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Innovation Space and the Transition of Revealed Technology Advantage

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Innovation Space and the Transition of Revealed Technology Advantage

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Abstract

Specialisation in technologies varies between countries over time. The evolution of knowledge is believed to be a gradual process that relies on established innovation capabilities to support disadvantaged industries and expand technological specialisation in those fields. While the path-dependent diversification of product exporting has been extensively studied, the general pattern of technological progression across multiple regions has rarely been explored. In this paper, we investigate the transition of technological advantage among major countries from 1992 to 2019 using an Innovation Space model and a comprehensive patent dataset. Our analysis shows that technology transition happens gradually — on average, more than 90% of the technology advantages or disadvantages remain unchanged from one year to another. We also explore the dynamics of innovation space and find that computer & electronics and computer programming are thriving fields and have become increasingly central in the innovation network.

Keywords: PATSTAT, Patent, Technology, Innovation, Product Space

1 Introduction

The rapid evolution of technology has resulted in dynamic changes within the global competition landscape. Countries develop comparative advantages in new technologies while rendering obsolete ones as they advance. Cutting-edge technologies, such as 5G, artificial intelligence, and quantum computing, have become major battlegrounds for both developed countries and emerging economies. As countries continue to invest in research and development, it is crucial to study the pattern of such technological changes and their implications on global power dynamics.

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This paper highlights the significance of "path-dependency" as a critical factor in predicting technology transition. New technologies are often built on existing frontier knowledge, known as the "standing-on-shoulder" effect. Moreover, ideas are produced using combinations of local resources (e.g. human capital, laboratory equipment, entrepreneurial skills) (Bergek, 2019). Resource sharing and transformation make it easier to launch innovation in "related" areas. However, on the other hand, idea generation is also limited by the "fishing-out" constraint. As knowledge accumulates in a specific field, the discovery of new ideas becomes increasingly challenging, which potentially will undermine the predictive power of "path-dependency". Considering the two opponent forces, we would like to empirically test how strong "path-dependent" is in the innovation and technology transition process.

A challenge that follows is to define "relatedness" of technologies. One potential approach is to delineate the characteristics of technologies and assign weights. However, this method is arduous due to the substantial workload it entails. Alternatively, we follow an outcome-based method introduced by Hidalgo et al. (2007) and Hausmann and Klinger (2007) to quantify the relatedness between technological fields. The method was initially implemented in the "Product Space" model to formalise the network of products traded worldwide and to analyse the relationship between export dynamics and economic growth. It has been applied to test path-dependent evolution of countries' trade specialisations (Coniglio et al., 2018, 2021). This paper differs from existing literature in that we focus on the "innovation space" by utilizing patent data from the PATSTAT database.[1]

Our research provides robust evidence for "path-dependency" during technology transition. On average, more than 90% of the technology advantages or disadvantages remain unchanged from one year to another. Based on the aforementioned relatedness measure, we find that the newly developed fields are not randomly chosen but instead exhibit significant relatedness to local advantageous fields in the past. Using a long panel of patent data from 1992 to 2019, we further explore the dynamics of the "innovation space". We find that over the recent decades, computer & electronics and computer programming are thriving fields and have become increasingly central in the innovation network.

The rest of the paper is organized as follows. The second section briefly reviews related literature on the Product Space model and methods for quantifying technology networks. The third section provides a detailed explanation of the PATSTAT dataset and the methodology for testing path-dependency mathematically. This is followed by the fourth section, including descriptive analysis and empirical results, which leads to the last discussion section.

[1]PATSTAT database is a comprehensive patent database constructed by European Patent Office.

2 Literature Review

2.1 Product Space Theory

Since "Product Space" model was originated by Hidalgo et al. (2007) and Hausmann and Klinger (2007), it has been widely applied across various topics, including the visualisation of countries' export diversification process and its implications on countries' growth and development. The Product Space model operates on the fundamental assumption that countries tend to co-export products that share similar requisite production factors, demonstrating high comparative advantages simultaneously. The relatedness between products is then quantified by the observable probability of dual specialisation. This is an outcome-based approach. It does not explicitly identify which capabilities are shared but rather focuses on the outcome of product similarities resulting from overlapping production processes. By tracing the related product pairs and countries' specialisation dynamics, researchers concluded that the appearance of new economic activities is conditional on relevant capabilities and know-how being acquired and combined by countries to develop various products (O'Clery et al., 2021).

Efforts have also been made to apply the Product Space method to study the transition of competitiveness within certain types of products (Campi et al., 2020; Qi et al., 2020; Talebzadehhosseini et al., 2020; Mealy and Teytelboym, 2022), firms (Leten et al., 2007), regions (Boschma et al., 2013; Cicerone et al., 2019), or countries (Hidalgo, 2009). These studies all echo the core argument of the Product Space model that products exhibit different levels of relatedness and that existing productive capabilities shape the evolution of comparative advantages. Interestingly, it has been discovered that escaping from the static path-dependency trajectory is possible for sub-national regions with more sophisticated, complex, and diverse local capabilities (Coniglio et al., 2018).

