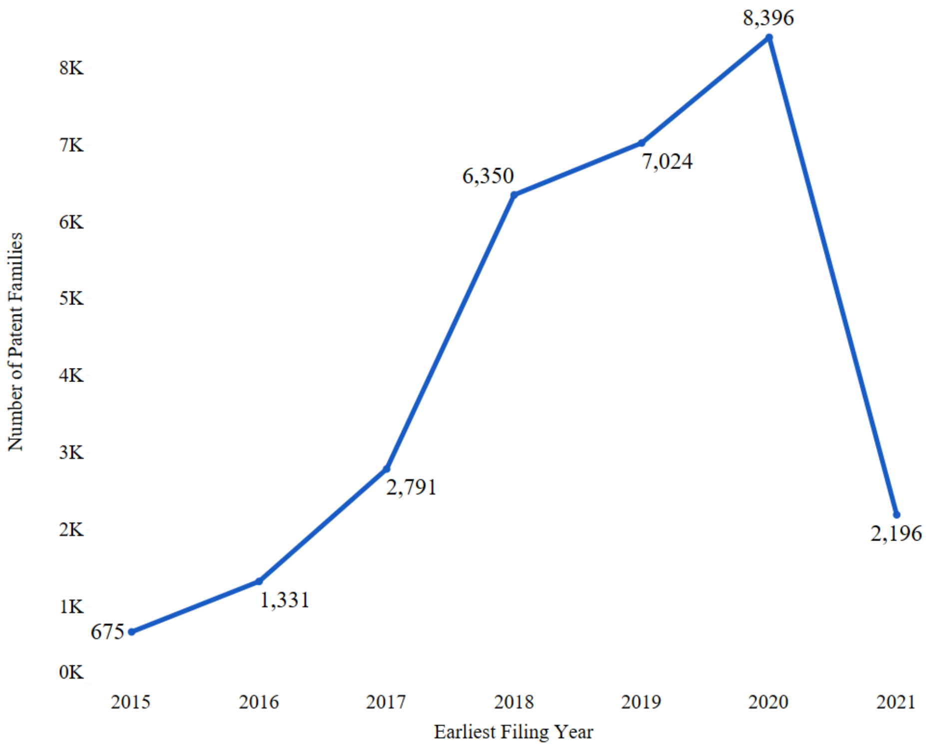


Figure 3: Number of blockchain patent families by earliest filing year

Across the world, we find that blockchain development is concentrated in North America, Europe, and Asia. Aggregating the number of patent families by inventor country code, we present the distribution in Fig. 4. To ensure accuracy and avoid double counting, we count a country only once when multiple inventors reside in the same location. Notably, the United States and China have emerged as two prominent giants in blockchain inventions, contributing 5,439 and 3,025 patent families, respectively. Major OECD countries such as South Korea, Germany, the United Kingdom, and Japan also play prominent roles in the landscape of blockchain innovation. Notably, India demonstrates a comparable level of prowess in blockchain innovation, positioning itself on par with these developed countries. This observation underscores India's rising significance and influence in blockchain technology.

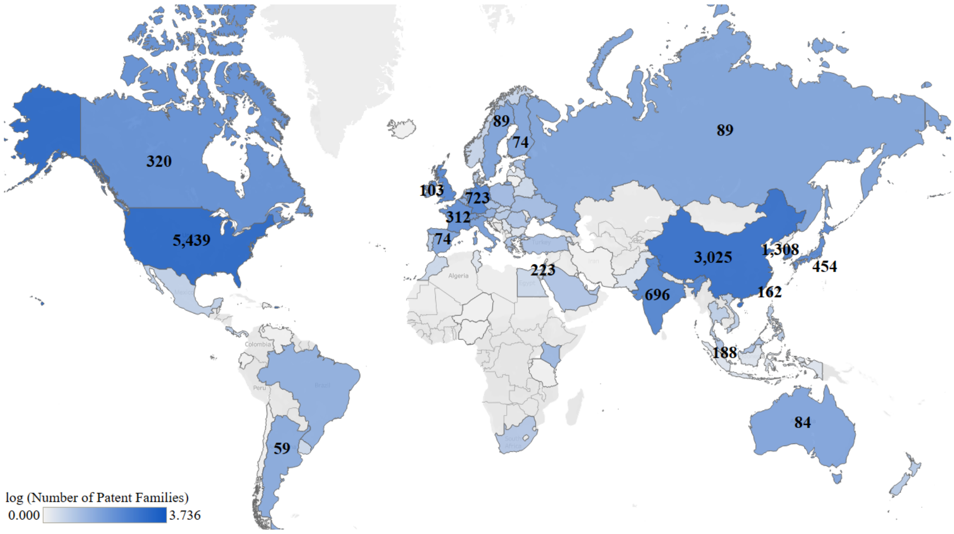
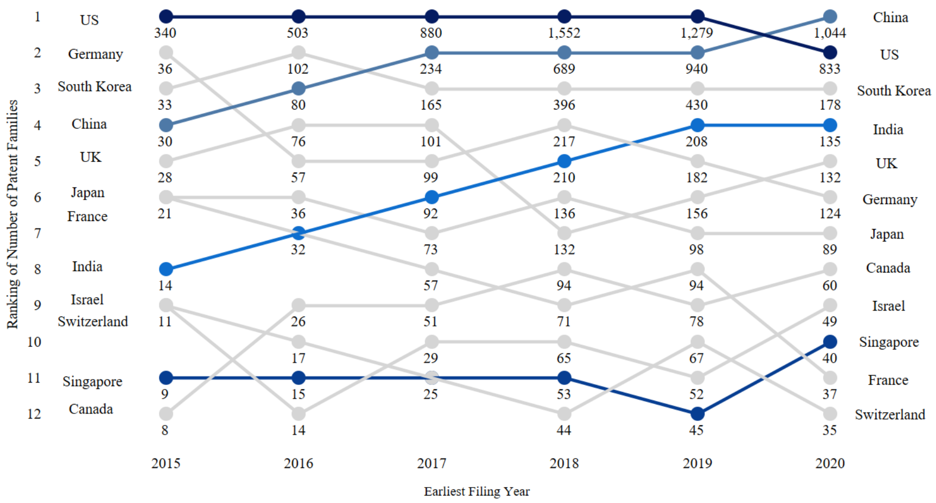


Figure 4: Geographical distribution of blockchain patent families by inventor country (2015-2021)

Referring to Fig. 5, which demonstrates the ranking of the top 12 countries based on the number of blockchain patent families, one can observe that the ranking of the top 12 countries is relatively stable. Notably, China and India stand out with remarkable development from 2015 to 2020.



Note: After 2020, the data is not complete.

Figure 5: Ranking of inventor countries by number of patent families

Turning our attention to the top applicants on a global scale, it is important to note that the applicant of a patent is considered the legal owner of the patent. Fig. 6 provides a comprehensive list of the top 20 players in this regard. The first column displays the names of these applicants, all of which are private companies, with a majority being widely recognized in the world of finance or technology. The second column reveals the headquarters of these companies, with half of them being U.S.-based companies, closely followed by Chinese companies. Furthermore, countries such as the United Kingdom, Switzerland, Germany, South Korea, and Ireland each have one company represented on the list. Despite the Chinese companies being half in number compared to the United States, the number of patent families attributed to them is nearly 1.5 times higher than that of the United States.

