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THE IMPACT OF R&D EFFICIENCY ON ECONOMIC GROWTH IN CHINA: NON-LINEAR THRESHOLD EFFECTS

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Abstract. This study uses a threshold estimation technique to examine whether the effect of R&D efficiency on economic growth in China differs according to the level of financial development. The results broadly confirm a nonlinear relationship between R&D efficiency and economic growth due to the dynamic and static threshold effects of financial development and R&D expenditure. This finding suggests that R&D efficiency does not significantly impact growth in the low and middle-financial development provinces at conventional levels. Hence, the benefit of R&D efficiency in China could stem from the positive effect of R&D in highly financially developed provinces. Though R&D efficiency is poor, R&D investment still enhances economic growth because the amount of R&D investment is enormous. This finding suggests that while it is most important to not unthinkingly expand R&D gross investment, it is also necessary to make full use of R&D investment by improving R&D efficiency.

Keywords: R&D efficiency, R&D investment, economic growth, SBM-DEA model, panel threshold model, dynamic panel threshold model.

JEL Classification: G22, L13, L25, L44.

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1. Introduction

The relationship between economic growth and innovation is of great interest to scholars and institutions and is therefore a well-debated topic in the literature. Schumpeter (1942) proposes the concept of creative destruction, where competition through innovation promotes economic growth. Numerous studies investigate innovation processes and their diffusion as a characteristic of the contemporary knowledge and technology–driven economy. Innovation is often proxied by R&D investment or data on patent activity. The latter promotes economic growth by boosting innovation and total factor productivity (TFP) (Romer, 1990). However, R&D investment carries the risk of uncertainty, as it may contribute only significantly to new production output or cost cutting. Alternatively, it may have a nonlinear relationship. Wu et al. (2020) and Alvarez-Pelaez and Groth (2005) argue that different levels of R&D investment have different effects on economic growth. Therefore, we test whether R&D activities always play a growth-enhancing role, assuming that the effect of R&D on economic growth has a tipping point, and R&D over-expenditure may create inefficient resource allocation.

According to the National Center for Science and Engineering Statistics (NCSES), the US continues to rank first in R&D expenditure worldwide, with $612.7 billion in 2019. However, China ranks second, with $514.8 billion in 2019, and began to surpass many EU countries after 2015. In addition, according to the National Bureau of Statistics of China, R&D expenditure has grown substantially from RMB 371 billion in 2007 to RMB 3.08 trillion in 2022, a nearly nine-fold increase; however, the global R&D investment growth rate over two decades was only 6.2% (2000–2020). The Chinese government is concerned about R&D investment and has implemented several strategic arrangements for technological and application innovation in recent decades. For example, the Innovation-Driven Development Strategy 2016 national outline proposed a multi-stage strategic placement plan for technological innovation. The plan emphasizes technology business incubators and accelerators, the construction of more science and technology parks and innovation incubation centers, and strategies to encourage enterprises to set up R&D departments and enlarge R&D investment.

Most existing research evaluates R&D (innovation) performance in a country using R&D investment or the number of patents as a proxy. Blanco et al. (2016) state that measuring the contribution of R&D activities to economic growth requires care, given the significant heterogeneity in R&D investment and economic growth across nations. This argument suggests that using only R&D investment or the number of patents to evaluate a nation's R&D performance may be ineffective. Some studies suggest using data envelopment analysis (DEA) as a measure, as in Afzal (2014) and Chen et al. (2011), who argue that R&D efficiency is more appropriate than other methods. Therefore, we use R&D efficiency to study the impact of innovation performance on economic growth and compare it with traditional R&D indicators. Further, we first analyze the relationship between R&D efficiency and economic growth using dynamic and static panel threshold models to determine whether the threshold effect of financial development and R&D expenditure affects R&D efficiency and economic growth in China from 2008 to 2020.

This study contributes to the existing literature in several ways. First, technical efficiency influences the efficiency of an R&D unit in transforming inputs into outputs. Few studies use R&D efficiency measured by quantitative models instead of R&D investment to investigate the impact of R&D activities on economic growth. The conventional DEA provides an efficiency score that generates many decision-making units (DMUs) that are difficult to rank. Following Tone's (2002) slacks-based measure (SBM) super-efficiency model can help with the ranking of DMUs and issues of infeasibility, making the SBM DEA model better than the conventional DEA model.

Second, many existing studies only employ R&D expenditure (investment) and study an association between R&D and economic growth; the realistic R&D activity effect cannot be reflected without a holistic perspective. Additionally, such studies ignore their nonlinear relationship, which has vital theoretical and practical significance for maximizing the role of R&D. Following Hansen (1999), use the panel threshold model to estimate the multi-threshold effect of R&D on economic growth to provide more detailed research conclusions. Further, we test the potential dynamic threshold effect of R&D efficiency on economic growth with financial development and R&D investment threshold variables.

Third, studying how R&D efficiency affects economic growth in China is significant as government policies encouraging R&D play a substantial role in ensuring adequate R&D inputs. R&D expenditure is 401.539 billion USD, rapidly growing to 15,271.29 billion USD from 2010 to 2020, an increase of 380.32% and significantly higher than average worldwide. Additionally, China has unique market mechanisms. The Chinese government's feature project screening mechanisms, the financing process, and invisible budget constraints make R&D activities in centralized economies more inefficient (Huang & Xu, 1998). Therefore, we explore the nexus between R&D activities and GDP growth using Chinese province-level panel data.

In the following, Section 2 provides a literature review. Section 3 briefly introduces the super-efficiency DEA-SBM model and defines the input–output variables as well as the dynamic and static panel threshold models. Section 4 presents the empirical results, after which the final section presents the conclusions and outlines policy implications.