2.2 Technology Relatedness

Economic geographers are keen to study "Technology Space" using patent data, focusing on how existing knowledge structure and sectoral composition impact small-scale knowledge transfer. Compared with the research on export product path-dependency, fewer studies have applied the Product Space framework to technology and innovation. Some scholars posited that the high conditional probability of joint occurrence utilized by the Product Space model may be attributable to unspecified economic relationships beyond common innovation capabilities, given the multifaceted nature of technology creation (Rigby, 2015). Citations have therefore been proposed to be another proxy for relatedness. Leten et al. (2007) studied the patent portfolios of high-R&D firms and measured the distances between technology classes by cross-field citations. Their conclusion suggests that engaging in activities within technology fields that possess a shared knowledge base with existing patent portfolios may serve as a strategy to alleviate the drawbacks associated with excessive diversification of technologies at the firm level. Acemoglu et al. (2016) conducted a study specifically on inter-technological spill-over. They utilised U.S. patent citations to map an "Innovation Network" demonstrating how downstream technologies build upon the research outcomes of pre-existing network structures and patent growth in upstream technological fields. This finding provides evidence for the path-dependent evolution of technology by highlighting the potential role of upstream-downstream linkages.

While the concept of technological proximity based on citations has gained broad acceptance in the context of technology, patents, and national innovation networks, it falls short in capturing the dynamic evolution of technology specialization across both time and various regions. Conversely, the revealed proximity in the product space model relies on observed co-exporting and co-specialisation while preserving national characteristics. Considering our research objective is to uncover the general patterns of technology growth and examine potential implications for global technology competitions, we deem the Product Space model more suitable for our research inquiry.

3 Methodology

3.1 Data Description

Patenting activity is one of the conventional indicators of technological strength. Specifically, for each country, we calculate the number of DOCDB patent families [2] in each industrial sector. If inventors from a country make significant contributions to a substantial number of patents within a specific sector, it may be inferred that the country possesses a technological advantage in that particular field. We use the data from the European Patent Office's Worldwide Patent Statistical Database (PATSTAT), 2022 Spring edition, which is recognized as one of the most comprehensive bibliographical patent databases, encompassing information from 199 patent offices worldwide. However, an inherent limitation of PATSTAT is the occasional absence of data regarding inventors' country of residence and technology classifications. To address this issue, we employ the after-imputation PATSTAT datasets generated using the SQL algorithm proposed by de Rassenfosse and Seliger (2021) and Ge et al. (2022). Our sample focuses on 52 patent offices with highly complete inventors' information spanning the period between 1992 and 2019. For a complete listing, please refer to Table 2 of Appendix.

While patent applications are classified using International Patent Classification (IPC) codes, PATSTAT provides a concordance table mapping IPC codes to 2-4 digits NACE2 codes (Statistical Classification of Economic Activities in the European Community, version 2). Each patent can be mapped to one or multiple NACE2 codes, with weights that sum up to 1. To ensure consistency, we aggregate patents into 2-digit industrial sectors. For each year t, the number of DOCDB patent families in a NACE2 sector j for a country n is calculated by summing the weights associated with j for all patent families whose inventors

[2] The DOCDB patent family comprises a collection of patent applications that address identical technical content, regardless of being filed through different application authorities or at different dates. By considering the count of DOCDB families instead of individual patent filings, one can prevent an overestimation of the actual innovation performance. Source: Data Catalog for PATSTAT Global, Version 5.19

are from country n. To account for the quality of inventions, we use a weighted metric that considers the average patent family size in sector j of country n in year t. A larger-sized DOCDB family indicates that the applicants perceive the invention's potential value as significant enough to warrant seeking broad geographical protection through multiple patent applications. To smooth potential fluctuations, we calculate the 5-year moving average of this weighted number, excluding the records from the first 4 years.

3.2 Technology Advantage

To define a country's technological specialisation, we use X_{jnt} to compute Revealed Technology Advantage (RTA) index. The RTA is adapted from the measure Revealed Comparative Advantage (RCA) in international trade Balassa (1965). It is the comparison between a particular economy and the world average regarding the relative strength of a specific sector among all the industries. Denote country $n = 1, 2, ...N$, year $t = 1, 2, ...T$, NACE2 industrial sector $j, k = 1, 2, ...M$. Variable X_{jnt} is the 5-year moving average of the weighted number of patents in sector j invented by residents from country n in year t.

$$RTA_{jnt} = \frac{X_{jnt}}{\sum_{j=1}^{M} X_{jnt}} / \frac{\sum_{n=1}^{N} X_{jnt}}{\sum_{j=1}^{M} \sum_{n=1}^{N} X_{jnt}}$$

The index RTA_{jnt} is above 1 when country n exhibits better patenting performance than the world average in sector j in year t, and hence, a technological specialisation. This is captured by a binary variable x_{jnt}.

$$x_{jnt} = \begin{cases} 1 & \text{if } RTA_{jnt} > 1 \\ 0 & \text{otherwise} \end{cases}$$