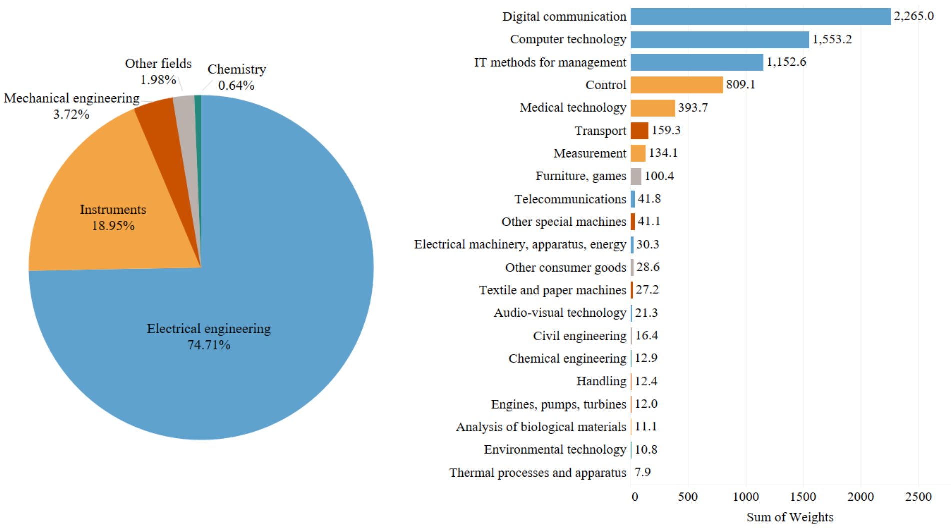
Applicant	Headquarters	Number of patent families
ALIBABA GROUP	China	3230
ADVANCED NEW TECHNOLOGIES COMPANY	United Kingdom	1838
IBM (INTERNATIONAL BUSINESS MACHINES CORPORATION)	United States	872
ALIPAY (HANGZHOU) INFORMATION TECHNOLOGY COMPANY	China	765
PING AN TECHNOLOGY COMPANY	China	669
CAPITAL ONE SERVICES	United States	628
NCHAIN HOLDINGS	Switzerland	422
INTEL CORPORATION	United States	348
MICROSOFT TECHNOLOGY LICENSING	United States	309
SIEMENS	Germany	299
TENCENT TECHNOLOGY (SHENZHEN) COMPANY	China	288
MICRON TECHNOLOGY	United States	283
CISCO TECHNOLOGY	United States	280
MASTERCARD WORLDWIDE	United States	272
HUAWEI TECHNOLOGIES COMPANY	China	270
ONECONNECT	United States	263
VISA INTERNATIONAL SERVICE ASSOCIATION	United States	223
SAMSUNG ELECTRONICS COMPANY	South Korea	194
ACCENTURE GLOBAL SOLUTIONS	Ireland	182
BLACK GOLD COIN	United States	168

Figure 6: Top 20 blockchain invention applicants globally (2015-2021)

Regarding the analysis from a technical field perspective, patents in the PATSTAT database are classified under the World Intellectual Property Organization (WIPO)'s classification, comprising 35 technical fields further aggregated into five technical sectors, namely, "Electrical engineering," "Instruments," "Mechanical engineering," "Chemistry," and "Other Fields" (EPO, 2022). It is important to note that a single patent filing could belong to one or multiple technical fields, and in cases of multiple fields, PATSTAT assigns different weights, where a higher weight indicates a stronger relationship between the application and the technical field. It is essential to maintain a total weight of 1 for each patent application. To analyze the technical constitution of blockchain technology more accurately, we sum the weights associated with each technical field using patent family-level data, thus avoiding duplication issues that could arise at the patent level.

A significant proportion (96.37%) of blockchain patent families belong to the electrical engineering (EE) sector. However, such a high percentage can potentially distort our analysis of cross-sector integration of blockchain technology. Among the 28,726 blockchain patent families, 2,821 (approximately 9.8%) are "hybrid" families, consisting of at least one non-EE technical field. As depicted in Fig. 7, the presence of non-EE technical fields rises drastically, from less than 5% to slightly over a quarter, highlighting the significance of cross-sector applications of blockchain technology.

An analysis of the word clouds of key terms extracted from abstracts shows that data storage and



Note: The pie chart on the left presents the distribution of hybrid blockchain patents across the five technical sectors. The bar chart on the right reports the total sum of weights over the period of 2015-2021 by each technical field. 14 fields with less than 5 total weights are omitted from the bar chart.

Figure 7: Number of hybrid blockchain patent families by technical sectors and fields (2015-2021)

transactions represent blockchain technology's most popular application scenarios in non-EE fields. Fig. 8 highlights frequent occurrences of terms such as "transaction," "payment," "wallet," and "financial," signifying the prominence of transactions as a popular application scenario of blockchain technology. Moreover, terms like "database," "storage," "computing," and "memory" also appear frequently, underscoring another popular application scenario related to data storage. For instance, blockchain technology helps to securely store health insurance account details, game account passwords, and biometric information.

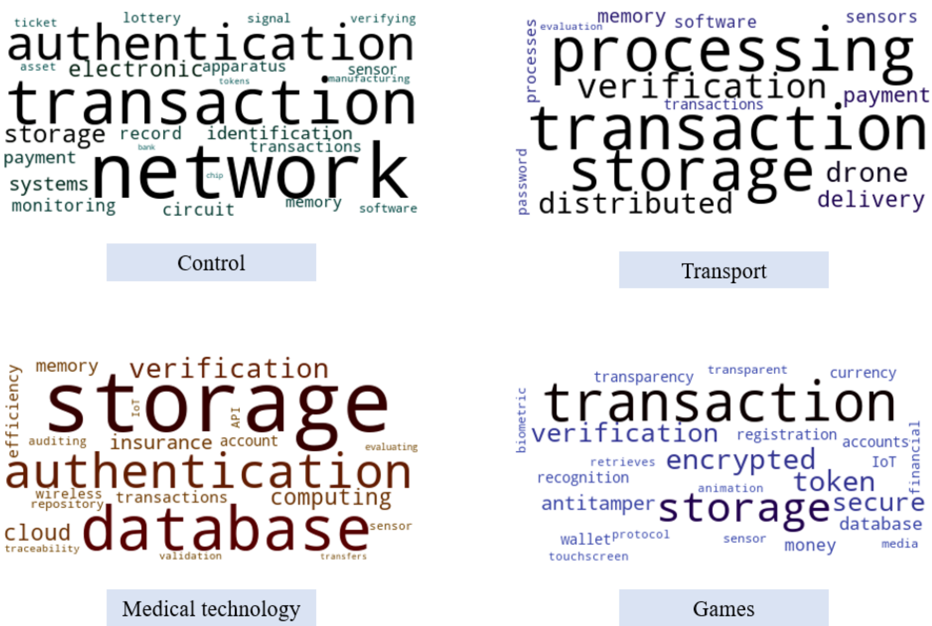


Figure 8: Keywords from the abstracts in non-electrical engineering (non-EE) blockchain patents

Fig. 9 shows the share of blockchain patent families in non-EE fields between two distinct periods, namely, 2015-2017 and 2018-2020. The key players exhibit heterogeneity in the blockchain application evolution. Notably, the United States exhibits the most stable and balanced integration of blockchain technology. India emerges as a fast-growing player, displaying remarkable diversification in its applications. In contrast, Japan appears to focus on integrating blockchain technology with control and transport systems, while China's emphasis lies in applications related to control and medical technology.

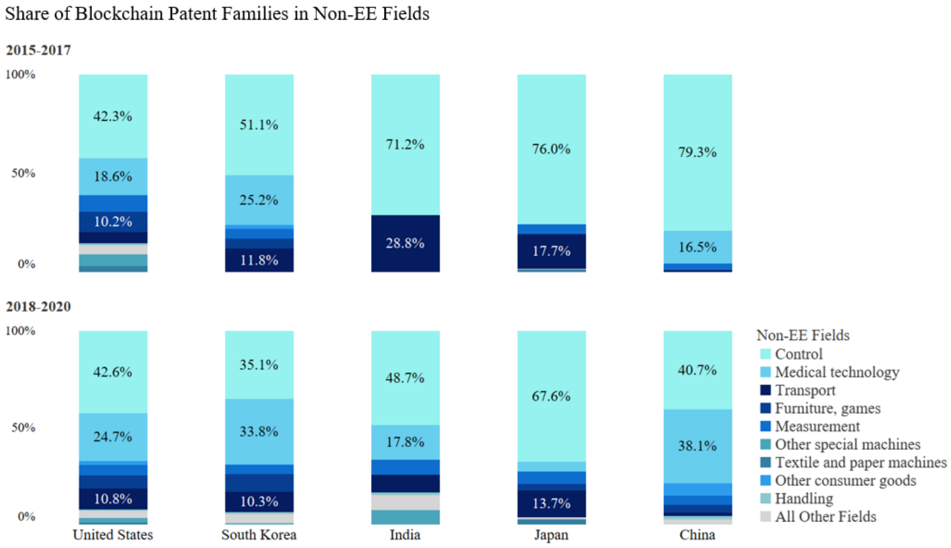


Figure 9: The evolvement in non-electronic engineering (non-EE) fields by inventor country code

3. Empirical framework

With preliminary evidence of country-level heterogeneity arising in the extent of blockchain technology development and its application in other technical fields in Section 2, we use regression analysis to further examine the driving factors of diversification and specialization. We utilise the Revealed Technological Advantage framework to derive the measure of blockchain specialisation and diversification:

$$RTA_{c,j,t} = \frac{Patents_{c,j,t}}{\sum_j Patents_{c,j,t}} \Bigg/ \frac{\sum_c Patents_{c,j,t}}{\sum_{c,j} Patents_{c,j,t}}, \tag{1}$$

where $RTA_{c,j,t}$ is the revealed technological advantage of country c in blockchain applications in technical field j at period t, $Patents_{c,j,t}$ pertains to the number of blockchain patent families. Thus, $RTA_{c,j,t}$ compares country c's share of blockchain patent families in the technical field j to the worldwide share of blockchain patent families across all technical fields.

