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Related technological density and regional industrial upgrading from perspective of product space theory: evidence from China

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ABSTRACT

When the product space theory is applied to study regional technology and industry evolution, both the theory exploitation and practical application are not comprehensive and detailed enough. This article traces the connotation of 'density' in the product space theory, explains the micro-foundation of regional industrial upgrading from a firm's perspective, and abstracts industrial upgrading into four processes at two stages. Empirical research shows that an increase in related technological density (i.e. the average proximity of related technologies in a certain region) is beneficial for all processes of industrial upgrading. Marketization has a positive moderating effect on the static stage but a certain 'counterproductive' effect on the dynamic stage. Regional heterogeneity analysis shows that, on the whole, the industrial upgrading effect of the related technological density increase is relatively stronger on static processes but relatively weaker on dynamic processes in eastern China, and such results may be attributed to differences in regional resource dependence.

KEYWORDS

Related technological density; regional industrial upgrading; product space theory; China

JEL CLASSIFICATION

O33; R58

I. Introduction

With the US-China technology trade friction in recent years, China's manufacturing industry is experiencing the double squeeze of high-end reflux and low-end diversion, which may decrease the density of related technologies, China is gradually facing a possible security crisis in industrial chain. However, the relation between regional technological density and industrial upgrading of China has not yet been explored in the literature. As the world's largest developing country, China has achieved remarkable economic and industrial performance over recent decades, which provides the whole world valuable insights into the mechanism between related technological density (RTD hereinafter) and regional industrial upgrading (RIU hereinafter), and that is our real objective in this article.

RTD comes from the idea of the product space theory (Hidalgo et al. 2007), it refers to the average proximity of related technologies in a certain region, comprehensively reflecting the characteristics of the relatedness and diversity of regional technology categories.[1] RTD considers technology as a combination of endowments and comprehensive production capabilities that are inherent in international trade competitiveness, providing a new approach to study industrial structural evolution and economic growth

The connotation of RTD is often observed in the field of evolutionary economic geography, in which one of the core concepts is 'technological relatedness'. Its measurement ideas and methods include standardized industrial classification (SIC), resource similarity measurement, and so on (Essletzbichler 2015; Guo and He 2017). In recent years, it has been more common to use the index of 'product proximity/density' in the product space theory to refer to 'technological proximity/relatedness' in relevant researches. This research approach mainly draws on the co-existence analysis in the product space theory, defining technological or industrial relatedness based on the co-occurrence frequency of two products or industries in the same economy. The more countries or regions that can simultaneously produce both products, the closer of the

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[1]The relatedness and diversity levels are characterized in the sense of co-occurrence, and are calculated and conceptually analysed in the following sections.

products' relationship, and also the closer of the two industries represented by the two products. Studies of this field mainly focus on solving the problem of 'cognitive proximity' (Boschma and Frenken 2011; Boschma, Minondo, and Navarro 2013; Neffke, Henning, and Boschma 2011; Timmermans and Boschma 2014; Zhu, He, and Luo 2019), and the research content is mainly about technological relatedness (Boschma and Iammarino 2009; Boschma et al. 2023; Corrocher, Grabner, and Morrison 2024; Frankort 2016).

Outside the field of evolutionary economic geography, studies of 'technological relatedness' or 'technological density' are also commonly seen drawing on the idea of product space theory. Scholars usually make appropriate improvements to relevant research methods or replace product data with patent data. Their research topics include the emergence of new technology-based industries (Tanner 2016), green technologies and smart specialization (Montresor and Quatraro 2020), the role of technological relatedness on diversifying renewable energies (Moreno and Ocampo-Corrales 2022), the relation between technological density and new industry development (H. Zhang and Liu 2019), the relation of regional technological density and related/unrelated technological diversification as well as economic growth rates (Zheng and Ran 2021), and so on.

Concerning RIU, we focus only on technological relatedness and RIU that draws on the ideas of product space theory, that is, the evolution of comparative advantage and the path of industrial upgrading. Although some scholars have criticized the product space theory approach for its difficulty in identifying specific sources of relatedness (Essletzbichler 2015) and its lack of explanatory power for unrelated diversity (Coniglio et al. 2018), the argument about path dependence and path creation in industrial evolution remains the focus of this research paradigm. Product space theory proposed the concept of 'comparative advantage evolution', arguing that traditional comparative advantage theory ignored the impact of the initial labour division in a country or region and that the initial structure of a country's product space affects its development path (Hidalgo et al. 2007), called the 'HK model' (named as Hausmann and Klinger, two of the founders of product space theory). Q. Zhang (2008) used the concept of 'industry degree' to establish the 'extended HK model' and analysed the evolution path of China's comparative advantage and the risk of industrial upgrading breaks. Thereafter, Deng and Cao (2016) constructed the 'extended HK model with capacity accumulation' and pointed out that China's industrial upgrading over the past 50 years had been characterized by a relative deviation from comparative advantage through empirical tests. A large number of studies have proven the ubiquity of path dependence in regional industrial evolution (Boschma, Minondo, and Navarro 2012; Colombelli, Krafft, and Quatraro 2014; Essletzbichler 2015) and have shown the path breakthroughs as well as path dependence in China's regional industrial development (Cao and Xie 2023; Guo and He 2017; He 2018; Li and He 2021).

To summarize, analysis at corporate behaviour level is scarce when applying product space theory to study regional technology and industry evolution. And scholars usually focus solely on the connotation of technology 'relatedness' or 'diversity', this can be considered a significant loss in the application of product space theory. Furthermore, when the product space theory employed for empirical research of RIU, the stage division and explanations are not comprehensive and detailed enough. In this article, we try to clarify the mechanism and influence factors between RTD and RIU through conceptual tracing and methodological improvement.

The possible marginal contributions of this article are as follows: first, by taking into account the dual economic connotations of 'relatedness' and 'diversity' of density, we clarify the micro-mechanism of RIU promoted by RTD at enterprise level and provide empirical evidence; Second, through appropriate method improvement, we abstracts industrial upgrading into four processes at two stages and position the static stage of industrial upgrading equally important to the dynamic stage, revealing hidden but essential roles of the static stage in RIU; Third, we further explore the regional heterogeneity and find it may be attributed to differences in regional resource dependence.

II. Theoretical analysis and research hypotheses

Regarding the measurement of RTD, as mentioned in the previous literature review, studies (drawing on the idea of the product space theory) generally referred to 'technological relatedness' directly by the indicator of 'product density', or conducted corresponding research after making moderate improvements to the formula of 'product density'. They usually use the international trade data of product categories to refer to corresponding technology categories.[2] The calculation formulas are:

$$RCA_i = \frac{v(p,i,t)/\sum_i v(p,i,t)}{\sum_p v(p,i,t)/\sum_{p,i} v(p,i,t)} \tag{1}$$

$$\emptyset_{i,j,t} = min\{P(RCA_i|RCA_j), P(RCA_j|RCA_i)\} \tag{2}$$

$$Den_{p,i,t} = \frac{\sum_j x_{p,j}\emptyset_{i,j}}{\sum_j \emptyset_{i,j}} \tag{3}$$

where RCA_i and RCA_j respectively represent 'revealed comparative advantage'[3] of technology i and j, $x_{p,j}$ is the logical value of RCA_j, $x_{p,j} = 1$ if RCA_j >1 and 0 otherwise (similarly, $x_{p,i}$ below is the logical value of RCA_i). Consequently, $\emptyset_{i,j,t}$ represents the proximity between technology i and j during period t, indicating the minimum conditional probability for both technologies having comparative advantage (RCA >1). Thus, $Den_{p,i,t}$ is the average proximity of advantage technology set related to i in province p during period t, which is defined as 'related technological density (RTD)' herein.