2. Literature review

2.1. Innovation and R&D efficiency

Technology progress and innovation are the primary driving force of sustainable economic growth, and R&D activities are the main driving force of technology progress and innovation. R&D activities involve a process of knowledge and know-how, creation, development, production, transmission, and application. Existing studies evaluate R&D activity levels using single or multiple indicators, such as R&D expenditures, R&D personnel, patents, journal articles, and so on. Kacprzyk and Doryn (2017) define innovation as proxied by patents and R&D expenditures, and Wu et al. (2020) evaluate R&D activities at provincial-level regions by government and enterprises' R&D expenditures. However, using single or multiple indicators to evaluate R&D levels is inappropriate as it may cause estimation bias. For example, authors often criticize patents as it measures only a single component of creative output; however, inventors may choose other protectionist strategies such as secrecy, thereby leading to an underestimation of actual innovative activity (Cullmann et al., 2012).

Thus, several studies employ quantitative approaches to R&D efficiency. Among them, DEA is a popular method to measure R&D efficiency at the national or firm level. Dobrzanski and Bobowski (2020) measure ASEAN countries' R&D expenditure efficiency by DEA, finding that different return-to-scale assumptions' DEA methods for efficiency ranking provide different results. They also confirm that increased spending on innovation has disproportionate effects. Wang and Huang (2007) employ DEA to evaluate efficiency across countries and use Tobit regression to control for external environmental factors. The authors show that numerous countries are inefficient; only a few countries have been perfectly efficient in their R&D activities.

How to introduce new technology into the economy? Some scholars suggest building a national innovation system (NIS), which is a network of agent systems, and a set of policies and institutions. Therefore, DEA is also widely applied to measure the R&D efficiency of an NIS (Chen et al., 2011; Afzal, 2014). Several studies also employ firm-level data to investigate the relationship between R&D activities and firms' productivity. Zhang et al. (2003) examine the impact of ownership on the R&D efficiency of Chinese firms; their results show that the non-state sector has significantly higher R&D and productivity efficiency than the state. Baumann and Kritikos (2016) discuss the impact of R&D activity on productivity in small enterprises; this finding suggests that product innovation through R&D intensification has significant effects, thereby increasing firm productivity. In summary, prior studies applied the DEA model to measure R&D efficiency and productivity change using a ranking system. Still, empirical work on R&D efficiency is limited, especially with respect to the impact of R&D efficiency on micro and macroeconomic factors such as economic growth, firms' sustainable development, operations, and so on.

2.2. R&D activities and economic growth

Modern economic theory has long sought to determine the driving force of economic growth. Schumpeter (1942) introduced the concept of innovation as a force of creative destruction and analyzed how innovation affects the economic cycle. Romer (1990) considered that technological progress benefits economic growth; growth depends on the results of R&D activities, reflected in the technological progress companies use to maximize profits. From an enterprise perspective, R&D is at the core of an enterprise's competitive advantage because it helps firms develop excellent products or technologies with a well-defined competitive advantage (Wu et al., 2020). From a macroeconomic perspective, technological innovation should have a positive association with economic growth. However, technological innovation does not always enhance economic growth. In some cases, R&D investment resources are insufficient, the conversion efficiency of R&D input–output is too low, or endowment allocative unsuitable degree of economic growth.

Importantly, it is unclear whether R&D investment can effectively advance economic growth or even negatively impact it. The existing literature lacks a consensus on the association between R&D activities and economic growth. Numerous scholars hold a positive opinion that R&D activities can enhance economic growth in the long run, often stressing the essential role of R&D in driving economic growth. For example, Blanco et al. (2016) show that R&D within a state significantly positively affects the state's GDP through TFP. Ang and Madsen (2011) studied R&D activities in the six Asian miracle economies' growth experiences and stated that R&D activities drove high economic growth over their study period.

However, insufficient private capital investment in R&D partly results from market imperfections; compared with other forms of investment, it has high levels of investment and risk (Sokolov-Mladenović et al., 2016). R&D activities are not always growth-enhancing for nations or firms. Kacprzyk and Doryn (2017) find that patent activities enhance economic growth; however, the impact of R&D activities on economic growth is insignificant in the European Union-13. This result suggests that R&D activities might not be the sole factor in economic growth. In summary, R&D investment contributes less to the regional economy than R&D efficiency.

Numerous studies examine samples from different countries; these findings show different effects of R&D activities on economic growth due to the differences in economic development. For example, Inekwe (2015) finds that R&D investment promotes economic growth in emerging countries; however, the positive effect only exists in upper-middle-income countries. By contrast, Rodríguez-Pose (2001) shows that capital returns for technology investments are decreasing in lagging areas; thus, other conditions being equal, R&D investment in the periphery is more efficient than R&D investment in the core.

Other studies were conducted at the industry and regional levels and analyzed how the regional heterogeneity of R&D activity affects economic growth. Wu et al. (2020) argue that the spatial distribution of R&D activities is nonhomogeneity, showing that technological innovation tends to be localized due to highly uneven economic development. Li (2009) indicates that China's innovation plans and R&D policies have solid regional characteristics. Thus, analyzing innovation activities and evaluating R&D efficiency at a regional level is meaningful. In summary, this study investigates the impact of R&D efficiency on economic growth at the province level in China, including both linear and nonlinear aspects.