Specialisation:. $S_{c,j,t}$ is a binary variable that takes the value 1 if country c's revealed technological advantage in blockchain patent family applications ($RTA_{c,j,t}$) exceeds 1 in technical field j at time t and 0, otherwise:

$$S_{c,j,t} = \begin{cases} 1, & RTA_{c,j,t} > 1 \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

In other words, $S_{c,j,t} = 1$ implies country c's specialisation in blockchain technology application in field j at period t since the share of blockchain patent applications exceeds the global average.

Diversification:. Fig. 10 shows that many countries attained blockchain specialisation ($S_{c,j,t} = 1$) in the Electrical Engineering (EE) sector in 2015. Other than established blockchain innovators like the U.S. or China, most countries do not achieve a comparable level of specialisation across non-EE fields in 2020. This motivates further investigation of the diversification patterns of blockchain technology applications.

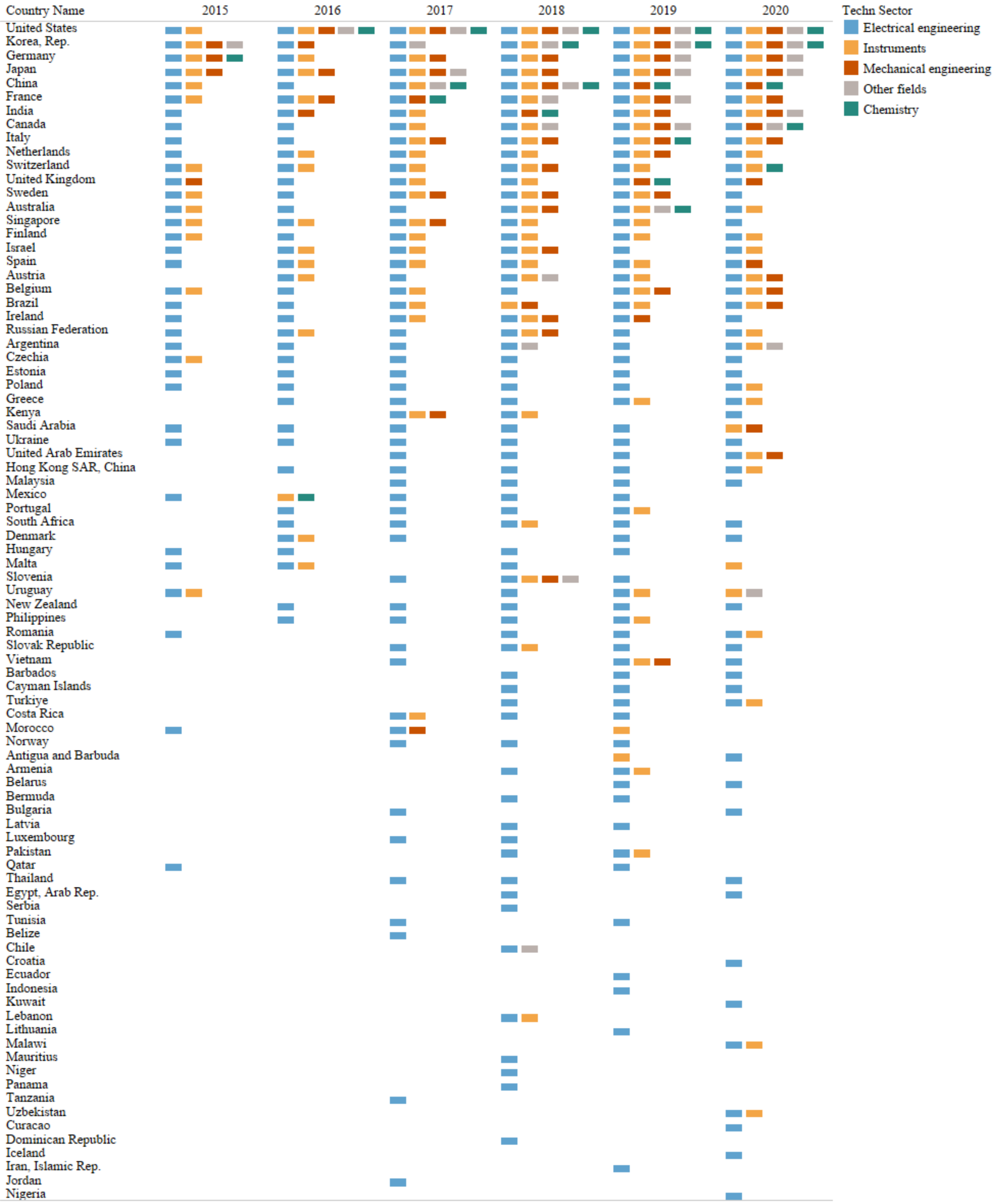


Figure 10: The geographic and sectoral distribution with $RTA > 1$

We identify the diversification of blockchain technologies using an "upgrade event" which pertains to the period t when country c starts diversifying to blockchain technology applications in field j. First, we characterise short-term diversification as cases with blockchain specialisation in the current period while specialisation was absent in the previous period ($S_{c,j,t} = 1$ and $S_{c,j,t-1} = 0$). Second, we characterise medium-term diversification as cases where there was no blockchain technology specialisation at the beginning period of the sample, albeit with specialisation in the current period ($S_{c,j,t} = 1$ and $S_{c,j,2015} = 0$).

Following Perruchas et al. (2020), we estimate two separate probit models to identify the driving forces of diversification and specialization:

Diversification

$$P(S_{c,j,t} = 1, S_{c,j,q} = 0) = \Phi\left(\theta_0 + \theta_1 Density_{c,j,t-1} + \theta_2 Density_{c,j,t-1} \times \log GDP_{c,t} + \theta_3 \log GDP_{c,t} + \theta_4 DIV_{c,t} + \theta_5 DIV \times DIV + \theta_6 \log Size_{j,t} + \theta_7 HI_{j,t} + \theta_8 ITC_{j,t} + \delta_c + \gamma_j + \lambda_t + \epsilon_{c,j,t}\right), \ q \in \{t-1, 2015\}, \tag{3}$$

Specialisation

$$P(S_{c,j,t} = 1) = \Phi\left(\theta_0 + \theta_1 Density_{c,j,t-1} + \theta_2 DIV_{c,t} + \theta_3 DIV \times DIV + \theta_4 \log Size_{j,t} + \theta_5 HI_{j,t} + \theta_6 ITC_{j,t} + \theta_7 \log Size_{j,t} \times DIV_{c,t} + \theta_8 HI_{j,t} \times DIV_{c,t} + \delta_c + \gamma_j + \lambda_t + \epsilon_{c,j,t}\right), \tag{4}$$

where $q = t - 1$ and $q = 2015$ in Eq. (3) refers to the context of short-term and medium-term diversification, respectively. The explanatory variables in Eqs. (3) and (4) are elaborated as follows:

Technological space. Literature shows that existing patent bundles can help to facilitate the establishment of new technological strengths (Perruchas et al., 2020; Acemoglu et al., 2016; Leten et al., 2007). We incorporate this in Eqs. (3) and (4) using the lagged $Density_{c,j,t}$ term corresponding to linkages within a country's technological space on the diversification of blockchain applications. A higher value of $Density_{c,j,t}$ indicates that given the technology field j in year t, country c has strong technical capabilities in j's related fields. $Density_{c,j,t}$ variable is derived using two components: (1) the number of technical fields in which a country holds patent families and (2) the inter-technology relatedness of such technical fields. To measure the inter-technology relatedness, we follow Hidalgo et al. (2007); Neffke (2009) to construct the below relatedness matrix $R_{i,j,t}$ for each pair of technical fields, i and j, covered by blockchain patents in period t:

$$R_{i,j,t} = \frac{N_{i,j,t}}{\sqrt{N_{i,t}N_{j,t}}}, \tag{5}$$

where $N_{i,j,t}$ counts the co-occurrences of technical fields i and j, while $N_{i,t}$ and $N_{j,t}$ count the number of patent families at period t. Consequently, a higher value $R_{i,j,t}$ indicates that technical fields i and j are associated more with the same patent families, indicating a stronger relatedness. However, one must note here that the relatedness of non-EE technologies mostly reflects the patent portfolios of just a handful of technologically advanced countries. The majority of blockchain patents (96.37%) are related to EE. Advanced countries dominate the smaller share of non-EE blockchain patent families (see Fig. 10).

Using $R_{i,j,t}$ in Eq. (5), we capture $Density_{c,j,t}$ as follows:

$$Density_{c,j,t} = \frac{\sum_i R_{i,j,t} X_{c,i,t}}{\sum_i R_{i,j,t}}, \tag{6}$$

where $X_{c,i,t}$ is a binary variable that takes the value 1 if country c patents in blockchain technology i during period t and 0, otherwise. A country with patent families in diverse fields will likely have a high value of $Density_{c,j,t}$. In other words, countries with patent families in every technical field exhibit a $Density_{c,j,t}$ value close to 1. When considering countries with equally diverse patent family portfolios, those characterized by inherently high inter-technology relatedness ($R_{i,j,t}$) exhibit greater density.

Technological distribution. Leten et al. (2007) shows the importance of equitable distribution of technology across different industries as a determinant of technological performance. Technological distribution pertains to the scale of expansion in patent applications to various technology fields. Our empirical specification in Eqs. (3) and (4) accounts for technological distribution using the variable $DIV_{c,t}$, which is defined as:

$$DIV_{c,t} = \frac{1}{\sum_j \left(\frac{C_{c,j,t}}{\sum_j C_{c,j,t}} \right)^2}, \tag{7}$$

where $C_{c,j,t}$ is the count of blockchain patent families in country c within technology field j during period t. A high value of $DIV_{c,t}$ implies that country c has a blockchain technological portfolio distributed almost evenly across many technical fields. The minimum value of $DIV_{c,t}$ is capped at 1, which occurs when all of the country c's patents belong to a single technical field. Fig. 11 visualises the correlation between the country-level diversity, density and GDP per capita averages. Generally, countries with a high level of equitable blockchain technological distribution witness high blockchain technological density, while no discernible pattern is associated with GDP per capita. This reflects a positive relationship between the diversity of blockchain innovation and inter-technological connectivity in its applications, regardless of economic performance.

The effect of $DIV_{c,t}$ on blockchain technology specialisation may not be linear. On the one hand, a diverse and balanced technology portfolio implies great potential to expand innovation capabilities in more fields. On the other hand, not strategically dedicating resources to a few potential technologies could hinder the country from establishing its comparative advantages. To account for a possible non-linear association, $DIV \times DIV$ is also included as an explanatory variable in Eqs. (3) and (4).

Other control variables.

- $ITC_{j,t}$ refers to the Index of Technological Complexity. This variable quantifies the average ubiquity of the technology field j across all blockchain inventor countries.[1] A high $ITC_{j,t}$ implies that the technology field j has a high geographical concentration among a few countries , suggesting that a high entry barrier exists for most countries in the technical field j in period t.

- $\log Size_{j,t}$ is the log of the number of blockchain patent families in the technical field j during period t. This variable accounts for the time-varying volume of blockchain patents in different technical fields.

[1] See Appendix Appendix A for the construction of $ITC_{j,t}$.

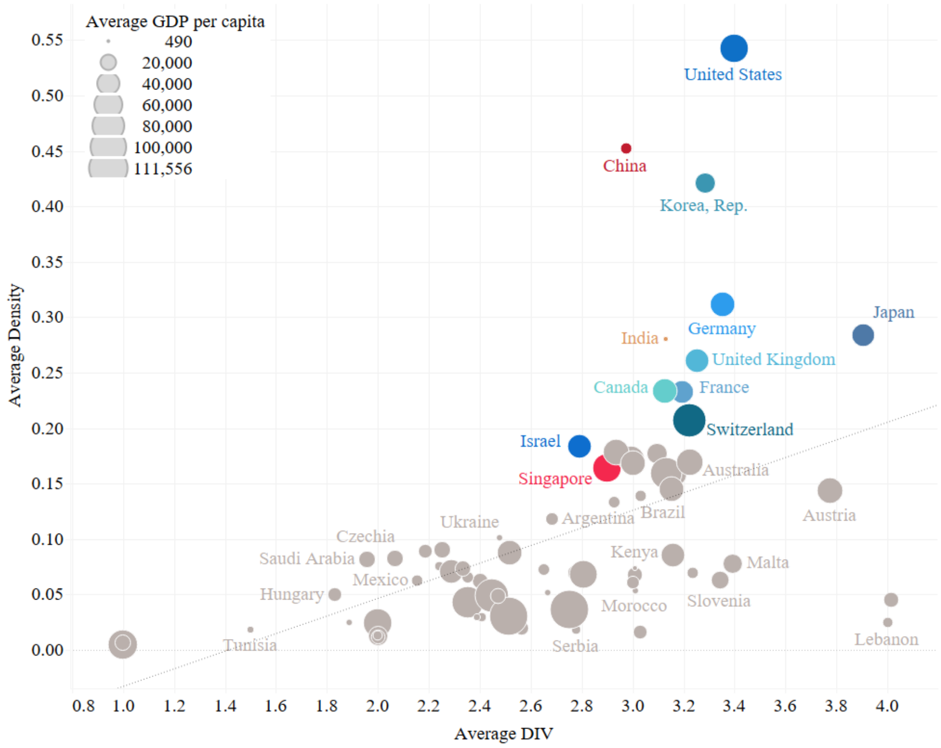


Figure 11: The relationship between average $GDP\ Per\ Capita_{c,t}$, average $DIV_{c,t}$ and average $Density_{c,j,t}$

- $HI_{j,t}$ corresponds to the Herfindhal index that measures the degree of geographical concentration of blockchain patent families within each technical field. $HI_{j,t}$ is defined by:

$$HI_{j,t} = \sum_c \left(\frac{C_{c,j,t}}{\sum_j C_{c,j,t}} \right)^2 \tag{8}$$

- log $GDP\ Per\ Capita_{c,t}$ controls for the country-level economic development in each period. A stronger economy provides solid financial foundations and motivations for technological innovation.

Table 1 shows the summary statistics of all the variables.

Table 1: Summary statistics

	N	Mean	Min	p25	p50	p75	Max	SD
RTA	18060	0.41	0	0.00	0.00	0.00	1054.45	9.17
Density	18060	0.10	0	0.00	0.00	0.08	1	0.21
Log Size	18060	1.62	0	0.00	0.70	2.36	8.33	2.13
ITC	18060	11.61	0	0.00	15.23	18.68	18.86	7.99
HI	18060	0.36	0	0.00	0.28	0.57	1	0.35
DIV	10885	2.39	1	1.85	2.50	2.94	5.26	0.71
GDP	18060	9.55	5.74	8.74	9.67	10.65	11.67	1.24

Fixed effects. δ_c, γ_j and λ_t control for country, tech-field and year fixed effects, respectively.