It should be noted that, we emphasize the dual connotations of 'relatedness' and 'diversity' of $Den_{p,i,t}$ (i.e. density, Hidalgo et al. 2007).[4] The higher the density of a potential technology, the more developed technologies surrounding it in the country or region, and the easier it becomes for enterprises to leapfrog. Formulas 1 and 2 show that 'density' is based on 'proximity' and corrected by the logical value of RCA, which implies the dual economic essences of 'relatedness' and 'diversity' in the sense of regional co-occurrence, that is, the level of diversity and average proximity of advantageous technologies set that are closely related to i in province p during period t.

Enterprise-level technological choices and leaps

A firm's behaviour is the micro-foundation of RTD and RIU. Q. Zhang (2008), Deng and Cao (2016) introduced the concept of 'industry degree' in their studies of China's industrial upgrading path, which provide a reference for this article. The 'industry degree' is the number of subsequent upgrading opportunities of a certain technological node in product space graph. As shown in Figure 1(a), technology nodes are represented by letters, and the industry degree signifies the number of edges connecting each technology node, that is, the number of technology paths that available for enterprises to upgrade their products. In Figure 1(a) (under the initial state without technology E), the industry degrees of technology A, B, and C are respectively 2, 3, and 1.

Enterprises' choice of technology path for product upgrading depends on three motivations. First, the benefit P_{ij} of the technology jump, which is proportional to jump distance δ, (i.e. $P_{ij}=f\delta$). Second, the number of technological choices that can be realized in the region, that is, the density of related technologies, expressed by industry degree d ($d \geq 1$). The higher the industry degree of a potential technology, the greater its universality, the lower the sunk cost of the subsequent technology upgrading of this potential jump,[5] and the greater the motivation for enterprises to jump to it. Third, the cost generated by the technology jump, which is proportional to the square of the jump distance, and at the same time, obviously inversely proportional to the industry degree, that is, $C = c\delta^2/2d$.

Then, the profit of a firm's technology jump in the initial regional industry state is

$$\pi_0 = f\delta - c\delta^2/2d \tag{4}$$

It is easy to obtain the maximum jump distance δ_{0max} for the firm to keep its profit positive, as well

[2]The data used by the product space theory are usually on the national scale. Scholars have replaced it with a sub-national scale (e.g. provincial level) to study regional economic issues. We also use export data at the provincial level in China.
[3]This indicator was first proposed by Balassa (1965). In this article, $v(p,i,t)$ represents the export value of product i in province p over period t.
[4]In the field of evolutionary economic geography, due to its theoretical mission, the concept of 'technological relatedness' borrowed from product space theory is aimed to solve the problem of 'cognitive/knowledge proximity', focusing more on 'relatedness' but less on 'diversity'.
[5]The more versatile the technology jump, the more conducive it is for enterprise to integrate the existing production, logistics, rules and regulations, corporate culture and other hardware and software resources in the subsequent product upgrading, which can greatly reduce the cost of the technology jump and product upgrading.

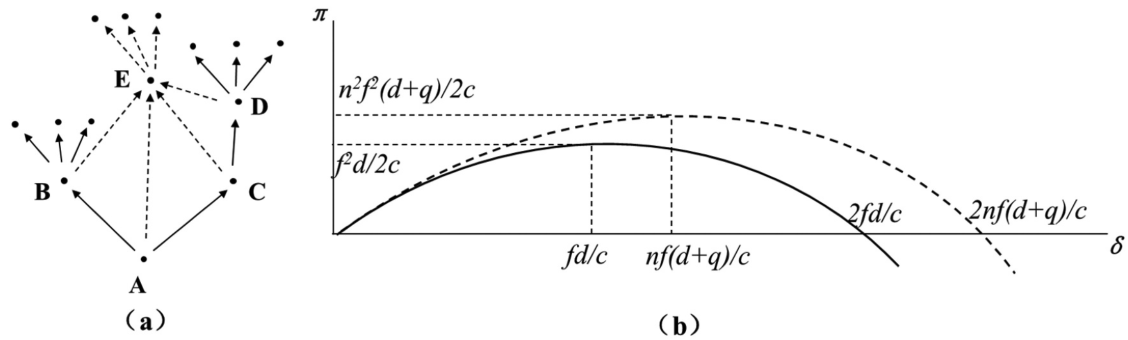

Figure 1. Relation between firm-level technology jumps and the profits.

as the optimal jump distance δ_0* and the maximized profit π_0* for the firm in the first-order condition:

$$\delta_{0max} = 2fd/c, \delta_0* = fd/c, \pi_0* = f^2d/2c \quad (5)$$

The above result is the optimal solution in the initial state of the regional industry. The relation between firm's technology jump and profit is shown as the real curve in Figure 1(b).

When the technology density of the region increases, that is, there are additional related technologies (e.g. technology E in Figure 1(a)) to choose from, assuming that the firm's initial technology is A. On the one hand, it is possible to increase the benefit from this technology jump (when $\delta_{A\text{-}E} \geq \min\{\delta_{A\text{-}B}, \delta_{A\text{-}C}\}$), that is, $P_{ij}=nf\delta$, n is positive and $n\geq 1$[6]; On the other hand, due to the increase of industry degree (let the number of additions be q), the versatility of subsequent upgrading is improved, which inevitably reduces the cost of this technology jump, that is, $C=c\delta^2/2(d+q)$, with q as a positive integer.

Thus, the firm's profit from this technology jump is:

$$\pi_1 = nf\delta - c\delta^2/2(d+q) \quad (6)$$

Then we obtain the maximum jump distance δ_{1max} for the firm to keep its profit positive after an increase in regional technological density, as well as the optimal jump distance δ_1* and maximized profitπ_1^* in the first-order condition:

$$\delta_{1max} = 2nf(d+q)/c, \delta_1* = nf(d+q)/c, \pi_1* = n^2f^2(d+q)/2c \quad (7)$$

This result is the optimal choice for enterprise after the increase of RTD in the region. At this time, the relation between the enterprise's technology jump and the profit gained is shown in the imaginary curve in Figure 1(b).

Obviously, since $n \geq 1$, d and q are positive integer, the maximum distance δ_{1max}, the optimal distance δ_1*, and the maximized profit π_1* for the jump after the increase of RTD in the region are all greater than δ_{0max}, δ_0* and π_0* of the initial state.

This implies that, in the process of RIU, enterprises' technological capabilities (i.e. jumping distances δ_{max} and δ*) are directly proportional to the RTD of the region (i.e. industry degree d). The increase of RTD on one hand likely to enlarge the profit and on the other hand will certainly reduce the cost of technology upgrading, which in fact enhances the overall enterprises' technological capability (i.e. the optimal jumping distance δ*) in the region. More importantly, from a regional perspective, an increase in the density of regionally related technologies magnifies the firms' maximum jump distance (δ_{max}) that maintains profits positive, which enlarging firms' space for trial and error, stimulates firms' incentives of exploring new technologies and thereby promotes RIU.

Thus, we propose the following hypothesis:

Hypothesis 1. An increase in the density of related technologies can enhance enterprises' technological leapfrogging ability, thereby promoting RIU.

[6]When $\delta_{A\text{-}E} < \min\{\delta_{A\text{-}B}, \delta_{A\text{-}C}\}$, n takes the value of 1, which means that the firm, as a 'rational person', will not choose a technology jump path that is lower than the initial payoff state.