Among all the technological sectors, those with $RTA_{nt} > 1$, or $x_{jnt} = 1$ are called country n 's "Patent Basket (PB)" at period t. All the remaining fields that the country doesn't specialise in are named "Option Set (OS)".

$$PB_{nt} = \{j = 1, ..., M | x_{jnt} = 1\}$$

$$OS_{nt} = \{k = 1, ..., M | x_{knt} = 0\}$$

In order to study the evolution of technological specialization, it is essential to consider that countries can experience fluctuations in their advantages within specific technologies over time. To address this nature, we employ a dynamic grouping method. We introduce the concepts of "New Entries (NE)" and "Drop Out (DO)". If a sector j has $RTA < 1$ in year t but $RTA \leq 1$ in time $t+1$. In other words, it is the intersection of OS_{nt} and $NE_{n,t+1}$, we call this industry j as a NE. Similarly, if an industry k used to be in the PB set but loses its advantage and downgrades to OS one period later, k is then classified as a DO.

$$NE_{nt} = \{j = 1, ..., M | x_{jnt} = 0, x_{jn,t+1} = 1\}$$

$$DO_{nt} \equiv \{k = 1, ..., M | x_{knt} = 1, x_{kn,t+1} = 0\}$$

Based on the aforementioned definitions, we have classified the technologies of each country in each period based on their relative strengths. Our research places particular emphasis on the NE_{nt} group, as it encompasses all the successful ladder-climbers that enable us to identify patterns of technological advancement from 1996 to 2019. However, to substantiate the path-dependency hypothesis, it is necessary to quantify the relationship between NE_{nt} and PB_{nt}. Besides, in order to address the fundamental question of why only certain technologies from the pool of OS_{nt} qualify as NE_{nt}, further investigation is required.

3.3 Pairwise Proximity Between Technologies

Quantifying relationships between different industries poses significant challenges. Hausmann and Klinger (2007) proposed an innovative outcome-based approach to infer relatedness by considering the probability of dual specialization. The underlying concept is that if industries j and k are closely-related in that they share similar innovation resources such as scientific knowledge, talent group, and institutional partnerships, we should observe many countries specialising in both j and k simultaneously. Mathematically, this implies that the conditional probability of j being in the PB given that k is also in PB, denoted as $\Pr(x_{jt}|x_{kt})$, is high, and the same holds true in the reverse direction, $\Pr(x_{kt}|x_{jt})$. It is important to note that these two conditional probabilities may not necessarily be equal when computed. However, an ideal measure of relatedness between any pair of technologies should yield a unique number regardless of direction. To address this, we take the minimum and define the proximity, or inverse distance, between j and k at time t as d_{jkt}:

$$\begin{aligned} d_{jkt} &= \min\{\Pr(x_{jt}|x_{kt}), \Pr(x_{kt}|x_{jt})\} \\ &= \min\left\{\frac{\sum_n x_{jnt} \cdot x_{knt}}{\sum_n x_{knt}}, \frac{\sum_n x_{jnt} \cdot x_{knt}}{\sum_n x_{jnt}}\right\} \end{aligned}$$

At this stage, we've obtained a dynamic pairwise proximity matrix, changing each year from 1996 to 2019. But for the benchmark result of the average pattern, we assume the proximity matrix is constant over time. That means that the d_{jk} matrix is a 26×26 matrix summing over time dimension, whose entry d_{jk} is the average proximity between any industry pair (j, k). The complete matrix can be found in Table 3 of Appendix

$$d_{jk} = \frac{1}{T} \sum_t d_{jkt}$$

3.4 Relatedness Between Industry Sets

Having obtained the proximity matrix between individual technologies, we are ready to examine the relationship between the industry sets, NE and PB. For each new entry $j \in NE_{nt}$, we define a proximity set between j and each $k \in PB_{nt}$. And the "relatedness" between industry and this proximity set, denoted as $\mathbf{d_{NE}}_{jnt} = \max_k \{d_{j,1,t}, d_{j,2,t}, ..., d_{j,k,t} | k \in PB_{nt}\}$, represents the pairwise proximity between j and its most closely connected industry in PB. Similarly, we construct the relatedness between an OS industry and the PB set, $\mathbf{d_{OS}}_{int}$, where $i \in OS_{nt}$.