4. Results

4.1. Baseline results

Table 2: Regression Results

	(1) Diversification (ST)	(2) Diversification (MT)	(3) Specialization
DIV	1.031***	0.596**	2.388***
	(0.350)	(0.298)	(0.357)
DIV × *DIV*	−0.104	−0.0324	−0.173***
	(0.0640)	(0.0564)	(0.0542)
Density	−5.798*	0.727	0.0569
	(3.435)	(1.055)	(0.120)
Log Size	0.297***	0.172**	0.546***
	(0.101)	(0.0867)	(0.0980)
Herfindahl Index	−1.268***	−1.030***	0.878
	(0.217)	(0.180)	(0.642)
ITC	0.365***	0.291***	0.230***
	(0.120)	(0.0471)	(0.0192)
Log Size × DIV			−0.186***
			(0.0200)
Herfindahl Index × DIV			−0.666***
			(0.219)
Density × GDP	0.402	−0.0707	
	(0.336)	(0.103)	
GDP	−1.871***	−1.037*	
	(0.619)	(0.531)	
Observations	8576	8798	9660
Pseudo R-squared	0.428	0.415	0.429

Standard errors in parentheses after accounting for country, year, tech-field fixed effects.
$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table 2 shows the baseline results. Columns (1) and (2) report the estimation results with the probability of short-term and medium-term blockchain diversification, respectively, as the dependent variable. Column (3) shows the results with blockchain specialisation as the dependent variable. First, we discuss the main variables of interest: *DIV* and *Density*. The *DIV* coefficient is positive and statistically significant at 5% confidence interval in all the columns. This implies that countries with blockchain patent families that are more evenly distributed across multiple technological fields are more likely to specialise and diversify in blockchain technology. Although $DIV \times DIV$ is negatively associated with blockchain specialisation and diversification, the coefficient is statistically significant in the context of results on specialisation alone. This is consistent with the findings of Leten et al. (2007), which shows that the probability of specializing in technology tends to increase as technology distribution becomes more equitable but declines after the country has attained a wide portfolio of technological innovations. Fig. 12, shows the relationship between the distribution of the country-level average of blockchain technology distribution and the predicted probability of specialising in blockchain technology using the estimation results of Eq. (4). The marginal effect of the blockchain distribution variable on specialisation increases initially as the value of DIV increases and starts to decline beyond a DIV threshold.

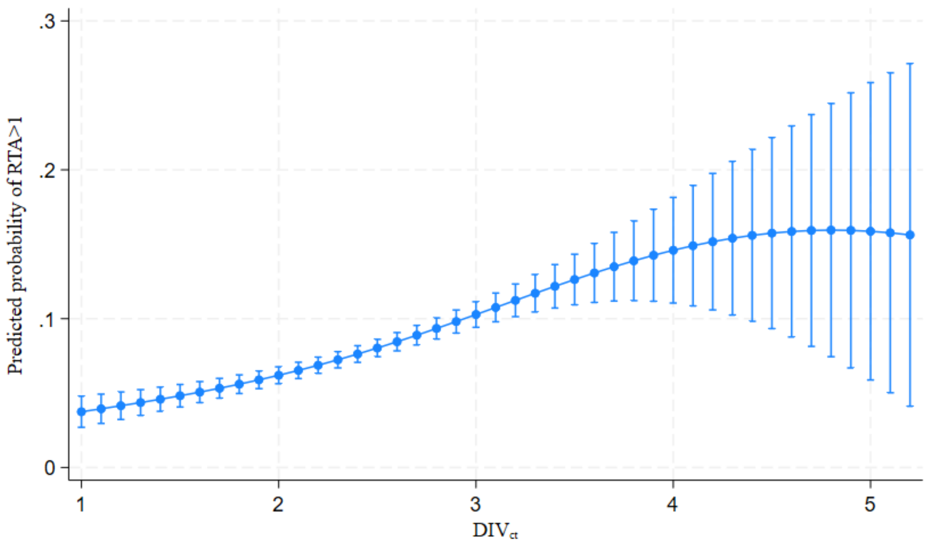
The results also show that *Density* is not an economically significant determinant of blockchain technology performance.[2] This contrasts with findings by Petralia et al. (2017); Perruchas et al. (2020) who highlights the role of technological density in explaining technological specialisation and diversification. We attribute our contradictory results to the limited application of blockchain technology across multiple technical fields, and the relatively short time period since the introduction of blockchain technology. More than a quarter of the blockchain innovations are in the EE field. Also, since the application of blockchain technology is nascent, the time period is not adequately long enough for technological density to emerge as a key determinant of blockchain diversification or specialization.

The results in Table 2 indicate that $Herfindahl\ index$, ITC and *Log Size* as important determinants of blockchain technology performance. The statistically significant and negative coefficient of $Herfindahl\ index$ in columns (1) - (2) indicates that countries with a smaller concentration of blockchain patenting activity are more likely to engage in blockchain technology diversification, both in the short and medium term. In contrast, $Herfindahl\ index$ is not an economically significant determinant of blockchain technology specialisation. Next, the positive and significant ITC coefficient across all three columns implies that technical fields with more entry barriers are likely to witness more blockchain diversification and specialisation. Finally, we also find the existing volume of blockchain patents, *Log Size*, as a positive and statistically significant determinant of the likelihood of blockchain specialisation and specialisation.

The results in column (3) show that the coefficients of the interaction terms *Log Size* $\times$ DIV and $Herfindahl\ index \times DIV$ are negative and significant. This implies that a larger volume of blockchain applications in the same field or a higher concentration of blockchain patenting activity weakens the effect of DIV on blockchain technology specialisation. Thus, although $Herfindahl\ index$ by itself is not a significant determinant of blockchain technology specialisation, it impacts the effect of DIV on the specialisation probability. Figs. 13a and 13b shows the visualisation of the results with darker blue regions corresponding to a higher predicted probability of blockchain specialisation. We can infer from the darker regions that countries with more equitable distribution of blockchain technology applications across technical fields (larger values of DIV) are more likely to achieve specialisation in technical fields with smaller blockchain patent activity volume (*Log Size*) or smaller entry barriers ($Herfindahl\ index$).

The GDP coefficient in Table 2 is negative and significant. This could be explained by the inclination of low-income countries to embrace blockchain technology due to socioeconomic needs and technological opportunities. For example, a significant proportion of the population in low-income countries is unbanked, largely due to inadequate traditional banking infrastructure, trust issues, or prohibitive costs. With its decentralized nature, blockchain offers promising solutions such as decentralized finance (DeFi) for financial inclusion. Additionally, these countries often rely heavily on cross-border remittances, a

[2]The coefficient is marginally significant and negative in the case of short-term blockchain diversification.



Note: The predicted probabilities are based on column (3) from Table 2. Predictions are obtained by varying $DIV_{c,t}$ of each record in the original sample from the minimum (1) to the maximum value (6.25) and then fitting the adjusted sample to the regression result from specialisation model in column (3) of Table 2 to compute the average of marginal effects at each level of $DIV_{c,t}$.

Figure 12: Adjusted predictions of $RTA > 1$ for different levels of $DIV_{c,t}$ (with 95% CI) - Specialisation

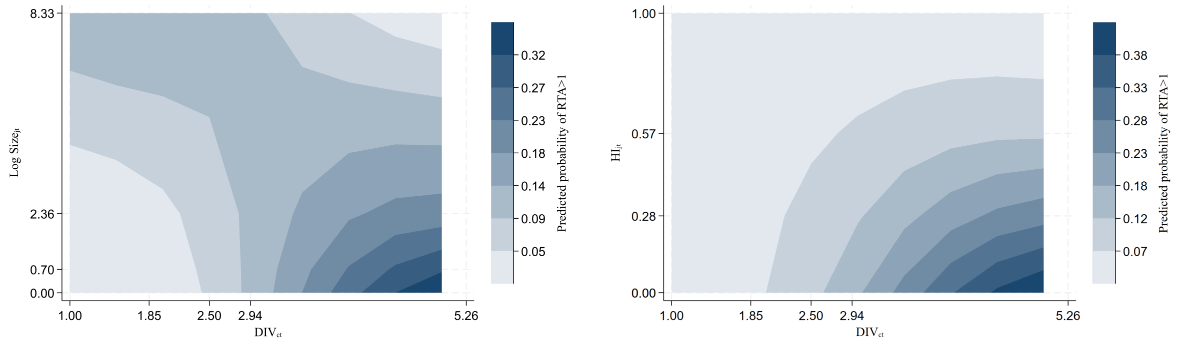
system currently bogged down by inefficiencies and high costs. Blockchain provides a more affordable, transparent, and swift method for transnational money transfers, making it an attractive alternative for streamlining remittances. Another compelling factor is the concept of "leapfrogging". Similar to how several low-income nations transitioned directly to mobile phones, bypassing the era of landlines, they now have the potential to leapfrog over traditional financial infrastructures in favour of advanced, blockchain-based systems. This propensity is further intensified in regions experiencing economic volatility, hyperinflation, or a generalized distrust in centralized institutions, where decentralized blockchain solutions appear as stable alternatives.