Static and dynamic stages

Hausmann and Klinger (two of the founders of product space theory) investigated two situations on industrial upgrading: ‘upgrading to new products’ and ‘abandoning current products’. Based on this, later scholars further differentiated the status of industrial upgrading by using the logical value of RCA ($x_{p,i}$, 0 or 1) as a criterion, dividing industrial transformation status into four processes: non-upgrading, successful upgrading, product decline, and keeping advantage (Deng and Cao 2016; Ma and Yu 2018). However, due to varied research themes, scholars usually only pay attention to the processes of successful upgrading and product decline. That is, they focus solely on the dynamic stage, neglecting a detailed analysis of the static processes of non-upgrading and keeping advantage.

We believe that the transition from the static to dynamic stage is processes of qualitative change driven by quantitative changes. Although the two static processes have a certain characteristic of being hidden, they play an essential role in RIU and should be positioned equally important to the dynamic stage. Hausmann and Klinger were the first to study the promotion of product advantage, but they overlooked a stage-based study. Furthermore, industrial development practices demonstrate that the capacity accumulation and advantage maintenance processes at the static stage are more general and common in the entire industrial upgrading cycle. Unfortunately, due to the different areas of focus, previous research lacked necessary analysis to static processes.

Drawing on previous studies, we abstract industrial upgrading into two stages: static and upgrading, corresponding to processes of the technological capacity accumulation before upgrading (Static 1), the industrial advantage maintenance after upgrading (Static 2), the successful transformation into new technologies at the upgrading stage (Dynamic 1), and the elimination of old technologies at the upgrading stage (Dynamic 2), all illustrated in Table 1.

Furthermore, from the perspective of the entire technological and industrial evolutionary process, the static and dynamic stage division is reasonable and realistic, it can fully explain the iterative upgrading of regional technological and industrial cyclical evolution. When a new technology or class of technologies emerges in a region, an industry enters the dynamic upgrading stage, where competitive pressure forces enterprises to transfer to new technologies and give up old ones, thus realizing region-wide industrial upgrading. When the upgrading is completed, the regional industry enters the static stage, where it maintains the advantages of existing technologies and nurtures new technologies until the emergence of something new. Through these dynamic and static cycles, the regional industries achieve iterative upgrading.

Based on the above, we propose the hypothesis for stage classification of RIU:

Hypothesis 2. The increase of RTD contributes to all stages and processes of RIU.

Marketization’s moderating effect

Marketization has a crucial impact on technological progress in China (Fan, Wang, and Ma 2011), often considered one of the key factors in studies of technological evolution and RIU. However, its role is often complex and not simply promotional or inhibitory. According to relevant literature, marketization primarily exerts a moderating effect on RIU through two channels: the agglomeration effect of regional resources and the allocation efficiency of regional resources.

The first is the resource agglomeration effect of marketization. Marketization benefits the agglomeration of resources, such as talents and capital,

Table 1. Stages classification and interpretation.

Stage	Process	Current Period	Next Period	Implications of Product	Implications of Technology
static	Static 1	$x_{p,i} = 0$	$x_{p,i} = 0$	non-upgrading	capacity accumulation
	Static 2	$x_{p,i} = 1$	$x_{p,i} = 1$	keep advantage	advantage maintenance
upgrading	Dynamic 1	$x_{p,i} = 0$	$x_{p,i} = 1$	successful upgrading	successful transformation into new technologies
	Dynamic 2	$x_{p,i} = 1$	$x_{p,i} = 0$	product decline	elimination of old technologies

which promotes RIU (especially the static stage) indirectly. During the accumulation of technological capabilities before upgrading (Static 1) and the maintenance of industrial advantages after upgrading (Static 2), improved marketization brings about favourable business environments, higher levels of factor markets, and product markets (especially the market of intermediate technology), and more robust institutional environments. These factors facilitate the agglomeration of high-end talents, high-quality capital, and advanced technological resources, thereby increasing the concentration of related (and unrelated) advantageous technologies within the region. This in turn leads to a cumulative and amplifying effect on the increase in technological density. The increased variety of technologies within the region reduces the indispensability of intermediate suppliers (Sheng and Wang 2011), enhancing the enterprises' motivations to transform and upgrade. This is equivalent to reinforcing the role of technological capability accumulation before RIU (Static 1). Furthermore, the continuous agglomeration of related technologies ensures the continuous improvement of product quality and functionality, which guarantees the existing industries to keep their advantages (Static 2).

The second channel is the impact of marketization on the efficiency of resource allocation. Marketization reform promotes the improvement of resource allocation efficiency (Fan, Wang, and Ma 2011), while, particularly at the stage of dynamic industrial upgrading, market failures in resource allocation occur frequently at the same time, leading to industry shocks when new products enter (Q. Zhang and Qi 2023). A higher degree of marketization in a region implies greater freedom and more intense competition. In the early introduction of new products, industries, or business models, it often attracts a swarm of capital, resulting in chaotic competition and excessive resource waste, which will temporarily inhibit the successful transformation towards new technologies and the formation of new industries (Dynamic 1), thereby indirectly postponing the elimination of old technologies (Dynamic 2). Numerous studies have found that marketization does not always have a positive impact on technological evolution or innovation efficiency (Berkowitz, Moenius, and Pistor 2006; Lu and Zhu 2018; Lü, Qiao, and Li 2023; Rodrik 2000; Xiao and Lin 2014), and there are numerous realistic cases of suffering overall industry damage due to chaotic competitions or winner-takes-all in highly developed regions. Therefore, a high marketization level usually hampers the rapid formation of market advantages for new products, which means temporarily weakening the successful leap towards new technologies (Dynamic 1) as well as the elimination of old technologies (Dynamic 2) for regional enterprises.

Therefore, we propose the third hypothesis:

Hypothesis 3. Marketization respectively has a positive and negative moderating effect during the static (Static 1 and Static 2) and dynamic (Dynamic 1 and Dynamic 2) stages of RIU influenced by RTD increase.

The empirical research logic herein is summarized in Figure 2.

III. Variable description and model selection

Variable description

(a) **Dependent Variable: Industrial upgrading ($x_{p,i,t+1}$, i.e., logical value of a certain product's RCA in next period)**. As shown in Table 1, industrial upgrading is divided into four processes based on the combination of whether a certain product exhibits advantage in the export trade of the current and next period, determined by the changes of logical value from $x_{p,i,t}$ to $x_{p,i,t+1}$(0 or 1).

(b) **Core Explanatory Variable: RTD ($Den_{p,i,t}$)**. As shown in formula (3), the concept of RTD ($Den_{p,i,t}$) mainly considers the dual connotations of technological proximity and diversity.

(c) **Moderator Variable: Level of marketization ($MKT_{p,t}$)**. The widely used 'marketization index' of China (Wang, Hu, and Fan 2021) functions as the moderator variable. It measures the marketization level across different dimensions, including the government–market relationship, the development

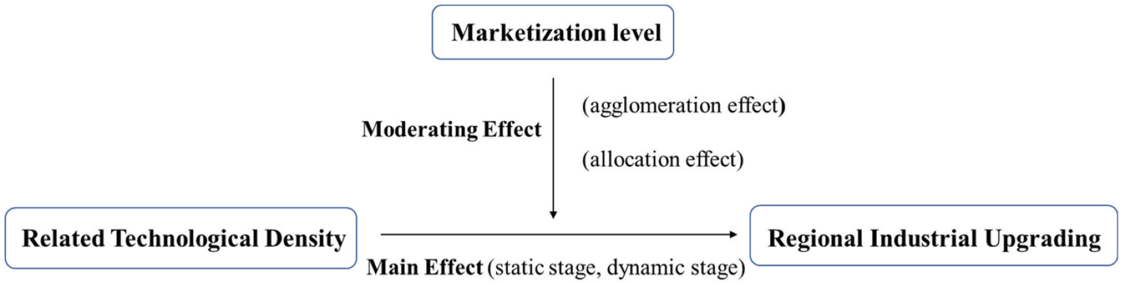

Figure 2. Empirical research logic of RTD and RIU.

of non-state-owned economy, the development of factor markets, the development of product markets, the development of market intermediary organizations, and the institutional environment of laws and regulations. It comprehensively reflects the market efficiency.