3. Methodology

3.1. Specification of the SBM – super-efficiency DEA model

The traditional DEA model, whether it is a model with constant or variable returns to scale, can only identify the relative efficiency of DMUs. There are often two or more DMUs with an efficiency score equal to 1, making it impossible to identify the optimal DMUs. Thus, to solve this problem, following Tone (2002), we use the SBM super-efficiency DEA model to evaluate the Chinese R&D efficiency of each province and enable the ranking of efficient DMUs. The model assumes n DMUs with the R&D input and output matrices $X = \left[x_{ij}\right] \in R^{m\times n}$ and $Y = \left[y_{ij}\right] R^{s\times n}$, respectively. To evaluate the R&D efficiency of (x_0, y_0), we formulate the fractional program SBM in λ, s^- and s^+ (Tone, 2002), and apply the following super-efficiency model under constant returns to scale (CRS) by SBM to calculate technical efficiency[1]:

$$\min\ \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} S_i^u / x_{i0}}{1+\frac{1}{s}\sum_{i=1}^{s} s_i^+ / y_{i0}}$$

$$\text{s.t. } x_0 = X\lambda + s^-,$$

$$y_0 = Y\lambda + s^+,$$

$$\lambda \geq 0,\ s^- \geq 0,\ s^+ \geq 0, \quad (1)$$

where s^- indicates excess input and s^+ indicates deficient output, which is represented as slack, where λ is non-negative vector in R^n. Thus, the super-efficiency under the assumption that the DMU (x_0, y_0) is SBM-efficient is $\rho^* = 1$. Tone (2002) defines the super-efficiency of (x_0, y_0) as the optimal objective function value δ^*:

[1] See Tone (2002) for more details.

$$\delta^* = \min \delta = \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x}_i / x_{i0}}{\frac{1}{s}\sum_{r=1}^{s} s_i^+ \bar{y}_r / y_{r0}}$$

$$\text{s.t.} \quad \bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j,$$

$$\bar{y} \leq \sum_{j=1,\neq 0}^{n} \lambda_j y_j,$$

$$\bar{x} \geq x_0 \text{ and } \bar{y} \leq y_0, \ \bar{y} \geq 0, \ \lambda \geq 0. \tag{2}$$

In this context, while we will relax the CRS assumption and extend the CRS results to the variable returns to scale (VRS) case, we impose the following constraint $\sum_{j=1}^{n} \lambda_j = 1$ in the CRS model. We can then write the SBM-super-efficiency under VRS as

$$\delta^* = \min \delta = \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x}_i / x_{i0}}{\frac{1}{s}\sum_{r=1}^{s} s_i^+ \bar{y}_r / y_{r0}}$$

$$\text{s.t.} \quad \bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j,$$

$$\bar{y} \leq \sum_{j=1,\neq 0}^{n} \lambda_j y_j,$$

$$\bar{x} \geq x_0 \text{ and } \bar{y} \leq y_0, \ \sum_{j=1,\neq 0}^{n} \lambda_j = 1 \bar{y} \geq 0, \ \lambda \geq 0. \tag{3}$$

Griliches (1990) describes the R&D production process from some observable measures of resources, such as R&D expenditure or R&D personnel invested in innovative activities. We consider R&D activities to be a production process and regard individual provinces as DMUs. Choosing variables and models may lead to different conclusions and may even yield unsuitable estimations. Thus, following Wang and Huang (2007) and Cullmann et al. (2012), we include two inputs, R&D expenditure and number of R&D personnel, and two outputs, patent applications and revenue from new production[2].

3.2. Panel threshold model

The panel threshold model explains a jump or structural break in the relationships among variables. To determine the potential presence of financial development and R&D expenditure thresholds in Chinese economic growth we use the panel threshold regression developed by

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[2] Other studies use R&D capital stock to measure R&D efficiency; however, such data are unavailable from any database in China. Following Shi et al. (2022), Li et al. (2022) and Wang et al. (2023), we mainly employ R&D expenditure instead. Further, even if the capital stock measured by the perpetual inventory method (PIM) is unavailable from 2008 to 2011 and after 2020 in the Chinese sample. Therefore, we take a pragmatic method and focus on R&D expenditure (flow). This study also uses the PIM to measure R&D capital stock as input and reevaluate R&D efficiency to recheck our results for the period during which data are available.

Hansen (1999). If we only consider the single-threshold model:

$$YG_{it} = \mu_{it} + \beta_1 SE_{it} I\left(q_{it} \le \gamma\right) + \beta_2 SE_{it} I\left(q_{it} > \gamma\right) + \alpha_i \sum_{i=1}^{3} X_{it} + \varepsilon_{it}, \tag{4}$$

where YG_{it} is the natural logarithm of GDP for province i in period t; SE is the regime-dependent regressor, which is R&D efficiency according to the SBM model; q_{it} values are threshold variables that indicate financial development and R&D expenditure (we assume the q_{it} is exogenous or at least predetermined and time-variant); and the X_{it} is a vector of control variables. Depending on an unknown threshold. γ, we separate the samples into two groups (regions). If there is only one threshold, we group by whether the threshold variable q_{it} is higher or lower than the γ. The i and t indicate cross-sections and time effects, respectively, and ε_{it} is an error term.

Following Hansen (1999), for the threshold value γ estimator, to minimize the concentrated sum of squared errors (SSE) through ordinary least-squares (OLS) model, the estimator of γ is $\hat{\gamma} = \text{argmin } S_1\left(\gamma\right)$. In general, suppose γ is known and is equal to the ordinary linear model. However, the γ estimator's distribution is nonstandard when γ is unknown; a nuisance parameter problem must be considered.