If path-dependency exists, we anticipate observing a higher probability distribution of $\mathbf{d_{NE}}$ compared with $\mathbf{d_{OS}}$. To assess this, we adopt the two-sample one-sided Kolmogorov-Smirnov test, as employed by Coniglio et al. (2021). This nonparametric test allows us to quantify the difference between the empirical distribution functions of NE, $F_{nt}^{NE}(\mathbf{d})$, and a counterfactual cumulative distribution function (CDF) of OS, $F_{nt}^{OS}(\mathbf{d})$ under the assumption that new entries were randomly selected from the designated option set. Here, $|NE_{nt}|$ and $|OS_{nt}|$ represent the number of technologies in NE_{nt} and OS_{nt}, respectively. To study the global average pattern, we combine the country-specific relatedness of NE and OS and construct $F_{world,t}^{NE}$ and $F_{world,t}^{OS}$ [3]. The null and alternative hypotheses are defined as follows $H_0 : F^{OS} \leq F^{NE}$ and $H_1 : F^{OS} > F^{NE}$.

$$F_{world,t}^{NE}(\mathbf{d}) = \sum_{n=1}^{N} \frac{1}{|NE_{jnt}|} \sum_{j \in NE_{nt}} \mathbb{1}_{\mathbf{d_{jnt}} \leq \mathbf{d}}$$

$$F_{world,t}^{OS}(\mathbf{d}) = \sum_{n=1}^{N} \frac{|NE_{nt}|}{\sum_{n=1}^{N} |NE_{nt}|} \frac{1}{|OS_{nt}|} \sum_{i \in OS_{nt}} \mathbb{1}_{\mathbf{d_{int}} \leq \mathbf{d}}$$

4 Results

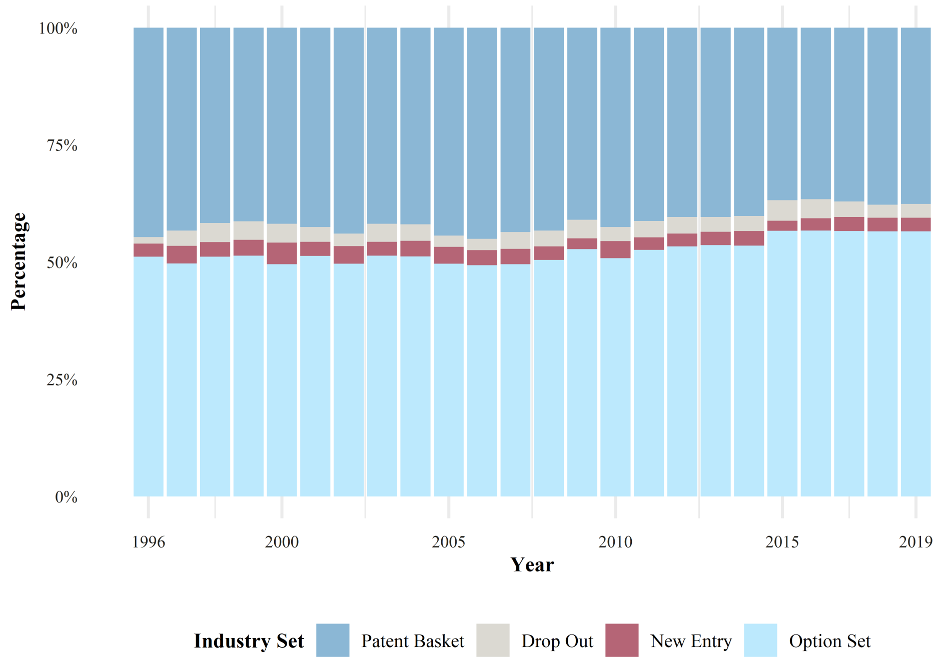
4.1 Descriptive Analysis

In Figure 1, we report the dynamic evolution of technological advantages from 1996 to 2019, categorised into different industry sets based on their yearly RTA. The results reveal a notable stability in RTA over time. On average, only 6% of the OS technologies transitioned into the NE group each year. Additionally, the proportion of PB has experienced a slight decline, suggesting that countries are more inclined towards specialization rather than diversification strategies.

Figure 2 depicts how the average relatedness of 26 industries changes from 1992-1996 (upper panel) to

[3] As outlined by Coniglio et al. (2021), the frequency of new entries exhibits significant heterogeneity across different economies. A simple aggregation of country-level counterfactual CDFs may lead to inaccuracies. Therefore, to establish a worldwide distribution, it is necessary to incorporate actual new entries as weights.

Figure 1: Transition of Technology Advantage (52 Countries, 1996-2019)