(d) **Control Variables**: The following control variables are included in this study: Economic development level (**pgdp**), represented by per capita GDP of each province; Industrial structure (**ind**), represented by the ratio of tertiary and secondary industry value added of each province; Market potential (**pop**), represented by resident population of each province; Level of openness to foreign countries (**for**), represented by foreign investment standardized by the GDP of each province; Fiscal gap (**gap**), represented by the ratio of the fiscal expenditures and revenues difference to the GDP of each province. In addition, to eliminate the influence of unobservable factors, province-fixed effects (**prov**) and year-fixed effects (**year**) will be also included.

Data source and statistical analysis

We utilize the HS four-digit code export trade data[7] of 31 provinces, autonomous regions, and municipalities (excluding Hong Kong, Macau, and Taiwan due to data availability and statistics calibre) in China covering 2002 to 2021. Control variables such as population size and per capita GDP are obtained from the statistical yearbooks of each province. The Python software is used to compute the relevant technical indicators via calculation formulas mentioned earlier. Table 2 shows descriptive statistics.

Model selection

Drawing on relevant literature (Deng and Cao 2016) and research hypotheses, we adopt the static benchmark model (Equation 8) and the corresponding marketization moderation model (Equation 10) to examine the relation between RTD and RIU during the static stage. We also adopt the dynamic benchmark model (Equation 9) and the corresponding marketization moderation model (Equation 11) to exam-

Table 2. Descriptive statistics of variables.

Variable	Sample size	Mean	Standard deviation	Min	Max
$x_{p,i,t}$	701871	0.204	0.403	0.000	1.000
$Den_{p,i,t}$	701871	0.221	0.128	0.003	1.000
$MKT_{p,t}$	701871	7.062	2.186	−0.161	11.934
pgdp	701871	3.865	2.843	0.315	16.489
ind	701871	1.076	0.595	0.494	5.297
pop	701871	17.304	0.858	14.798	18.654
for	701871	0.484	1.481	0.047	34.233
gap	701871	0.145	0.181	0.008	1.244

[7]According to relevant researches, we use product categories to refer to technology categories. The HS four-digit data consists of 22 categories, 98 chapters, more than 1,200 (the exact number varies from year to year) product items, representing more than 1,200 kinds of technologies.

ine the relation between them during the dynamic stage of industrial upgrading. $Z_{p,t}$ stands for control variables.

$$x_{p,i,t+1} = \alpha + \gamma x_{p,i,t} + \beta Den_{p,i,t} + \omega Z_{p,t} + prov + year + \varepsilon_{p,t} \tag{8}$$

$$x_{p,i,t+1} = \alpha + \gamma x_{p,i,t} + \beta_1(x_{p,i,t})Den_{p,i,t} + \beta_2(1 - x_{p,i,t})Den_{p,i,t} + \omega Z_{p,t} + prov + year + \varepsilon_{p,t} \tag{9}$$

$$x_{p,i,t+1} = \alpha + \gamma x_{p,i,t} + \beta_1 Den_{p,i,t} + \beta_2 MKT_{p,t} + \beta_3 Den_{p,i,t} MKT_{p,t} + \omega Z_{p,t} + prov + year + \varepsilon_{p,t} \tag{10}$$

$$x_{p,i,t+1} = \alpha + \gamma x_{p,i,t} + \beta_1(x_{p,i,t})Den_{p,i,t} + \beta_2(x_{p,i,t})MKT_{p,t} + \beta_3(x_{p,i,t})Den_{p,i,t}MKT_{p.t} + \beta_4(1 - x_{p,i,t})Den_{p,i,t} + \beta_5(1 - x_{p,i,t})MKT_{p,t} + \beta_6(1 - x_{p,i,t})Den_{p,i,t}MKT_{p,t} + \omega Z_{p,t} + prov + year + \varepsilon_{p,t} \tag{11}$$

IV. Analysis of empirical results

Benchmark regression

The benchmark models (Equations 8 and 9) examine the role of RTD in the four processes of static and dynamic stages of RIU. To ensure robustness and reliability of the empirical results, we use three regression methods – Probit, Logit, and OLS – considering the binary discrete response model and the characteristics of large samples, as well as the practices in previous literature. Table 3 reports the regression results.

Regarding the technological capacity accumulation of the pre-upgrade (Static 1) and industrial advantage maintenance of the post-upgrade (Static 2) in the static stage, the coefficient of $Den_{p,i,t}$ is positive and significant at the 1% level in all three regression results. This indicates that the closer and more diversified the regional related technologies, the higher the possibility for new products to appear in the export basket, the more beneficial for the cultivation and accumulation of technological capability before the upgrade, as well as for the maintenance of industrial advantages after the upgrade.

As for the transition to new technologies at the upgrading stage (Dynamic 1), coefficient β_2 of $(1 - x_{p,i,t})Den_{p,i,t}$ in Equation 9 is significantly positive at the 1% level in all three regression

Table 3. Regression results of the benchmark models.

Variable	(1) Probit	(2) Probit	(3) Logit	(4) Logit	(5) OLS	(6) OLS
$x_{p,i,t}$	2.177***	2.415***	3.777***	4.338***	0.691***	0.656***
	(281.64)	(169.42)	(251.30)	(163.51)	(430.99)	(188.07)
$Den_{p,i,t}$	1.892***		3.425***		0.333***	
	(40.68)		(36.20)		(49.14)	
pgdp	−0.013***	−0.014***	−0.026***	−0.027***	−0.002***	−0.002***
	(−3.74)	(−3.87)	(−3.70)	(−3.96)	(−3.31)	(−3.37)
ind	−0.002	0.004	−0.004	0.011	0.001	0.000
	(−0.15)	(0.34)	(−0.17)	(0.52)	(0.34)	(0.05)
pop	0.300***	0.282***	0.613***	0.573***	0.039***	0.042***
	(5.99)	(5.63)	(6.13)	(5.74)	(5.48)	(5.85)
for	−0.006**	−0.007***	−0.017***	−0.020***	−0.001***	−0.001***
	(−2.52)	(−2.82)	(−3.51)	(−3.82)	(−5.14)	(−4.71)
gap	−0.078	−0.096	−0.260*	−0.287*	−0.026***	−0.024***
	(−1.15)	(−1.36)	(−1.90)	(−1.95)	(−3.45)	(−3.12)
$(x_{p,i,t})Den_{p,i,t}$		1.629***		2.891***		0.388***
		(34.21)		(30.88)		(42.62)
$(1 - x_{p,i,t})Den_{p,i,t}$		2.565***		5.175***		0.263***
		(49.49)		(48.81)		(37.28)
_cons	−6.975***	−6.840***	−13.745***	−13.482***	−0.667***	−0.695***
	(−8.41)	(−8.25)	(−8.29)	(−8.17)	(−5.61)	(−5.85)
N	701871	701871	701871	701871	701871	701871
adj. R^2					0.571	0.571
pseudo R^2	0.495	0.496	0.495	0.496		
prov	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes

*, ** and *** respectively indicate significance at the 10%, 5% and 1% level.

results. This indicates that a higher density of related technologies is favourable for a successful transition to new technologies.