Hansen (1999) suggests using the "no-rejection region" model with a likelihood-ratio (LR) statistic to test $y = y_0$ to form the confidence interval and proved that $\hat{\gamma}$ is a consistent estimator for γ. It tests whether each regime's coefficient is the same to verify whether the threshold effect exists. Therefore, assume the null and alternative hypotheses of $H_0 : \beta_1 = \beta_2$ and $H_1 : \beta_1 \ne \beta_2$, respectively, where the F-statistic $F_1 = \frac{\left(S_0 - S_1\right)}{\widehat{\sigma^2}}$. Thus, under H_0, the threshold effect is unclear. If H_0 is rejected, then this function is a threshold regression (two-regime). For multiple thresholds representing multiple regimes, Eq. (4) can be rewritten as

$$\begin{aligned} YG_{it} = {} & \mu_{it} + \beta_1 SE_{it} I\left(q_{it} \le \gamma_1\right) + \beta_2 SE_{it} I\left(\gamma_1 < q_{it} \le \gamma_2\right) + \\ & \beta_3 SE_{it} I\left(q_{it} > \gamma_2\right) + \alpha_i \sum_{i=1}^{3} X_{it} + \varepsilon_{it}, \end{aligned} \tag{5}$$

where γ_1 and γ_2 are the threshold values that divide the equation into regimes with coefficients β_1, β_2, and β_3. We can apply the same estimation process for Eq. (4) with different regimes. Hansen (1999) argues that even though first-order asymptotic dependence is not important in the threshold estimate, the inference and estimation of β on the threshold estimate are still valid; thus, when γ is known we can infer the β estimator. The process is similar to a single threshold model for models with dual or more than double threshold parameters. (Hansen, 1999)[3].

Most studies confirm that R&D activities directly or indirectly promote economic growth. (e.g., Sokolov-Mladenović et al., 2016; Ang & Madsen, 2011). However, others report that R&D is not persistent in its effect on economic growth and might even have a negative impact. Alvarez-Pelaez and Groth (2005) differentiate the returns to specialization from the market power parameter and state that R&D waste can occur if returns to specialization are too low. Celli et al. (2021) state that R&D investments only promote GDP growth under particular

[3] See Hansen (1999) for more details.

situations; for example, given the capacity to successfully move from a capital-driven to an innovation-driven economy. Are R&D activities always growth-enhancing? This study explains whether an R&D expenditure threshold exists in the R&D–growth relationship, which may be contingent on R&D expenditure, where R&D efficiency promotes economic growth after R&D exceeds a certain threshold level.

Existing literature argues that financial development should be vital to economic growth; however, their relationship remains unresolved in the existing literature. Hassan et al. (2011) find that financial development positively correlates with GDP growth in developing countries, while Law et al. (2013) contend that under better financing, higher growth is a plausible conjecture, though they provide some evidence that institutions influence how financial development affects economic growth. Hence, we assume the regime-switching triggers of financial development and R&D investment as threshold variables and apply Hansen's (1999) threshold regression method to explain whether the R&D efficiency–economic growth nexus is nonlinear.

3.3. Empirical regression using dynamic panel data

In addition to the static panel threshold model, this section considers the dynamic panel threshold model, which has several advantages (Kremer et al., 2013; Ho & Saadaoui, 2022) – chiefly, it allows for endogenous variables when estimating the threshold effect. Therefore, following Kremer et al. (2013), we base our empirical specification on the dynamic panel data threshold model for each region, which we formulate as

$$YG_{it} = \mu_{it} + \delta_{it} YG_{i,t-1} + \beta_1 SE_{it} I\left(q_{it} \le \gamma\right) + \beta_2 SE_{it} I\left(q_{it} > \gamma\right) + \alpha_i \sum_{i=1}^{3} X_{it} + \varepsilon_{it}, \tag{6}$$

where YG_{it-1} is one lagged value of the natural logarithm of GDP, which makes the model dynamic. The linear empirical framework consists of estimating the following dynamic generalized method of moments (GMM)[4]:

$$\begin{aligned} YG_{it} &= \mu_{it} + \delta_{it} YG_{i,t-1} + \beta_1 SE_{it} + \beta_2 RDE_{it} + \beta_3 FIND_{it} + \\ &\alpha_i \sum_{i=1}^{3} X_{it} + \sum_{i=1}^{3} DV_{region_1} + \varepsilon_{it}, \end{aligned} \tag{7}$$

where SE is the R&D super-efficiency by the SBM model, which includes the super-efficiency under CRS (SECRS) and VRS (SEVRS). RDE denotes the R&D expenditures and FIND denotes the financial development level. X_{it} represents the control variables, which include human capital input level (HCI), industrial upgrading index (INDUP), and industrial collaborative agglomeration (CAGGL), DV_{ZONE} is a dummy variable representing the individual regions.

The nexus between financial development and GDP growth has received much attention for several decades. Levine (1997) states that a high degree of financial development is conducive to a country's economic growth. Still, other studies find that their relationship is insignificant or negligible, leaving the financial sector's role in economic growth an unresolved issue.

[4] Roodman (2009) notes many econometric issues that the system-GMM technique can solve, such as omitted variables, unobserved heterogeneity, and reverse causality.

We test whether a well-developed financial sector can contribute significantly to increasing fund sources and investment amounts, eventually leading to economic growth. This study uses financial sectors' added value as a proxy for financial development level (FIND)[5].

Frantzen (2000) reports strong evidence that innovation and human capital significantly impact productivity in a cross-country analysis. Human capital is the driver of innovation and technological progress, which enhances high-quality economic development. Teixeira and Queirós (2016) measure human capital by the number of years of schooling of the population aged 25 and above. However, since province-level data are limited, we employ scientific and education expenditures to the general budget as a proxy for HCI. Valderrama (2003) states that financial development contributes to economic growth because financial institutions are more capable of identifying or monitoring investments than individuals are, and the financial market combines funds and diversifies risks.