4.2. Front runners in blockchain specialisation

Section 2 discussed the concentration of blockchain patents among a few countries. This section investigates the disparities in blockchain technology specialisation between the top innovator countries and the remaining countries in our sample. Towards this objective, we revise Eq. (4) to:

$$P(S_{cjt} = 1) = \Phi(\theta_0 + \theta_1 Density_{c,j,t-1} + \theta_2 DIV_{c,t} + \theta_3 DIV^2_{c,t} + \theta_4 HI_{j,t} + \theta_5 \log Size_{j,t} + \theta_6 ITC_{j,t} + \theta_7 Top12Ctry + \sum_{s=2017}^{2020} \theta_{8,s} Year_s + \sum_{s=2017}^{2020} \theta_{9,s} Year_s \times Top12Ctry + \gamma_j + \epsilon_{cjt}) \quad (9)$$

where $Top12Ctry$ is a binary variable that takes the value 1 if the country c belongs to the cohort of the top twelve innovator countries with the most number of patent families during the year 2020 and 0, otherwise. θ_7 indicates the blockchain technology specialisation gap between the top 12 innovator countries and the remaining countries in the sample. $Year_s$ is a binary variable that takes the value 1 for the year s and 0, otherwise. Table 3 showcases the estimation results. The positive and statistically significant $Top12Ctry$ coefficient indicates that the top 12 innovator countries are, on average, more likely to specialise in blockchain technology as compared to the remaining countries. Additionally, the positive



(a) Log Size

(b) HI

Note: The predicted probabilities are based on column (3) from Table 2. To read the contour graph, we first fix a certain level of one dimension and observe how the adjusted prediction changes with the values of another dimension. For instance, in Fig. 13a, when keeping $DIV_{c,t}$ at a low level, the higher the $\log Size jt$, the more likely the country achieves technological advantages. However, for countries with highly diverse and well-balanced blockchain patent portfolios, the positive impact of large patent volumes disappears.

Figure 13: Adjusted predictions of $RTA > 1$ for different levels of $DIV_{c,t}$, $\log Size_{c,t}$ and $ITC_{j,t}$ - Specialisation

and statistically significant interaction coefficients show that such a blockchain technology performance gap persists over time.

Using the results from Table 3, we estimate and visualise the predicted probability of blockchain technology specialisation in Fig. 14.The red and blue lines show the time trends in the predicted probability of blockchain specialisation of the top 12 and the remaining innovator countries, respectively. In line with our expectations, we find a performance gap in blockchain technology specialisation, with the top 12 innovator countries surpassing that of the remaining countries. We also find the blockchain performance gap as widening over time.

With evidence that the blockchain technology specialisation performance of the top 12 innovator countries exceeds the remaining countries, we next evaluate the country-level performance. We repeat the baseline estimation (see Eq. (4)) separately for the top 12 innovator countries.[3] Using the estimation results, Fig. 15 visualises the predicted probability of blockchain technology specialisation for each of the top 12 innovator countries. We find wide disparities in the blockchain technology performance even within the top 12 innovator countries sample, with the United States leading in blockchain specialisation, followed by South Korea, Japan and Germany.

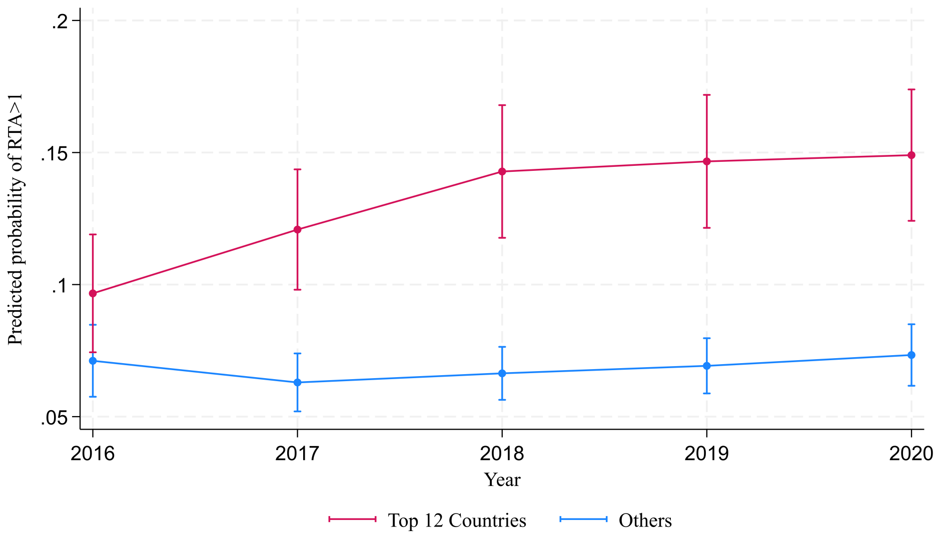
Cryptocurrency boom. There is a widespread belief that the year 2017 was a crucial time period for blockchain as the total market capitalization of major cryptocurrencies increased by a whopping 3200% during this period (Fry, 2018; Cross et al., 2021). The stylised facts in Fig. 3 also reveal that blockchain innovations largely started to pick up after 2017 post the cryptocurrency market boom. To identify the country-level performance of the top 12 innovator countries before and after the cryptocurrency boom, we again estimate the baseline model using the sub-sample of the top 12 innovator countries, albeit separately for the periods 2015-2017 and 2018-2020.[4] Using the estimation results, Fig. 16 shows the country-level blockchain technology performance before and after the 2017 cryptocurrency boom. In line with our expectations, we find that the disparities in the country-level blockchain technology performance

[3] Column (1) in Table B2 reports the estimation results.
[4] Columns (2)-(3) in Table B2 reports the estimation results.

Table 3: Front runners in blockchain specialisation

	Specialisation
$Top12Ctry$	0.300^{**}
	(0.152)
$Year = 2017$	-0.800^{***}
	(0.147)
$Year = 2018$	-1.590^{***}
	(0.205)
$Year = 2019$	-1.547^{***}
	(0.201)
$Year = 2020$	-1.357^{***}
	(0.192)
$Top12Ctry \times Year = 2017$	0.332^{*}
	(0.198)
$Top12Ctry \times Year = 2018$	0.362^{**}
	(0.182)
$Top12Ctry \times Year = 2019$	0.359^{**}
	(0.180)
$Top12Ctry \times Year = 2020$	0.290
	(0.178)
Controls	Yes
Observations	9660
Pseudo R-squared	0.397

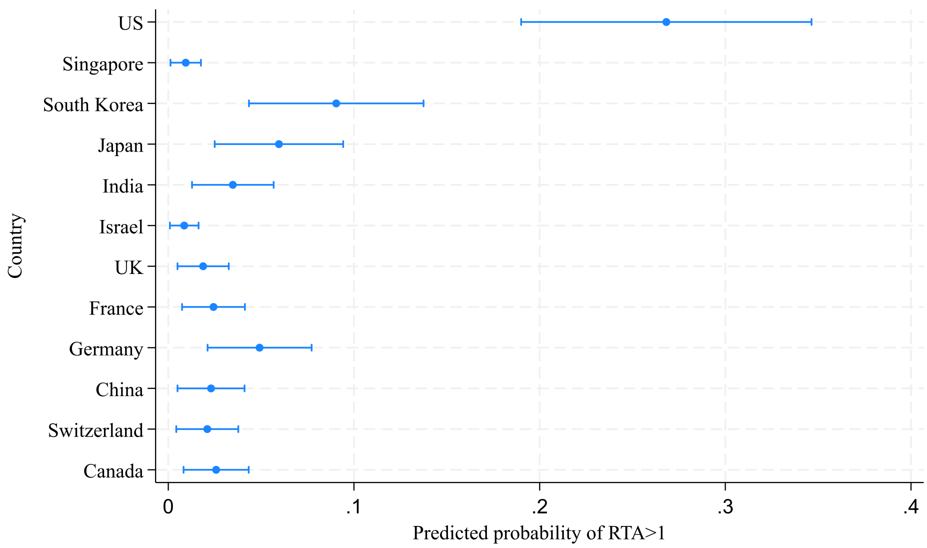
Standard errors in parentheses after accounting for tech-field fixed effects.
$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$