In the process of eliminating old technologies at the upgrading stage (Dynamic 2), coefficient β_1 of $(x_{p,i,t})Den_{p,i,t}$ in Equation 9 is positive and significant at the 1% level in all three regression results. It suggests that a higher density of related technologies increases the likelihood of eliminating old technologies.

Furthermore, in terms of the coefficient magnitude of static term $Den_{p,i,t}$, all the results of the three regression methods are comparable to the coefficient values of dynamic terms $(1-x_{p,i,t})Den_{p,i,t}$ and $(x_{p,i,t})Den_{p,i,t}$, which shows that the static stage is equally important as the dynamic stage in the cyclical evolution of industrial upgrading.

Thus, Hypothesis 1 and Hypothesis 2 are verified. In other words, there is a positive relation between RTD and RIU. The dual effects of narrowing technological proximity and increasing technological diversity brought by the increase of RTD contribute direct to all stages and processes of RIU. And this finding (the higher the density, the more conducive it is to achieve industrial upgrading) is same with other countries or regions in the world (Ma and Yu 2018).

The moderating effect of marketization

Moderating effect models (Equations 10 and 11) examine marketization's influence on RIU by RTD. Considering the large sample characteristics of the data used in this study, the OLS method was employed. Before conducting the regression, the variables involved in the interaction term were centred to reduce potential multicollinearity issues. The results are shown in Table 4.

The static coefficient of $Den_{p,i,t}MKT_{p,t}$ is significantly positive at the 1% level, while the dynamic coefficients of $(x_{p,i,t})Den_{p,i,t}MKT_{p,t}$ and $(1-x_{p,i,t})Den_{p,i,t}MKT_{p,t}$ are both significantly negative at the 1% level. Therefore, Hypothesis 3 is confirmed, indicating the existence of a moderating effect of marketization, manifesting positive moderation at the static stage and negative moderation at the dynamic stage.

Endogeneity discussion and robustness test

This study may suffer endogeneity issues from omitted variables or simultaneous causality. For potential omitted variable issues, all models have controlled factors may influence industrial upgrading such as economic development level, industrial structure, market potential, openness level, and fiscal pressure, furthermore, province-fixed effects and year-fixed effects are also controlled, all of these can alleviate endogeneity issues from potential omitted variables. For the possibility of bidirectional causality, since all econometric models regress the lagged values of industrial upgrading variables, they can partially mitigate the issue of reverse causality between industrial upgrading and RTD.

As for robustness tests, in addition to considering the different regression methods above, we also consider robustness issues caused by data fluctuations within the geographical and temporal scopes covered by the sample for the benchmark models (Equations 8 and 9). First, the original RCA values are used instead of discrete binary logical values (0 and 1) to reflect the continuous process of industrial upgrading from quantitative to qualitative changes, which is more vivid and accurate.

Table 4. Regression results of marketization moderating effect.

Variable	(1)	(2)
$x_{p,i,t}$	0.692***	0.688***
	(434.23)	(366.64)
$Den_{p,i,t}$	0.303***	
	(43.08)	
$MKT_{p,t}$	0.000	
	(0.25)	
$Den_{p,i,t}MKT_{p,t}$	0.025***	
	(12.18)	
$(x_{p,i,t})Den_{p,i,t}$		0.307***
		(27.56)
$(x_{p,i,t})MKT_{p,t}$		0.015***
		(14.66)
$(x_{p,i,t})Den_{p,i,t}MKT_{p,t}$		−0.027***
		(−6.53)
$(1-x_{p,i,t})Den_{p,i,t}$		0.322***
		(45.64)
$(1-x_{p,i,t})MKT_{p,t}$		−0.005***
		(−6.95)
$(1-x_{p,i,t})Den_{p,i,t}MKT_{p,t}$		−0.034***
		(−12.35)
Control Variable	Yes	Yes
_cons	−0.719***	−0.542***
	(−5.94)	(−4.50)
N	701871	701871
adj. R^2	0.571	0.572
prov	Yes	Yes
year	Yes	Yes

*, ** and *** respectively indicate significance at the 10%, 5% and 1% level.

Second, regressing after the core explanatory variable $Den_{p,i,t}$ is standardized to avoid the problem of comparability decline due to data differences among different years. Third, the data from municipalities are excluded to avoid the issue of unequal product trade volumes between city and province. Fourth, the data of 2008 and 2009 are excluded to avoid the effects of international trade data fluctuations caused by the financial crisis. Fifth, the data of 2003, 2020, and 2021 are excluded to avoid the impact of international trade data fluctuations caused by international public health events. All results show that the coefficients of all static and dynamic core explanatory variables are significantly positive, which passing the robustness test.

V. Further research on regional heterogeneity and its causes

We visualize $Den_{p,i,t}$ at the provincial level to describe the spatial and temporal evolutionary characteristics of technology distribution. Due to the impact of the COVID-19 on international trade, the data for 2020 and 2021 are excluded. Therefore, three time points representing the beginning, middle, and end of the sample data, namely 2002, 2010, and 2019, are selected for analysis. We calculate the average density values of various technologies for each province in these 3 years, and divide the average value range of each year into five intervals. ArcGIS software is used to colour-code. The results are shown in Figure 3.

Overall, during the first decade of the 21st century, the average values of RTD in Chinese provinces increased steadily. The lower and upper limits of the average values rose respectively from 0.046 and 0.408 to 0.053 and 0.430. As shown in Figure 3, during this period, technology and industry agglomeration was primarily in the eastern and the northeastern regions. From 2010 to 2019, the upper limit of average RTD increased from 0.430 to 0.471, while the lower limit decreased from 0.053 to 0.048I, indicating a more pronounced regional agglomeration effect. As shown in Figure 3, the agglomeration during this period was mainly in the eastern and the southern regions.

Therefore, it is evident that there is significant regional heterogeneity in RIU, which calls for further in-depth research.

Research on regional heterogeneity

Model selection

We divide the sample into two groups: the eastern group and the non-eastern group (the eastern group includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the other provinces belong to the non-eastern group). Then we set dummy variable static and dynamic models (Equations 12 and 13) accordingly.

$$x_{p,i,t+1} = \alpha + \gamma x_{p,i,t} + \beta_1 Den_{p,i,t} + \beta_2 Area_p + \beta_3 Den_{p,i,t} Area_p + \omega Z_{p,t} + prov + year + \varepsilon_{p,t} \tag{12}$$

$$x_{p,i,t+1} = \alpha + \gamma x_{p,i,t} + \beta_1 (x_{p,i,t}) Den_{p,i,t} + \beta_2 (x_{p,i,t}) Area_p + \beta_3 (x_{p,i,t}) Den_{p,i,t} Area_p + \beta_4 (1 - x_{p,i,t}) Den_{p,i,t} + \beta_5 (1 - x_{p,i,t}) Area_p + \beta_6 (1 - x_{p,i,t}) Den_{p,i,t} Area_p + \omega Z_{p,t} + prov + year + \varepsilon_{p,t} \tag{13}$$