Recently, researchers have focused on the effect of the collaborative agglomeration of manufacturing and service industries (e.g., Ellison et al., 2010; Zeng et al., 2021). However, few studies attempt to explain whether and how this collaborative agglomeration affects economic growth. Collaborative agglomeration has two driving forces: spillovers and natural advantage. The industrial agglomeration presence lowers transportation costs and intellectual spillovers. Thus, collaborative agglomeration promotes manufacturing and service industry development and improves their performance, leading to higher economic growth. Following Zeng et al. (2021) and Zhang et al. (2022), we construct an industrial collaborative agglomeration index,

$$CAGGL_{it} = \left(1 - \frac{Saggl_{it} - Maal_{it}}{Saggl_{it} + Maal_{it}}\right) + Saggl_{it} + Maal_{it},$$

where $CAGGL_{it}$ is the industrial collaborative agglomeration. $Maggl_{it}$ is the manufacturing industry agglomeration index and $Saggl_{it}$ is the service industry agglomeration index, where we calculate $Saggl_{it}$ and $Maggl_{it}$ using a location entropy index.

We also evaluate the impact of industrial upgrading on economic growth using an indicator measured by the Industrial Structure Coefficient,

$$\text{INDUP} = \sum_{i=1}^{3}\left(I_v.v\right) = I_1 \times 1 + I_2 \times 2 + I_3 \times 3,$$

where I_v is the industry value added v as a percentage of GDP and v is between 1 to 3. A larger INDUP value denotes a higher level of industrial upgrading.

Given the available data and consistency of the statistical indicators, we analyze the panel data of 31 provincial regions from 2008 to 2020. Data sources from the China Statistical Yearbook and China City Statistical Yearbook. We also supplement the missing data for individual years by taking the average value of the adjacent years. All the variables are measured in one hundred million RMB. Table 1 shows the empirical variables' descriptive statistics.

[5] Other studies employ several indicators to represent financial development, including the banking sector's domestic loans to GDP ratio, the private sector's domestic loans to GDP ratio, and the gross domestic saving to GDP (Hassan et al., 2011). This study also considers these indicators in the robustness test section to recheck our results.

Table 1. Summary statistics

	mean	Std.	Max.	Min
R&D Input-output variables				
R&D expenditure	498,729.02	613,453.58	2,684,020	25,125.6
R&D staff	12,556.45	14,344.05	50,753	784
Patent applications	3,118.37	3,940.14	22,949	79
Revenue from new Production	4,893,409.5	5,385,998.12	25,660,429	85,659
Regression variables				
LNGDP	9.5735	1.0357	11.6151	5.9811
EGR	0.1237	0.0763	0.2987	–0.2501
RDE	13.8709	15.6343	17.0344	7.0579
HCI	0.1831	0.2143	0.2532	0.1058
FIND	6.6990	7.9105	9.2010	2.0082
CAGGL	2.7806	0.2327	3.0458	1.7503
INDUP	2.5979	7.1530	92.9189	2.1025
RDTS	187.5518	102.4439	794.0257	7.1728
RDIN	0.9329	0.5536	2.3186	0.0000

Note: R&D expenditure and revenue from new production units are one hundred million RMB.

4. Empirical results

4.1. Province-level R&D efficiency

Table 2 presents the results from the SE by SBM model estimation of the R&D activities in China. R&D efficiency average was around 0.9051, with a minimum value of 0.8536. The R&D score of 0.8536 in 2008 increased gradually to 0.9349 in 2020, which implies high regional R&D efficiency in China. Wang and Huang (2007) analyze data from 30 countries and report the R&D activities of technical efficiency are 0.885, 0876, and 0.865 for the periods 1997–2000, 1998–2001, and 1999–2002, respectively. Cullmann et al. (2012) found a national R&D efficiency of only 0.046 for China relative to the OECD from 1995 to 2004. This result suggested that China should allow foreign investors to increase their business scope and remove entry barriers after accession to the WTO, which significantly increased R&D efficiency.

We can split the full sample into four subregions: eastern, middle, western, and northeast. As Table 3 shows, the eastern provinces had the highest R&D efficiency, with SEVRS and SECRS values of 0.9616 and 0.8451, respectively. In ascending order, the R&D efficiency was highest in the eastern region, followed by the western, northeast, and middle regions. The eastern region has higher economic development relative to the other regions, implying that the degree of economic development may benefit R&D efficiency. We can also divide the provinces into super-efficiency, efficiency, and low-efficiency groups. The super-efficiency category whose mean scores under the VRS assumption are greater than one, includes 7 provinces and cities, such as Shanghai. The low-efficiency category includes 8 provinces whose mean scores are below the average efficiency score of 0.8245, such as Henan. The 16 other provinces belong to the efficiency category, whose mean scores are between one and the average efficiency.

Table 2. Results of R&D efficiency

	SEVRS	SECRS
2008	0.8535	0.7884
2009	0.8736	0.8198
2010	0.9033	0.7421
2011	0.8792	0.7786
2012	0.9236	0.8094
2013	0.9264	0.8084
2014	0.9193	0.8484
2015	0.8956	0.7906
2016	0.9090	0.8370
2017	0.9136	0.8460
2018	0.9192	0.8754
2019	0.9151	0.8773
2020	0.9349	0.8964
mean	0.9051	0.8245

Note: SEVRS indicate super-efficiency under variables return of scale, and SECRS indicate super-efficiency under constant return of scale.