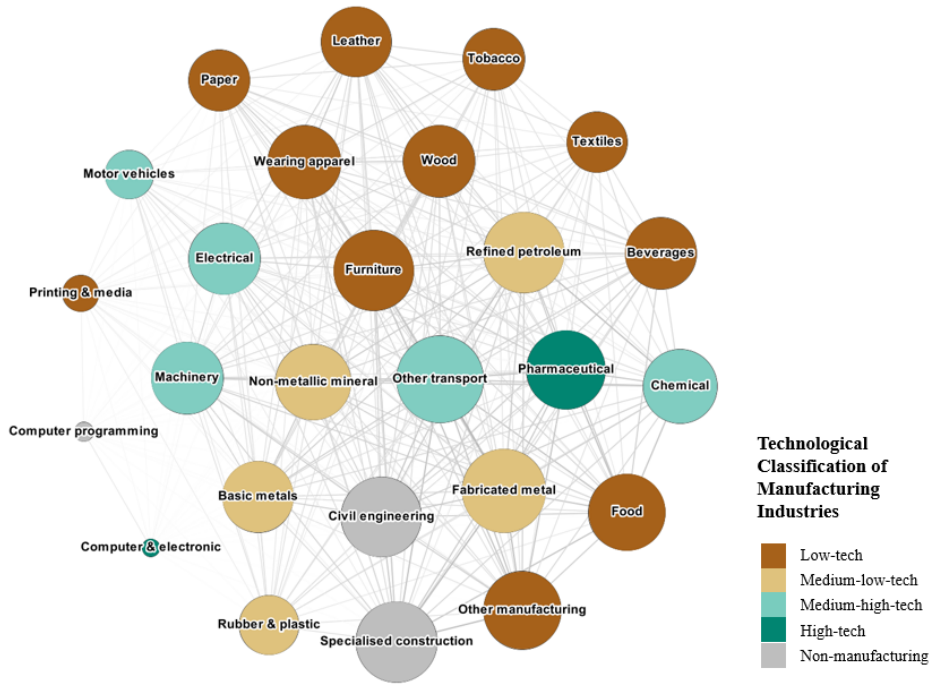
2015-2019 (bottom panel) [4]. The node size represents the average relatedness of each technology to all other fields, while the colour of each edge depicts the pair-wise proximity. Generally, industries exhibited higher average relatedness in the early 1990s (0.38) compared to recent years (0.36), as shown in Figure 6 of Appendix. Exceptions include computer programming, computer & electronics and printing & media, which are promising fields that have shown expanding influence on other industries. Notably, computer-related fields remain distant from other sectors within the innovation space. In contrast, a significant decline in proximity is observed in the tobacco and textiles industries, suggesting a diminishing inter-sectoral connection with other fields.

4.2 Path Dependency Test

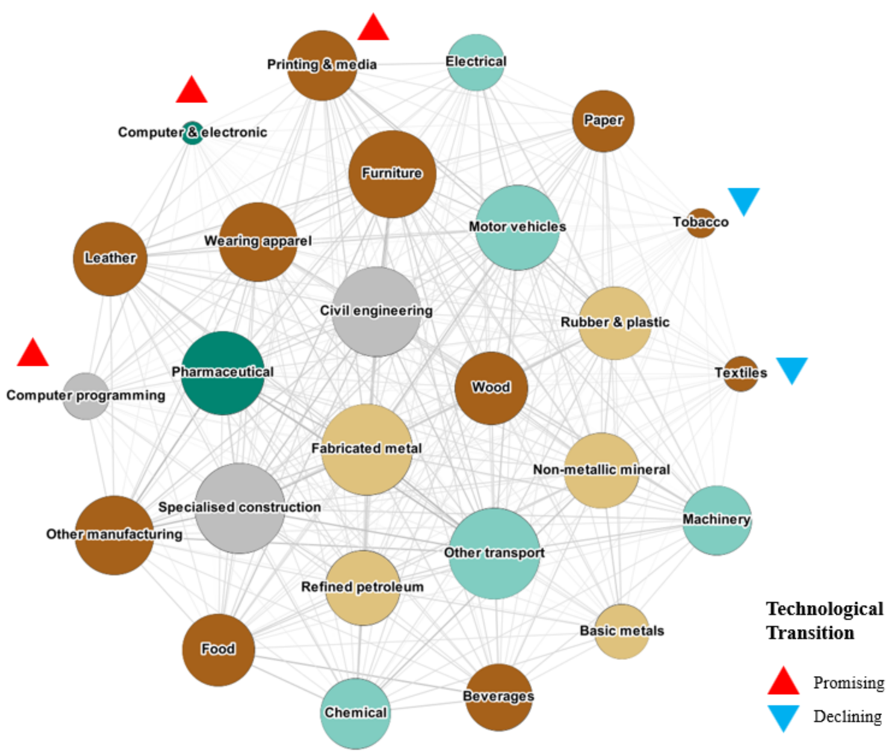
Recalling the path-dependency hypothesis postulates that a high relatedness with the existing patent basket potentially helps gain future technological advantages, it is expected that new entries would exhibit greater similarity to the incumbent technology advantages compared to other options. Evidence supporting this expectation is presented in Figure 3, where the average proximity of NE to the existing PB is higher than that of the entire OS sample. To further analyze this, we employ the Kolmogorov-Smirnov test. The world average distribution is reported in Figure 4. The blue line is the distribution of actual relatedness between the NE and the existing patent basket, while the orange is the counterfactual distribution under

[4] To capture the pair-wise proximity between industries in the two periods, we calculated their 5-year average to smoothen the fluctuations. Then we determined each industry's average proximity with respect to all other industries.

Figure 2: Transition of Innovation Space



(a) 1992-1996 (Five-year Average)



(b) 2015-2019 (Five-year Average)

random selection from all OS. The test result confirms a statistically significant difference in the proximity distribution between the NE and OS.