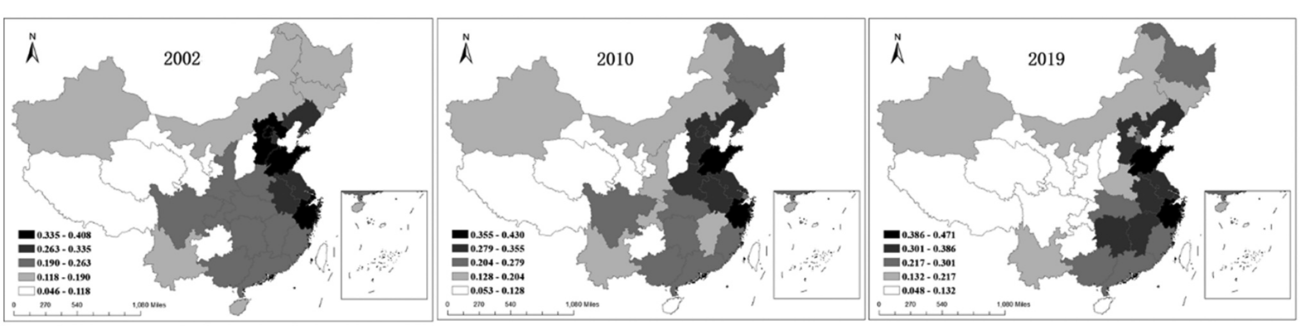

Figure 3. Distribution of average density value at provincial level in 2002, 2010, and 2019. The map was obtained from the Standard Map Service Website of China (Approval No: GS(2019)1822). The base map remains unaltered.

$Area_p$ is regional dummy variable, with a value of 1 for the eastern region and 0 for the non-eastern region; the other variables are the same as mentioned earlier. The models mean that the group with the value of 0 serves as the benchmark group, and the regression results reflect the performance of the group valued 1 relative to the benchmark group.

Empirical results analysis

Considering the characteristics of large sample, we use OLS regression. Variables involved in the interaction terms were centred prior to the regression. The results are shown in Table 5.

The coefficient of $Den_{p,i,t}Area_p$ is positive and significant at the 1% level, indicating that at static stage of industrial upgrading, RTD increase has a relatively stronger effect on technological capacity accumulation before upgrading (Static 1) and on the maintenance of industrial advantages after upgrading (Static 2) in the eastern region compared to the non-eastern region. The coefficients of $(x_{p,i,t})Den_{p,i,t}Area_p$ and $(1 - x_{p,i,t})Den_{p,i,t}Area_p$ are both negative and significant at the 1% level, suggesting that at dynamic stage of industrial upgrading, the promoting effects of RTD increase on the successful transition to new technologies (Dynamic 1) and on the elimination of outdated technologies (Dynamic 2) are both relatively weaker in the eastern region compared to the non-eastern region.

Considering Chinese economic practices and referring to previous empirical findings, it is not difficult to explain these results. Although the conclusion that the increase of RTD promotes industrial upgrading throughout all stages and processes is applicable to all over China, the eastern regions usually have a relatively stronger effect of aggregating high-quality resources due to the higher levels of marketization, leading to a relatively stronger effect in terms of technological capacity accumulation (Static 1) and industrial advantages maintenance (Static 2). However, along with the relatively high level of marketization in the eastern regions, market failures such as disorderly competition and resource misallocation often occur at the emergence of a new product, technology or business format, which could temporarily hinder the transition to new technologies (Dynamic 1) and the elimination of outdated technologies (Dynamic 2), thereby making the promoting effect on industrial upgrading during dynamic stage relatively weaker in the eastern region.

Table 5. Regional heterogeneity regression results.

Variable	(1)	(2)
$x_{p,i,t}$	0.691***	0.663***
	(432.62)	(298.53)
$Den_{p,i,t}$	0.263***	
	(32.46)	
$Area_p$	0.019***	
	(3.05)	
$Den_{p,i,t}Area_p$	0.134***	
	(13.94)	
$(x_{p,i,t})Den_{p,i,t}$		0.395***
		(25.70)
$(x_{p,i,t})Area_p$		0.090***
		(12.17)
$(x_{p,i,t})Den_{p,i,t}Area_p$		−0.180***
		(−8.70)
$(1 - x_{p,i,t})Den_{p,i,t}$		0.329***
		(38.60)
$(1 - x_{p,i,t})Area_p$		0.007
		(1.13)
$(1 - x_{p,i,t})Den_{p,i,t}Area_p$		−0.086***
		(−5.65)
Control Variable	Yes	Yes
_cons	−0.813***	−0.577***
	(−6.55)	(−4.64)
N	701871	701871
adj. R^2	0.571	0.572
prov	Yes	Yes
year	Yes	Yes

*, ** and *** respectively indicate significance at the 10%, 5% and 1% level.

Research on resource dependence heterogeneity

What are the reasons for the regional heterogeneity in addition to the difference of marketization levels (the eastern group is usually also the high marketization region)? We posit that different resource dependence levels are the fundamental cause of regional heterogeneity. Compared to non-resource-dependent (generally the eastern) regions of China, the high resource-dependent (usually the non-eastern) regions exhibit significantly different effects on both the static and dynamic industrial upgrading stages.

At the static stage, high resource-dependent regions, dominated by resource-dependent industries, have exclusionary and inhibitory effects on non-resource-dependent industries, hindering the aggregation of high-quality resources and directly or indirectly inhibiting technological proximity reduction and diversification improvement, making the promotional effects of RTD increase on technological capacity accumulation (Static 1) and industrial advantage maintenance (Static 2) in high resource-dependent regions relatively weaker. However, during the dynamic stage, due to relatively lower levels of technological and industrial density in high resource-dependent regions, enterprises' profit space enabled by each unit increase in RTD is relatively larger, providing relatively stronger incentives for local enterprises to transfer to new technologies, making the marginal effect of RTD increase on promoting the dynamic stage upgrading (especially the successful transition to new technologies of Dynamic 1) in high resource-dependent regions relatively stronger.

Grouping and model selection

To verify the cause of regional heterogeneity interpreted above, we sort and group 31 provinces based on their resource dependence, measured by the average proportion of mining industry value-added products to the industrial output from 2003 to 2017. Provinces with ratios exceeding 10% are collectively defined as the high resource-dependent group (Table 6).

As mentioned, the eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan, which are spread across medium and low resource-dependent groups, but do not overlap at all with the high resource-dependent group. Therefore, the high resource-dependent group in Table 6 is able to represent the non-eastern region to a considerable extent, which is consistent with the reality of China's regional economic and industrial distribution.

Similar to the previous method, we set dummy variable Rdt_p to represent the resource dependency characteristic of province p, with a value of 1 assigned to high resource-dependent provinces and a value of 0 to others. The other variables remain the same as mentioned. Then, the resource-dependent heterogeneity static (Equation 14) and dynamic (Equation 15) models are constructed as follows, and the regression results reflect the performance of the high resource-dependent group relative to the non-resource-dependent group.

$$\begin{aligned} x_{p,i,t+1} = \alpha + \gamma x_{p,i,t} + \beta_1 Den_{p,i,t} + \beta_2 Rdt_p \\ + \beta_3 Den_{p,i,t} Rdt_p + \omega Z_{p,t} + prov + year \\ + \varepsilon_{p,t} \end{aligned} \tag{14}$$

$$\begin{aligned} x_{p,i,t+1} = \alpha + \gamma x_{p,i,t} + \beta_1 (x_{p,i,t}) Den_{p,i,t} \\ + \beta_2 (x_{p,i,t}) Rdt_p + \beta_3 (x_{p,i,t}) Den_{p,i,t} Rdt_p \\ + \beta_4 (1 - x_{p,i,t}) Den_{p,i,t} + \beta_5 (1 - x_{p,i,t}) Rdt_{p,i,t} \\ + \beta_6 (1 - x_{p,i,t}) Den_{p,i,t} Rdt_p + \omega Z_{p,t} \\ + prov + year + \varepsilon_{p,t} \end{aligned} \tag{15}$$

Empirical results and analysis

We centre the variables involved in the interaction terms and then use OLS method to regress Equations 14 and 15. The results are shown in Table 7.