Table 3. Results of R&D efficiency by subarea

	Eastern		Western		Northeast		Middle	
	SEVRS	SECRS	SEVRS	SECRS	SEVRS	SECRS	SEVRS	SECRS
2008	0.9757	0.8588	0.8716	0.8308	0.7569	0.6954	0.6621	0.6327
2009	0.9561	0.8290	0.8750	0.8533	0.9421	0.9142	0.6994	0.6905
2010	1.0803	0.8193	0.8973	0.7343	0.7547	0.7040	0.6947	0.6481
2011	0.9457	0.8254	0.8954	0.7672	0.8041	0.7578	0.7733	0.7340
2012	1.0121	0.8627	0.9127	0.7820	0.8617	0.8012	0.8287	0.7793
2013	0.9960	0.8563	0.9199	0.7775	0.7824	0.6930	0.8952	0.8478
2014	0.9461	0.8642	0.9081	0.8266	0.8216	0.7649	0.9460	0.9074
2015	0.8862	0.7888	0.9085	0.7729	0.8314	0.7504	0.9177	0.8491
2016	0.9111	0.8342	0.9032	0.8067	0.8701	0.8226	0.9363	0.9097
2017	0.9368	0.8177	0.9124	0.8580	0.8891	0.8722	0.8896	0.8563
2018	0.9214	0.8641	0.9172	0.8679	0.9394	0.9016	0.9093	0.8962
2019	0.9474	0.8657	0.9125	0.9080	0.9635	0.9357	0.8422	0.8059
2020	0.9858	0.9004	0.9207	0.9124	0.9380	0.9273	0.8771	0.8424
mean	0.9616	0.8451	0.9042	0.8229	0.8581	0.8108	0.8363	0.8000

Note: SEVRS indicate super-efficiency under variables return of scale, and SECRS indicate super-efficiency under constant return of scale. This study follows the National Bureau of Statistics in China's classification of four subareas: eastern, middle, western, and northeast. The eastern region including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The Middle region includes Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan. The western areas include Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The northeast region has Liaoning, Jilin and Heilongjiang.

We also evaluate R&D efficiency using the conventional DEA model. The mean PTE exceeds the mean SE, which shows that scale inefficiency is a significant source of regional R&D inefficiency in China[6]. Thus, the government should improve scale efficiency by encouraging the use of more inputs and the correct selection of input–output combinations. Our findings suggest that regional R&D inefficiency may be attributable to underperformance in terms of the optimal returns to scale rather than underutilization of inputs or the incorrect selection of input combinations.

4.2. What drives economic growth in China?

In this section, we use GDP as the dependent variable to clarify the relationship between economic growth and R&D activities at the province level in China. In Table 4, the empirical results of the dynamic system-GMM estimation are reasonably satisfactory[7]. The AR(1) result rejects the null hypothesis in all models while the AR(2) result indicates that no estimations have the problem of second-order serial correlation, as the AR(2) result does not reject the null hypothesis of no second-order serial correlation[8]. The coefficients of lagged GDP are significant and positive, which indicates persistent economic growth at the province level.

Does the increase in R&D efficiency transfer innovation output into economic growth? The results of R&D efficiency are not consistent. The coefficient of SEVRS shows a significantly positive impact on economic growth, but the SECRS is significant and negative, implying that high R&D in the super-efficiency group under the CRS assumption has not benefited economic growth. One possible reason is that the CRS assumption presumes that all DMUs have the optimum production scale, which may not be compatible with actual operating conditions. Thus, R&D super-efficiency under VRS is appropriate to reflect actual macroeconomic conditions and R&D resource allocation. This suggestion is consistent with our expectations and those of previous studies (e.g., Chen et al., 2011). Another possible reason for the negligible contribution of R&D efficiency to economic growth is that while R&D efficiency is poor, there is still a positive relationship between R&D investment and economic growth due to considerable R&D investment. The public sector provides considerably more R&D funds than the private sector in China, but valuable innovation technology and patents are mainly from the private sector.

The coefficient of RDE is positive and significant in all columns except Column 3. This result is in line with Sokolov-Mladenović et al. (2016) and Wu et al. (2020). The coefficient of HCI is positive and significant in all columns, indicating that increasing scientific and education expenditures has a positive effect on economic development. Bodman and Le (2013) state that improving the workforce's skills through an increased stock of human capital positively impacts productivity. The empirical result shows that previous spending on science and edu-

[6] For brevity, these results are not reported here, but are available on request from the authors.

[7] This study did not have collinearity problems; all variables' variance inflation factor (VIF) results were below 10.

[8] This study uses the Hansen test to test for an over-identification problem and these results do not reject the null of exogenous instruments for all models, except for Model A. Still, our main models confirm the validity of the instruments.

Table 4. Results of determinants of economic growth

	LNGDP	LNGDP	LNGDP	LNGDP
$LNGDP_{t-1}$	0.903 (20.26)***	0.878 (17.69)***	0.900 (16.550)***	0.891 (19.040)***
SEVRS	0.405 (3.820)***	0.385 (4.34)***	0.305 (3.150)***	0.261 (3.270)***
SECRS	–0.560 (–4.080)***	–0.552 (–3.150)***	–0.465 (–2.91)***	–0.466 (–4.250)***
RDE	0.047 (1.97)**	0.038 (1.750)*	0.025 (1.080)	0.043 (2.000)**
HCI		1.609 (3.710)***	1.299 (2.460)***	0.965 (2.660)***
FIND		0.022 (0.650)	0.012 (0.330)	0.003 (0.110)
CAGGL		–0.0012 (–0.030)	0.053 (1.510)	0.068 (1.170)
INDUP		–0.0000859 (–0.100)	–0.00041 (–0.520)	–0.002 (–0.890)
DVE		–0.049 (–2.36)**		
DVM			0.025 (0.710)	
DVW				0.025 (1.190)
Cons.	0.463 (4.72)***	0.415 (2.32)**	0.395 (2.21)**	0.367 (2.050)**
Obs.	403	403	403	403
AR(1)	–3.930	–3.870	–3.880	–3.860
P-value	0.000	0.000	0.000	0.000
AR(2)	–0.540	–1.510	–1.620	–1.480
P-value	0.589	0.131	0.106	0.140
Hasen test	27.600	25.460	28.710	28.080
P-value	0.024	0.549	0.375	0.355