Figure 3: Yearly Average Proximity

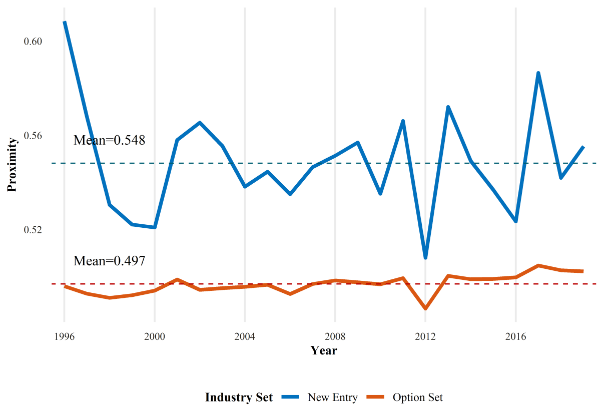
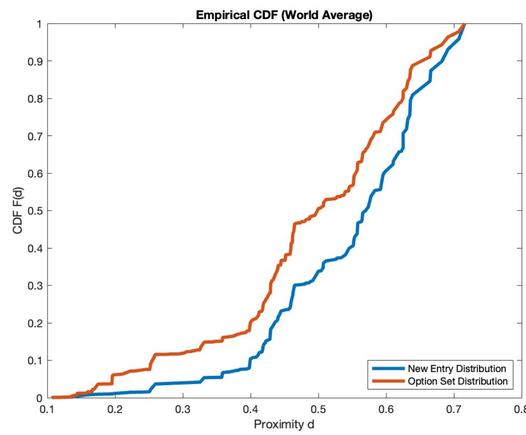


Figure 4: Result of Kolmogorov-Smirnov Test



As Figure 1 displays, only a small proportion of technologies from the option set advanced into the patent basket in the subsequent period. To further assess the impact of relatedness to the pre-existing PB in year t on the likelihood of gaining technological advantages in time $t+1$, which indicates potential for future diversification, we construct Equation 1 and perform logit and probit regressions. The variable RTA_{njt+1} is a binary indicator that equals one if industry j of country n at time $t+1$ exceeds one, and zero otherwise. P_{jnt} represents industry j's relatedness to the country's entire PB set in the previous period t. Controlling for the preceding technological specialisation RTA_{njt} is necessary since most technologies exhibit limited changes in relative technological advantage over time.

$$RTA_{njt+1} = \beta_0 + \beta_1 P_{njt} + \beta_2 RTA_{njt} + FE_n + FE_j + FE_{t+1} + \epsilon, \tag{1}$$

Columns (1) and (2) in Table 1 report the baseline full-sample results for the full sample, and the last two columns focus on all technologies in the OS to capture the true explanatory power of relatedness. The reason for the sub-sample regressions is the substantial persistence of technological advantage within industries over consecutive years. In other words, when an industry is observed above the $RTA = 1$ threshold, it may have always been in PB. The positive and statistically significant proximity coefficients demonstrate that greater similarity to the existing patent baskets increases the likelihood of gaining technological advantages. Moreover, when restricting the sample to option sets where RTA_t is constantly zero, the magnitude of the coefficient increases. This provides additional compelling evidence for path-dependency.

Table 1: Logit/Probit Regression

	Full Sample		Option Set	
	(1)	(2)	(3)	(4)
$(Intercept)$	-4.54^{***}	-2.37^{***}	-7.89^{***}	-3.93^{***}
	(0.31)	(0.15)	(0.71)	(0.32)
$Proximity_t$	3.30^{***}	1.53^{***}	6.90^{***}	3.12^{***}
	(0.36)	(0.17)	(0.91)	(0.41)
RTA_t	3.66^{***}	2.23^{***}		
	(0.17)	(0.08)		
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	31668	31668	17471	17471

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. Columns (1) and (3) are run on logit models, (2) and (4) are on probit models.

5 Discussion

Using patent data from 52 major countries from 1992 to 2019, this paper adapts the "Product Space" model to analyse knowledge diffusion and technology innovation. Analogous to trade specialisation, countries' technological advantages undergo subtle changes. On average, approximately 6% of new technologies enter the advantageous group, while a similar proportion exits. However, the overall trend is that each country concentrates on fewer and fewer fields, indicating a specialisation strategy.

Examining the transition of inter-sectoral relatedness over time, it is noteworthy that, whilst most technologies display a slight decline in average proximity, the textiles and tobacco industries - two low-tech manufacturing sectors - are moving away from other industries. Conversely, computing-related sectors exhibit strong momentum in influencing other sectors.

The study then constructs rigorous mathematical models to investigate the role of relatedness to the pre-existing patent basket for new-entry technologies. This finding demonstrates a highly path-dependent pattern in technological evolution. This discovery carries significant policy implications. While developing countries may initially face limited innovation capabilities and find themselves at the lower rungs of the innovation ladder, path-dependency implies a cost-effective and potentially successful shortcut by targeting innovation resources to identified innovation clusters in high-value-added sectors within the same domain.