It shows that the static coefficient of $Den_{p,i,t} Rdt_p$ is negative and significant at the 1% level, while the dynamic coefficient of $(1 - x_{p,i,t}) Den_{p,i,t} Rdt_p$ is significantly positive at the 1% level. These results indicate that during the static stage (technological capacity accumulation of Static 1 and industrial advantage maintenance of Static 2), the promoting

Table 6. Ranking and grouping of resource dependency.

High Resource-Dependent			Non-Resource-Dependent					
High Resource-Dependent Group			Medium Resource-Dependent Group			Low Resource-Dependent Group		
Ranking	Province	Resource Dependence	Ranking	Province	Resource Dependence	Ranking	Province	Resource Dependence
1	Shanxi	35.69	12	Hebei	8.83	22	Beijing	3.83
2	Xinjiang	29.13	13	Tianjin	8.69	23	Chongqing	3.67
3	Heilongjiang	26.18	14	Sichuan	8.03	24	Guangxi	3.36
4	Shaanxi	24.83	15	Yunnan	8.01	25	Hubei	3.27
5	Inner Mongolia	24.04	16	Jilin	6.99	26	Hainan	3.26
6	Qinghai	23.88	17	Anhui	6.47	27	Fujian	1.74
7	Xizang	23.67	18	Liaoning	6.12	28	Guangdong	1.12
8	Guizhou	14.40	19	Shandong	5.65	29	Jiangsu	0.64
9	Ningxia	12.90	20	Hunan	5.52	30	Zhejiang	0.34
10	Gansu	10.30	21	Jiangxi	4.29	31	Shanghai	0.07
11	Henan	10.27						

Table 7. Regression results of resource dependency heterogeneity.

Variable	(1)	(2)
$x_{p,i,t}$	0.690***	0.702***
	(430.30)	(305.50)
$Den_{p,i,t}$	0.360***	
	(49.67)	
Rdt_p	0.054***	
	(5.66)	
$Den_{p,i,t}Rdt_p$	−0.187***	
	(−12.95)	
$(x_{p,i,t})Den_{p,i,t}$		0.326***
		(31.01)
$(x_{p,i,t})Rdt_p$		0.017
		(1.64)
$(x_{p,i,t})Den_{p,i,t}Rdt_p$		0.003
		(0.08)
$(1-x_{p,i,t})Den_{p,i,t}$		0.278***
		(34.64)
$(1-x_{p,i,t})Rdt_{p,i,t}$		0.076***
		(7.97)
$(1-x_{p,i,t})Den_{p,i,t}Rdt_p$		0.056***
		(3.49)
Control Variable	Yes	Yes
_cons	−0.801***	−0.621***
	(−6.72)	(−5.21)
N	701871	701871
adj. R^2	0.571	0.572
prov	Yes	Yes
year	Yes	Yes

*, ** and *** respectively indicate significance at the 10%, 5% and 1% level.

effect of RTD increase on industrial upgrading in high resource-dependent region is relatively weaker than that in non-resource-dependent region. However, at the dynamic stage (especially the successful transition to new technologies of Dynamic 1), that effect in high resource-dependent region is relatively stronger than that in non-resource-dependent region. Therefore, the resource dependence explanation for regional heterogeneity is confirmed.

VI. Conclusions and remarks

Returning to the concept of 'density' in the product space theory and considering the dual economic implications of 'relatedness' and 'diversity', the explanatory power on technological evolution and RIU research can be significantly enhanced. An increase in RTD reduces technological proximity and improves technological diversity, promoting the accumulation of regional technological capabilities and the maintenance of industrial advantages. It also stimulates local enterprises' motivation to leapfrog to adjacent superior technologies and abandon outdated technologies. Through this cycle of static and dynamic processes, regional industries undergo iterative and cyclical upgrading. This conclusion applies to all over China, also basically same with other countries or regions in the world from other literature.

The resource agglomeration effect of marketization can strengthen the role of RTD increase at the static stage of RIU. However, at the same time, it may bring about market failure in resource allocation and thus 'backfire' the processes of successful transition to new technologies and abandonment of old technologies at the dynamic stage.

Regional and resource dependence heterogeneity are mainly manifested in a relative sense. The high resource-dependent region (non-eastern region) has exclusion and inhibition effects on non-resource-dependent industries, which are not conducive to the agglomeration of industrial factors, thus relatively weakening the accumulation of technological capabilities and the maintenance of industrial advantages at static stage of industrial upgrading compared with the non-resource-dependent region (eastern region). However, due to the relatively homogeneous industrial structure and lower initial technological and industrial density in the high resource-dependent region (non-eastern region), the marginal effect of RTD increase on the promotion of industrial upgrading at the dynamic stage (especially the process of successful transition to new technologies) is relatively stronger compared to that in the non-resource-dependent region (eastern region).

The empirical evidence from China has important policy implications in terms of regional industrial upgrading. First, given the importance of diversity, technological and industrial diversification should be maintained and promoted, and excessive and rapid deindustrialization should be firmly curbed. Second, due to the moderating effect of marketization, RIU should combine 'efficient markets' with 'proactive government'. Third, because of the regional and resource dependence heterogeneity, policies of RIU for different industries in different regions should have different emphases.

An unavoidable limitation of our article is that the theoretical ideas and methods of product space theory are based on physical goods, it cannot directly analyse the role of service industries in industrial upgrading, which is integrated into the emergence of advantageous products. In addition, the specific areas or variables that may not consider in our study but could be relevant in future research are the particularities of Chinese economy, such as the impact of environmental regulations on the manufacturing industry in recent years, and the impact of central and local fiscal decentralization, etc.

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References

Balassa, B. 1965. “Trade Liberalization and ’Revealed’ Comparative Advantage.” *The Manchester School* 33 (2): 99–123. https://doi.org/10.1111/j.1467-9957.1965.tb00050.x.

Berkowitz, D., J. Moenius, and K. Pistor. 2006. “Trade, Law, and Product Complexity.” *The Review of Economics and Statistics* 88 (2): 363–373. https://doi.org/10.1162/rest.88.2.363.

Boschma, R., and K. Frenken. 2011. “The Emerging Empirics of Evolutionary Economic Geography.” *Journal of Economic Geography* 11 (2): 295–307. https://doi.org/10.1093/jeg/lbq053.

Boschma, R., and S. Iammarino. 2009. “Related Variety, Trade Linkages, and Regional Growth in Italy.” *Economic Geography* 85 (3): 289–311. https://doi.org/10.1111/j.1944-8287.2009.01034.x.

Boschma, R., E. Miguelez, R. Moreno, and D. B. Ocampo-Corrales. 2023. “The Role of Relatedness and Unrelatedness for the Geography of Technological Breakthroughs in Europe.” *Economic Geography* 99 (2): 117–139. https://doi.org/10.1080/00130095.2022.2134005.

Boschma, R., A. Minondo, and M. Navarro. 2012. “Related Variety and Regional Growth in Spain.” *Papers in Regional Science* 91 (2): 241–256. https://doi.org/10.1111/j.1435-5957.2011.00387.x.