Note: This graph is based on the full-sample regression result of Eq. (9). The predicted probabilities are obtained by: first, restricting the sample to each year; second, fitting the model using observations in the original sample, with all other independent variables kept as observed, but treating all observations to be either in the "Top 12 Countries" group or in the "Others" group. Finally, the averages of marginal effects within both groups are calculated. Top 12 countries are those with the most number of patent families in 2020, including (1) China, (2) US, (3) South Korea, (4) India, (5) UK, (6) Germany, (7) Japan, (8) Canada, (9) Israel, (10) Singapore, (11) France, (12) Switzerland.

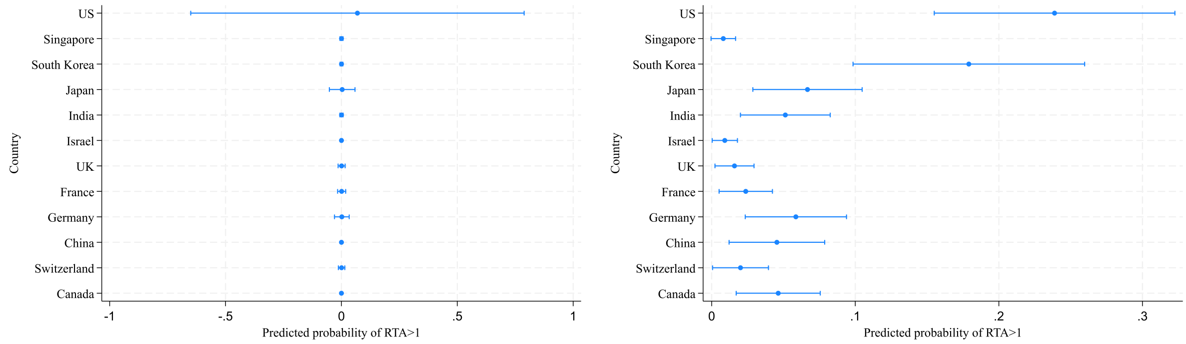
Figure 14: Adjusted predictions of $RTA > 1$ (with 95% CI)

largely started to emerge after the cryptocurrency boom. The predicted probabilities of blockchain technology specialisation spiked and became economically significant in countries like the United States, South Korea, Japan and Germany in the latter period. This result highlight the importance of the 2017 cryptocurrency boom as a catalyst event in the blockchain technology specialisation capabilities of the top 12 innovator countries.



Note: This graph is based on the regression result of column (1) of Table B2. The predicted probabilities are obtained by: first, restricting the sample to country; second, fitting the model with the country-level means of all the independent variables; finally, the averages of marginal effects at means within each country are calculated.

Figure 15: Adjusted predictions of $RTA > 1$ at the means of covariates for each country (with 95% CI)



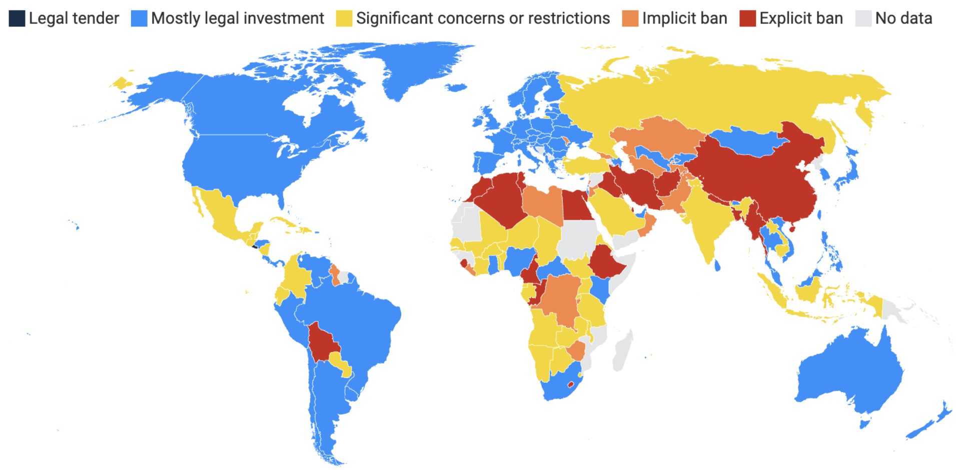
(a) 2015-2017 (b) 2018-2020

Note: The predicted probabilities are based on columns (2) and (3) from Table B2.

Figure 16: Adjusted predictions of $RTA > 1$ at the means of covariates for each country (with 95% CI)

Regulations. Policymakers are increasingly concerned about the risks posed by cryptocurrencies, with regulatory frameworks continuously evolving to mitigate the risks. Cryptocurrency regulations could also have implications for blockchain innovation performance. We analyse the impact of the cryptocurrency regulatory framework on blockchain technology specialisation using cryptocurrency regulation data from Finder.[5]

Broadly, the country-level cryptocurrency regulatory framework is classified into five levels by the degree of stringency: level 1 - explicit ban, level 2 - implicit ban, level 3 - significant concerns or restrictions, level 4 - mostly legal investment and level 5 - legal tender. The ordering of the levels is inversely related to the stringency. For example, level 1 - explicit ban is the most stringent, with cryptocurrency entirely banned. On the other hand, level 2 is the least stringent and considers cryptocurrency as legal tender. As per our data, the top 12 innovators follow level 1, level 3 or level 4. Using this framework, Fig. 17 shows the nature of cryptocurrency regulations worldwide.



Source: Corva (2023).

Figure 17: Cryptocurrency regulations worldwide

To assess the impact of the regulatory framework on blockchain technology specialisation performance

[5]See https://www.finder.com/.

of the top 12 innovator countries, we revise the baseline model in Eq. (4) to:

$$P(S_{c,j,t} = 1) = \Phi\left(\theta_0 + \theta_1 \mathit{Significant\ concerns\ or\ restrictions}_{c,t} + \theta_2 \mathit{Mostly\ legal\ investment}_{c,t}\right.$$
$$+\theta_3 \mathit{Density}_{c,j,t-1} + \theta_4 \mathit{DIV}_{c,t} + \theta_5 \mathit{DIV}^2_{c,t} + \theta_6 \log \mathit{Size}_{j,t} + \theta_7 \mathit{HI}_{j,t} + \theta_8 \mathit{ITC}_{j,t} + \theta_9 \log \mathit{Size}_{j,t} \times \mathit{DIV}_{c,t}$$
$$\left. + \theta_{10} \mathit{HI}_{j,t} \times \mathit{DIV}_{c,t} + \delta_c + \gamma_j + \lambda_t + \epsilon_{cjt}\right), \quad (10)$$

where *Significant concerns or restrictions*$_{c,t}$ and *Mostly legal investment*$_{c,t}$ are binary variables which take the value 1 if country c's cryptocurrency regulatory framework is level 3 and level 4, respectively in year t. Otherwise, both these variables take the value 0. Coefficients θ_1 and θ_2 indicate the gap in the blockchain technology specialisation likelihood between countries with less stringent cryptocurrency regulations at level 3 and level 4, respectively, as compared to the benchmark of the more stringent cryptocurrency regulatory framework at level 1. A finding of $\theta_1 > 0$ or $\theta_2 > 0$ indicates that blockchain technology specialisation is more likely in countries with less stringency cryptocurrency regulations. Column (1) in Table 4 shows the estimation results. Although the coefficients of the regulatory measures are negative, we find *Mostly legal investment* coefficient alone to be marginally significant. Since our earlier results highlight the period post-2017 as mostly explaining the blockchain technology performance of the top 12 innovator countries, we repeat the estimation using the sub-sample of the top 12 innovator countries for the period 2018 to 2020. The positive and statistically significant coefficients of *Significant concerns or restrictions* and *Mostly legal investment* in column (2) indicate that the top 12 innovator countries with less stringent cryptocurrency regulation are more likely, on average, to specialise in blockchain technology when compared to the top innovators with the most stringent cryptocurrency regulatory framework after the cryptocurrency boom.