Note: *α = 0.1 significant at the 10% level, **α = 0.05 significant at the 5% level, ***α = 0.01 significant at the 1% level.

cation contributes to current economic growth; scientific and education expenditures are the driver of human capital accumulation, enhancing technological innovation and R&D efficiency and promoting economic growth.

The coefficient of FIND is positive and insignificant, implying that financial development does not benefit economic growth, which is inconsistent with our expectations. One possible reason is that in most developing countries, financial repression and credit controls mean that financial development does not promote economic growth. Lucas (1988) argues that the financial sector is overemphasized in the economic system, considering technological innovation as the main driver of economic growth. Khan and Senhadji (2003) also find an insignificant financial development and economic growth nexus; their relationship may be nonlinear. A partially developed country's financial development may be slow while the volatility of economic growth is much higher. Thus, evaluating financial development indicators may not suitably represent the change in financial structure.

The coefficients of CAGGL and INDUP are insignificant in all columns, implying that industrial collaborative agglomeration does not obviously affect economic growth. This finding implies that industrial collaborative agglomeration affects economic growth negatively due to scale inefficiency, where intense economic activity can lead to increased urban infrastructure load and congestion effects on services. Thus, the negative externalities would outweigh the benefits of industrial cooperation and technological spillover, making its effect on economic growth insignificant. This result shows that industrial upgrading does not promote economic growth, which is inconsistent with our expectations. Additionally, the result suggests that the active encouragement of industrial upgrading has been ineffective and slow in China in the past decade.

4.3. Additional analysis: determinant of economic growth rate

In this section, we replace Eq. (7) using a variable for the economic growth rate. As Table 5 shows, the previous economic growth rate does not affect the current economic growth rate, implying that the economic growth rate is not persistent. These empirical results are similar to those of the main analysis, but some control variables are insignificant. We obtain the conflicting result that R&D expenditure does not influence the economic growth rate but promotes GDP growth. This could be because GDP is static while the economic growth rate is dynamic. The findings show that both dependent variables, GDP and the regional economic growth rate dummy variables, are not positive or insignificant, implying that the gap in economic growth is not evident in different regions over the study period.

These results confirm that super-efficiency under VRS is a key determinant of economic growth for either dependent variable (GDP or economic growth rate). Thus, the R&D super-efficiency indicator is appropriate to reflect actual economic conditions rather than a single R&D indicator.

4.4. Panel data threshold model results

We test for a nonlinear relationship and a potential threshold effect between R&D efficiency and economic growth using financial development and R&D expenditure as the threshold variables. Tables 6 and 7 report the respective results of estimating Eq. (5). To evaluate the threshold estimators' statistical significance, we use *p*-values calculated using the bootstrap approach with three hundred replications and a 5% trimming percentage (Hansen,1999).

Table 6 shows the two threshold values of financial development 6.2647 and 7.7522, for Model A. This result implies that financial development exhibits a double-threshold effect on the relationship between SECRS and economic growth. Hence, we classify provinces with threshold values of less than 6.2647 as financially underdeveloped provinces, values ranging from 6.2647 to 7.7522 as medium financial development provinces, and values above

Table 5. Results of the robust test: Dep: Economics growth rate

	EGR	EGR	EGR	EGR
EGR_{t-1}	0.163 (2.850)***	0.001 (1.600)	0.072 (1.060)	0.088 (1.410)
SEVRS	41.549 (4.150)***	0.385 (2.860)***	0.245 (2.220)**	0.473 (3.000)***
SECRS	–55.956 (–4.410)	–0.533 (–3.850)***	–0.388 (–3.150)***	–0.627 (–3.740)***
RDE	–0.975 (–1.730)	0.009 (0.640)	0.016 (0.740)	0.011 (0.660)
HCI		0.475 (1.610)	0.613 (1.240)	0.422 (1.190)
FIND		–0.037 (–1.600)	–0.056 (–2.000)**	–0.039 (–1.520)
CAGGL		0.051 (0.960)	0.120 (2.180)**	0.058 (1.170)
DVE		–0.011 (–0.570)		
DVM			–0.022 (–0.690)	
DVW				0.019 (0.750)
Cons.	30.540 (2.870)	0.141 (1.310)	0.046 (0.440)	0.102 (0.690)
Obs.	403	403	403	403
AR(1)	–4.180	–3.890	–3.680	–3.740
P-value	0.000	0.000	0.000	0.000
AR(2)	–0.980	–1.350	–1.250	–0.820
P-value	0.329	0.176	0.210	0.409
Hasen test	26.850	30.450	30.27	30.140
P-value	0.008	0.170	0.176	0.145

Note: *α = 0.1 significant at the 10% level, **α = 0.05 significant at the 5 % level, ***α = 0.01 significant at the 1% level.

7.7522 as high financial development provinces. We see that R&D efficiency has no effect on economic growth in financially underdeveloped areas, implying that the impact of financial development on economic growth is gradually strengthening, while high R&D efficiency enhances economic growth in high financial development areas rather than in medium financial development provinces.