Boschma, R., A. Minondo, and M. Navarro. 2013. “The Emergence of New Industries at the Regional Level in Spain: A Proximity Approach Based on Product Relatedness.” *Economic Geography* 89 (1): 29–51. https://doi.org/10.1111/j.1944-8287.2012.01170.x.

Cao, G., and J. Xie. 2023. “Path-Dependence or Path-Breakthrough ——The Evolution Model of China’s Regional Comparative Advantage.” *Inquiry into Economic Issues* 1:87–104.

Colombelli, A., J. Krafft, and F. Quatraro. 2014. “The Emergence of New Technology-Based Sectors in European Regions: A Proximity-Based Analysis of Nanotechnology.” *Research Policy* 43 (10): 1681–1696. https://doi.org/10.1016/j.respol.2014.07.008.

Coniglio, N. D., R. Lagravinese, D. Vurchio, and M. A. A. Notes. 2018. “The Pattern of Structural Change: Testing the Product Space Framework.” *Industrial and Corporate Change* 27 (4): 763–785. https://doi.org/10.1093/icc/dty009.

Corrocher, N., S. M. Grabner, and A. Morrison. 2024. “Green Technological Diversification: The Role of International Linkages in Leaders, Followers and Catching-Up Countries.” *Research Policy* 53 (4): 104972. https://doi.org/10.1016/j.respol.2024.104972.

Deng, X., and H. Cao. 2016. “Industrial Upgrading Path: Conform or Defy Comparative Advantage——An Empirical Analysis Based on Product Space Structure.” *China Industrial Economics* 2:52–67. https://doi.org/10.19581/j.cnki.ciejournal.2016.02.005.

Essletzbichler, J. 2015. “Relatedness, Industrial Branching and Technological Cohesion in US Metropolitan Areas.” *Regional Studies* 49 (5): 752–766. https://doi.org/10.1080/00343404.2013.806793.

Fan, G., X. Wang, and G. Ma. 2011. “Contribution of Marketization to China’s Economic Growth.” *Economic Research Journal* 46 (9): 4–16.

Frankort, H. T. W. 2016. “When Does Knowledge Acquisition in R&D Alliances Increase New Product Development? The Moderating Roles of Technological Relatedness and Product-Market Competition.” *Research Policy* 45 (1): 291–302. https://doi.org/10.1016/j.respol.2015.10.007.

Guo, Q., and C. He. 2017. “Production Space and Regional Industrial Evolution in China.” *Geo Journal* 82 (2): 379–396. https://doi.org/10.1007/s10708-015-9689-4.

He, C. 2018. “Regional Industrial Development and Evolution: Path Dependence or Path Creation?” *Geographical Research* 37 (7): 1253–1267.

Hidalgo, C. A., B. Klinger, A. L. Barabási, and R. Hausmann. 2007. “The Product Space Conditions the Development of Nations.” *Science* 317 (5837): 482–487. https://doi.org/10.1126/science.1144581.

Li, W., and C. He. 2021. “Regional Industrial Diversification of China: Based on Technological Relatedness and Complexity.” *Progress in Geography* 40 (4): 620–634. https://doi.org/10.18306/dlkxjz.2021.04.007.

Lu, D., and L. Zhu. 2018. “Marketization level, industrial Policy of Strategic Emerging Industries and Enterprise Innovation.” *Industrial Economics Research* 2:65–77. https://doi.org/10.13269/j.cnki.ier.2018.02.006.

Lü, M., P. Qiao, and X. Li. 2023. “Can International Expansion Continue the Technological Innovation of SMEs.” *Soft Science* 37 (3): 33–39. https://doi.org/10.13956/j.ss.1001-8409.2023.03.05.

Ma, H., and M. Yu. 2018. “Empirical Study on Product Complexity, product Density and Industrial Upgrading: Based on Product Space View.” *Finance & Trade Economics* 39 (3): 123–127. https://doi.org/10.19795/j.cnki.cn11-1166/f.2018.03.010.

Montresor, S., and F. Quatraro. 2020. “Green Technologies and Smart Specialisation Strategies: A European Patent-Based Analysis of the Intertwining of Technological Relatedness and Key Enabling Technologies.” *Regional Studies* 54 (10): 1354–1365. https://doi.org/10.1080/00343404.2019.1648784.

Moreno, R., and D. Ocampo-Corrales. 2022. “The Ability of European Regions to Diversify in Renewable Energies: The Role of Technological Relatedness.” *Research Policy* 51 (5): 104508. https://doi.org/10.1016/j.respol.2022.104508.

Neffke, F., M. Henning, and R. Boschma. 2011. “How Do Regions Diversify Over Time? Industry Relatedness and the Development of New Growth Paths in Regions.” *Economic Geography* 33 (2): 237–265. https://www.tandfonline.com/doi/abs/10.1111/j.1944-8287.2011.01121.x.

Rodrik, D. 2000. “Institutions for High-Quality Growth: What They are and How to Acquire Them.” *Studies in Comparative International Development* 35 (3): 3–31. https://link.springer.com/article/10.1007/BF02699764 .

Sheng, D., and Y. Wang. 2011. “Marketization, Technological Sophistication and Industrial Growth in Chinese Provinces and Regions.” *Journal of World Economy* 34 (6): 26–47. https://doi.org/10.19985/j.cnki.cassjwe.2011.06.003.

Tanner, A. N. 2016. “The Emergence of New Technology-Based Industries: The Case of Fuel Cells and Its Technological Relatedness to Regional Knowledge Bases.” *Journal of Economic Geography* 16 (3): 611–635. https://doi.org/10.1093/jeg/lbv011.

Timmermans, B., and R. Boschma. 2014. “The Effect of Intra-And Inter-Regional Labour Mobility on Plant Performance in Denmark: The Significance of Related Labour Inflows.” *Journal of Economic Geography* 14 (2): 289–311. https://doi.org/10.1093/jeg/lbs059.

Wang, X., L. Hu, and G. Fan. 2021. *Marketization Index of China’s Province: NERI REPORT 2021*. Beijing: Social Sciences Academic Press.

Xiao, W., and G. Lin. 2014. “Government Support, R&D Management and Technology Innovation Efficiency - An Empirical Analysis Based on Chinese Industrial Industries.” *Journal of Management World* 4:71–80. https://doi.org/10.19744/j.cnki.11-1235/f.2014.04.008.

Zhang, H., and W. Liu. 2019. “Comparative Advantage, spillover Effects and New Industry Development: Based on the Study of Product Space Theory.” *International Business* 5:25–40. https://doi.org/10.13509/j.cnki.ib.2019.05.003.

Zhang, Q. 2008. “Evolution of Comparative Advantage and Path of Industry Upgrading.” *China Industrial Economics* 9:58–68. https://doi.org/10.19581/j.cnki.ciejournal.2008.09.006.

Zhang, Q., and Y. Qi. 2023. “How Do Key Industrial Policies Suppress Industrial Shakeouts?” *Research on Financial and Economic Issues* 7:67–77. https://doi.org/10.19654/j.cnki.cjwtyj.2023.07.006.

Zheng, J., and Z. Ran. 2021. “Going Out of the “Comfort Zone” in Innovation: The Dynamics of Regional Technological Diversification and Its Growth Effect.” *China Industrial Economics* 5:19–37. https://doi.org/10.19581/j.cnki.ciejournal.2021.05.013.

Zhu, S., C. He, and Q. Luo. 2019. “Good Neighbors, Bad Neighbors: Local Knowledge Spillovers, Regional Institutions and Firm Performance in China.” *Small Business Economics* 52 (3): 617–632. https://doi.org/10.1007/s11187-017-9975-2.