Table 4: Effects of regulation on blockchain specialisation of Top 12 innovator countries

	(1) Specialisation	(2) Specialisation 2018-2020
Significant concerns or restrictions	-0.0573	0.656^{***}
	(0.414)	(0.240)
Mostly legal investment	-0.874^{*}	0.749^{***}
	(0.495)	(0.227)
Density	0.473^{***}	0.561^{***}
	(0.163)	(0.194)
DIV	3.369	4.411
	(2.312)	(3.103)
DIV × *DIV*	-0.316	-0.410
	(0.376)	(0.504)
Log Size	0.544^{*}	0.432
	(0.212)	(0.271)
Herfindahl Index	1.701	2.966
	(1.547)	(2.049)
ITC	0.249^{***}	0.334^{***}
	(0.0246)	(0.0223)
Log Size × *DIV*	-0.161^{***}	-0.178^{**}
	(0.0604)	(0.0697)
Herfindahl Index × *DIV*	-0.873^{*}	-1.377^{**}
	(0.518)	(0.658)
Observations	2100	1260
Pseudo R-squared	0.329	0.296

Standard errors in parentheses after accounting for country, year, tech-field fixed effects.
$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

5. Conclusion

This study leverages patent data extracted from the PATSTAT database spanning the years 2015 to 2021 to provide a comprehensive exploration into the spatial dynamics and determinants that underpin recent developments in blockchain technology. Combined with the measurement of technological density, national income level, existing technology complexity, and diversity, we uncover pivotal insights that collectively contribute to an enriched understanding of the dynamic landscape of blockchain innovation.

Firstly, a noteworthy deviation from conventional patterns in technology development is observed, as lower-income countries display a robust inclination towards blockchain innovation. This unexpected trend suggests a global impetus towards embracing blockchain solutions that transcends traditional economic boundaries, ushering in a new era of inclusive technological adoption.

Secondly, the impact of the 2017 cryptocurrency bubble emerges as a significant catalyst, instigating heightened enthusiasm and increased research activities within the realm of blockchain advancements. This temporal influence underscores the dynamic and responsive nature of blockchain innovation, showcasing its adaptability to external events that shape the technological landscape.

Thirdly, our findings unveil heterogeneous spillover effects in blockchain innovation, where leading innovators not only influence their peer nations but also exert a discernible impact on the global landscape. This interconnectedness emphasizes the collaborative and transnational nature of blockchain advancements, underscoring the importance of international cooperation in this domain.

Lastly, the regulatory environment surfaces as a pivotal determinant shaping the trajectory of blockchain innovation. Nations with lenient cryptocurrency regulations exhibit a greater proclivity to foster advancements in blockchain technology, while those enforcing strict bans encounter limitations. This underscores the imperative need for a supportive regulatory framework to facilitate and propel innovation within the blockchain space.

In essence, our research sheds light on the multifaceted nature of blockchain innovation, intricately influenced by economic factors, historical events, and regulatory frameworks. As the blockchain landscape continues its evolution, a nuanced understanding of these dynamics becomes imperative for policymakers, businesses, and researchers alike, enabling them to navigate the intricate and interconnected realm of emerging technologies.

Declaration of Generative AI and AI-assisted technologies in the writing process

While preparing this paper, the authors used ChatGPT to improve the paper's language and readability. After using this tool/service, the authors reviewed and edited the content as needed. The authors take full responsibility for the content of the publication.

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Appendix A. Detailed method for calculating ITC

We follow Hidalgo and Hausmann (2009)'s method to calculate ITC. After obtaining the country-technical field-time level RTA, we construct a country-technical field matrix as depicted in Fig. A1 for each year. Each cell $M_{c,j}$ in this matrix represents the value of $S_{c,j}$ at year t. For example, in the first row of the matrix, a value of "1" indicates that Country A is specialized in technical fields 1 and 3, while a "0" suggests that Country A is not specialized in technical field 2. Therefore, the row sum of each country's output $\sum_j M_{c,j}$ signifies the "diversity" of its technology portfolio. A high value indicates the country specialises in many technical fields which blockchain has . On the other hand, the column sum $\sum_c M_{c,j}$ denotes the "ubiquity" of a specific technical field. The high complexity of technology can be reflected by its low ubiquity since fewer countries have the required innovation capability to specialise in this field. Generally speaking, a more innovative country is likely to possess a more complex

	Field 1	Field 2	Field 3
Country A	1	0	1
Country B	1	1	1

Figure A1: Sample country-technical field matrix

technology portfolio consisting of more exclusive innovations. Similarly, non-ubiquitous innovations tend to be sourced from relatively few countries with superior productivity. In this way, we can infer the average diversity of countries' innovation outcomes and the ubiquity of all technical fields by employing an iterative process called the Method of Reflections. As Eq. (A1) show, the iteration starts with simple row and column summation ($k_{c,0}$ and $k_{j,1}$) and continues until the rankings of countries and technical fields stabilize. As such, $k_{c,0}$, $k_{j,1}$, $k_{c,2}$, $\cdots$, $k_{j,2n-1}$, $k_{c,2n}$ are used to measure the diversity of countries' technology portfolios, and $k_{j,0}$, $k_{c,1}$, $k_{j,2}$, $\cdots$, $k_{c,2n-1}$, $k_{j,2n}$ are used to measure the ubiquity of specific technical fields (Hidalgo and Hausmann, 2009). We define $k_{j,2n}$, the maximum number of iterations, as the Index of Technological Complexity (ITC). A higher ITC indicates a lower average ubiquity of the technological fields in which less countries specialise.

$$
\begin{aligned}
k_{c,0} &= \sum_j M_{c,j} \\
k_{j,0} &= \sum_c M_{c,j} \\
k_{c,n} &= \frac{1}{k_{c,0}} \sum_j M_{c,j} k_{j,n-1} \\
k_{j,n} &= \frac{1}{k_{j,0}} \sum_c M_{c,j} k_{c,n-1}
\end{aligned}
\tag{A1}
$$

Appendix B. Tables

Table B1: Correlation coefficient matrix

	RTA	Density	Log Size	ITC	HI	DIV	GDP
RTA	1.000						
Density	0.145	1.000					
Log Size	0.020	0.682	1.000				
ITC	0.031	0.359	0.484	1.000			
HI	0.008	0.002	-0.043	0.617	1.000		
DIV	0.028	0.263	0.025	0.060	0.013	1.000	
GDP	0.003	0.102	-0.010	-0.028	-0.010	0.222	1.000

Table B2: Sub-sample regressions using baseline model with top 12 innovator countries

	(1) Specialisation	(2) Specialisation 2015-2017	(3) Specialisation 2018-2020
Density	0.498***	0.399	0.561***
	(0.162)	(0.404)	(0.194)
DIV	2.513	3.754	4.411
	(2.036)	(5.238)	(3.103)
DIV × *DIV*	−0.170	−0.516	−0.410
	(0.334)	(0.838)	(0.504)
Log Size	0.543*	0.497	0.432
	(0.212)	(0.555)	(0.271)
Herfindahl Index	1.479	−2.131	2.966
	(1.551)	(3.072)	(2.049)
ITC	0.242***	0.854	0.334***
	(0.0235)	(0.965)	(0.0222)
Log Size × DIV	−0.159***	−0.187	−0.178**
	(0.0601)	(0.142)	(0.0697)
Herfindahl Index × DIV	−0.794	0.0621	−1.377**
	(0.519)	(1.017)	(0.658)
Observations	2100	624	1260
Pseudo R-squared	0.323	0.356	0.296

Standard errors in parentheses after accounting for country, year, tech-field fixed effects.
$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$