Admittedly, our research method faces a few challenges associated with the structure of patent data. As mentioned, the selected patent dataset sample was chosen for its relatively high data coverage. However, revolutionary technological shifts are almost impossible during a 28-year time frame. And the technological specialisation of each country is persistent in general. From this perspective, there is a potential overstatement of technological relatedness's impact on future development. On the other hand, the study might also underestimate the impact of path-dependency within more granular technological sectors. It is easier to observe incremental innovation within smaller sub-fields compared to cross-sector transformations. For example, it's easier to extend advantages from 20.16 plastics to 20.17 synthetic rubber (in primary forms), than from 20 chemicals to 21 pharmaceutical products. Unfortunately, PATSTAT patents cannot be classified using a more disaggregated standard, limiting the analysis in this regard.

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Appendix

5.1 List of Countries

Table 2: List of 52 Patent Offices

Number	Patent Office Code	Country Name	Number	Patent Office Code	Country Name
1	AU	Australia	27	KR	South Korea
2	AT	Austria	28	LT	Lithuania
3	BG	Bulgaria	29	LU	Luxembourg
4	BR	Brazil	30	LV	Latvia
5	CA	Canada	31	MA	Morocco
6	CH	Switzerland	32	MX	Mexico
7	CN	China, People's Rep.	33	MY	Malaysia
8	CO	Colombia	34	NL	Netherlands
9	CZ	Czech Republic	35	NO	Norway
10	DE	Germany	36	NZ	New Zealand
11	DK	Denmark	37	PE	Peru
12	EC	Ecuador	38	PH	Philippines
13	ES	Spain	39	PL	Poland
14	EE	Estonia	40	RO	Romania
15	FI	Finland	41	RU	Russian Federation
16	FR	France	42	SA	Saudi Arabia
17	GB	United Kingdom	43	SG	Singapore
18	GR	Greece	44	SK	Slovakia
19	HK	Hong Kong	45	SI	Slovenia
20	HU	Hungary	46	SE	Sweden
21	IN	India	47	TN	Tunisia
22	IE	Ireland	48	TR	Turkey
23	IS	Iceland	49	TW	Taiwan
24	IT	Italy	50	UY	Uruguay
25	JP	Japan	51	US	United States
26	KE	Kenya	52	ZA	Southafrican Union

Note: Due to low data coverage on inventor information in some years for specific patent offices, we remove observations for (1) Iceland in 2016; (2) Netherlands in 2012 and 2013; (3) Greece in 1993 and 1994; (4) South Korea between 1995 and 1997; (5) Turkey between 1992 and 1994; (6) Taiwan between 1992 and 1994; (7) India between 2016 and 2019.

5.2 Industrial Classification

Figure 5: Industrial Classification

Low-technology	
1	Manufacture of food products
2	Manufacture of beverages
3	Manufacture of tobacco products
4	Manufacture of textiles
5	Manufacture of wearing apparel
6	Manufacture of leather and related products
7	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
8	Manufacture of paper and paper products
9	Printing and reproduction of recorded media
10	Manufacture of furniture
11	Other manufacturing

Non-manufacture Technology	
24	Computer programming, consultancy and related activities
25	Specialised construction activities
26	Civil engineering

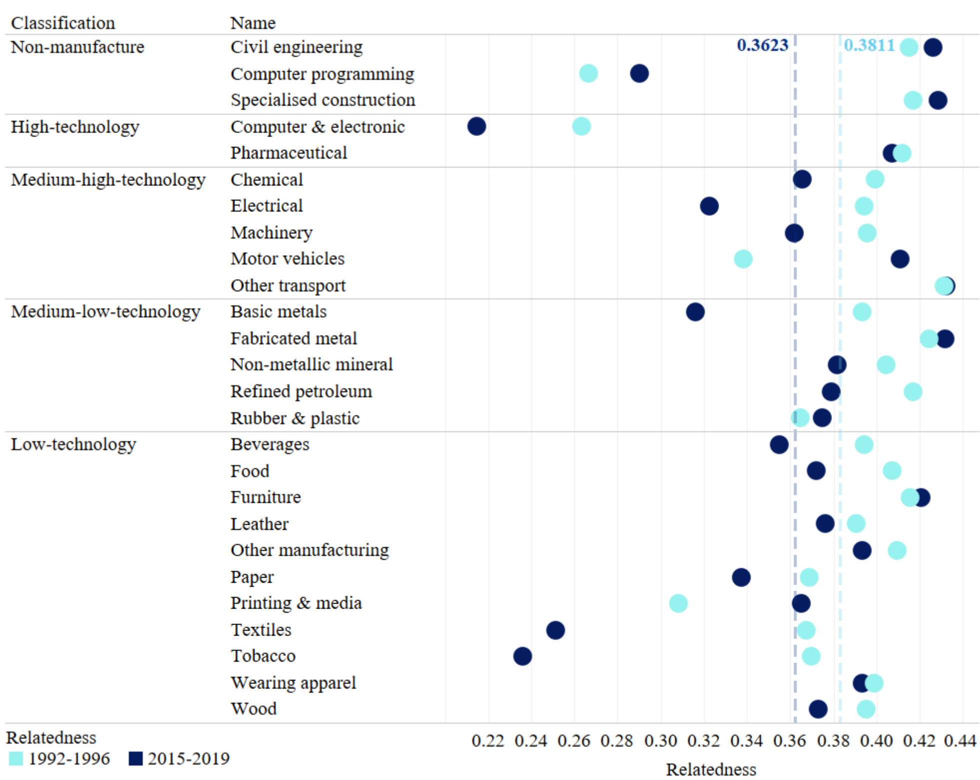
Medium-low-technology	
12	Manufacture of coke and refined petroleum products
13	Manufacture of rubber and plastic products
14	Manufacture of other non-metallic mineral products
15	Manufacture of basic metals
16	Manufacture of fabricated metal products, except machinery and equipment

Medium-high-technology	
17	Manufacture of chemicals and chemical products
18	Manufacture of electrical equipment
19	Manufacture of machinery and equipment n.e.c.
20	Manufacture of motor vehicles, trailers and semi-trailers
21	Manufacture of other transport equipment

High-technology	
22	Manufacture of basic pharmaceutical products and pharmaceutical preparations
23	Manufacture of computer, electronic and optical products

5.3 Transition of 5-Year Average Industrial Proximity (1992-2019)

Figure 6: Transition of Average Proximity by Technologies



5.4 Average Sectoral Relatedness Table

Table 3: Average Pairwise Matrix (1992-2019)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	1.00																									
2	0.61	1.00																								
3	0.33	0.37	1.00																							
4	0.37	0.40	0.34	1.00																						
5	0.40	0.42	0.36	0.42	1.00																					
6	0.42	0.41	0.37	0.39	0.55	1.00																				
7	0.46	0.50	0.36	0.37	0.41	0.40	1.00																			
8	0.31	0.33	0.34	0.38	0.39	0.40	0.44	1.00																		
9	0.25	0.25	0.30	0.27	0.27	0.29	0.29	0.32	1.00																	
10	0.47	0.44	0.38	0.39	0.57	0.55	0.52	0.42	0.30	1.00																
11	0.51	0.43	0.34	0.28	0.48	0.46	0.40	0.33	0.26	0.57	1.00															
12	0.63	0.57	0.35	0.38	0.41	0.44	0.46	0.35	0.24	0.47	0.47	1.00														
13	0.34	0.31	0.27	0.47	0.38	0.37	0.42	0.36	0.38	0.41	0.33	0.32	1.00													
14	0.54	0.57	0.33	0.49	0.40	0.47	0.51	0.38	0.33	0.46	0.41	0.57	0.45	1.00												
15	0.44	0.51	0.34	0.40	0.33	0.33	0.48	0.36	0.28	0.35	0.31	0.50	0.34	0.53	1.00											
16	0.56	0.49	0.35	0.37	0.42	0.46	0.54	0.37	0.31	0.59	0.57	0.54	0.42	0.54	0.46	1.00										
17	0.67	0.55	0.31	0.44	0.34	0.40	0.43	0.32	0.24	0.41	0.45	0.68	0.37	0.62	0.47	0.53	1.00									
18	0.27	0.25	0.29	0.36	0.39	0.43	0.35	0.32	0.28	0.39	0.26	0.24	0.36	0.35	0.30	0.35	0.25	1.00								
19	0.44	0.43	0.33	0.34	0.33	0.34	0.50	0.32	0.31	0.45	0.40	0.48	0.36	0.50	0.52	0.53	0.45	0.33	1.00							
20	0.22	0.24	0.28	0.37	0.27	0.32	0.29	0.26	0.29	0.29	0.20	0.23	0.38	0.33	0.34	0.32	0.24	0.47	0.33	1.00						
21	0.54	0.52	0.36	0.34	0.41	0.46	0.51	0.34	0.28	0.54	0.50	0.59	0.38	0.54	0.45	0.69	0.55	0.33	0.55	0.32	1.00					
22	0.62	0.45	0.33	0.35	0.42	0.43	0.41	0.35	0.26	0.52	0.60	0.56	0.37	0.46	0.32	0.58	0.56	0.25	0.34	0.23	0.54	1.00				
23	0.10	0.08	0.08	0.07	0.15	0.16	0.11	0.13	0.11	0.12	0.12	0.13	0.10	0.07	0.12	0.09	0.07	0.18	0.11	0.14	0.11	0.12	1.00			
24	0.17	0.13	0.15	0.15	0.25	0.22	0.15	0.15	0.23	0.19	0.24	0.18	0.18	0.14	0.11	0.14	0.16	0.14	0.14	0.13	0.16	0.22	0.38	1.00		
25	0.63	0.50	0.34	0.36	0.42	0.43	0.49	0.37	0.30	0.58	0.55	0.59	0.39	0.53	0.43	0.69	0.56	0.32	0.52	0.29	0.62	0.64	0.10	0.19	1.00	
26	0.58	0.53	0.39	0.32	0.42	0.44	0.47	0.34	0.28	0.50	0.50	0.59	0.29	0.51	0.46	0.56	0.56	0.30	0.55	0.26	0.59	0.49	0.12	0.18	0.63	1.00