Model B shows similar results; that is, financial development has a double-threshold effect on the relationship between SEVRS and economic growth. R&D efficiency harms economic growth in financially underdeveloped provinces; however, as the level of financial development improves, the effect of R&D efficiency on economic growth gradually emerged. This finding suggests that economic growth is stagnant under low levels of financial development and is beneficial only when financial development reaches a threshold level. Shen and Lee

(2006) state that financial development differences follow different economic development levels. Our results suggest that financial development has no direct effect on economic growth but plays an indirect role through R&D efficiency in China.

For Model C in Table 7, SECRS has a significant positive impact on economic growth and is influenced by the double-threshold effect of R&D expenditures, implying that the effect of R&D efficiency on economic growth is significantly different when R&D expenditures are at different thresholds. This finding shows that R&D expenditure is above the threshold value of 14.0158 (high provincial R&D expenditure), where R&D efficiency does not benefit economic growth. As the value of R&D expenditure decline to the threshold values of 14.0158 and 12.7868, the positive effect of R&D on economic growth efficiency improves. In Model D, the coefficient of SEVRS is significantly negative; thus, as R&D expenditures decline, this negative effect gradually becomes insignificant. This finding suggests that R&D input plays a vital role in economic growth, but R&D input is not always beneficial to economic performance when the overuse of inputs may cause a negative contribution.

In summary, the double threshold indicates that provinces differ in their level of financial development, thereby leading to different effects of R&D efficiency on economic growth. Thus, the nonlinear aspect of the financial development effect confirms its impact on converting R&D efficiency into beneficial economic growth. Are R&D activities always growth-enhancing? The existing literature reports a mixed relationship between R&D activities and economic growth. Our finding shows that R&D input has a critical value, but too much R&D expenditure does not enhance economic growth due to existing R&D resource allocative inefficiency.

Table 6. Results of panel threshold regression: Financial development

	Threshold variable: FIND	
	Model A	Model B
SEVRS	–0.3393 (–1.75)*	
SECRS		0.6424 (3.10)***
HCI	–3.291 (–3.23)***	–3.449 (–3.37)***
CAGGL	0.01 (0.13)	0.0154 (0.2)
INDUP	0.032 (0.03)	0.0298 (0.98)
	Regime–dependent variable: SECRS	Regime–dependent variable: SEVRS
FIND < 6.2647	0.0652 (0.30)	–0.967 (–4.88)***
7.7522 > FIND ≥ 6.2647	0.791 (3.85)***	–0.2854 (–1.58)
7.7522 ≤ FIND	1.431 (7.03)***	0.3042 (1.47)
R^2	0.4774	0.5273

Note: Significant level at the α = 0.1, **at α = 0.05 and ***at α = 0.01.

Table 7. Results of panel threshold regression: R&D expenditure

	Threshold variable: RDE	
	Model C	Model D
SEVRS	–0.6478 (–3.18)***	
SECRS		1.2011 (5.52)***
HCI	–3.4473 (–3.14)***	–3.621 (–3.27)***
CAGGL	0.0282 (0.35)	0.031 (0.38)
INDUP	0.0053 (1.64)	0.0047 (1.44)
	Regime–dependent variable: SECRS	Regime–dependent variable: SEVRS
RDE > 14.0158	0.2421 (1.05)	–1.6723 (–7.774)***
12.7865 < RDE ≤ 14.4803	0.9824 (4.51)***	–1.018 (–4.78)***
RDE ≤ 12.7865	1.72 (8.00)***	–0.3067 (–1.48)
R^2	0.5483	0.5961

Note: Significant level at the α = 0.1, **at α = 0.05 and ***at α = 0.01.

4.5. Dynamic panel threshold model results

In this section, we apply the dynamic data threshold model to analyze the impact of R&D efficiency on economic growth in China to avoid endogeneity bias. We provide the estimation of Eq. (6) in Table 8. The signs of the regime-dependent variable are positive with the SECRS equation, which is nearly consistent with the original results. By contrast, the signs are negative with the SEVRS equation. This finding shows that as financial development rises, the inhibitory effect of R&D efficiency on economic growth gradually declines. For the threshold variable, we find that R&D expenditure has a similar outcome, implying that with the preference for R&D investment, the role of R&D efficiency in promoting economic growth gradually becomes obvious.

In summary, we find similar results from the panel threshold model and dynamic panel threshold model, implying that the panel threshold model estimation suffered from insignificant endogeneity bias. Hence, R&D efficiency is not always growth-enhancing; various financial development and R&D investment levels cause differing effects of R&D efficiency on economic growth. These results suggest that a "one size fits all" policy for R&D investment plans may be an inappropriate approach in China; a suitable innovation strategy requires that each plan is tailored to the financial development level of each province.

Table 8. Results of dynamic panel threshold estimations

	Model E	Model F	Model G	Model H
$LNGDP_{t-1}$	0.843 (89.74)***	0.863 (40.95)***	0.831 (71.96)***	0.839 (85.73)***
SEVRS		–1.181 (–2.65)**		–0.234 (–3.89)***
SECRS	0.051 (1.16)		0.151 (2.66)***	
HCI	–0.268 (–2.73)***	–0.207 (–2.71)***	0.1001 (–0.86)	–0.079 (–0.78)
CAGGL	–0.0007 (–0.02)	0.029 (0.83)	0.024 (0.73)	0.004 (0.13)
INDUP	0.0005 (0.64)	0.003 (0.47)	0.006 (0.9)	0.0008 (0.8)
Regime-dependent variable:	SEVRS	SECRS	SEVRS	SECRS
Threshold value:	7.6511	6.312	15.457	15.457
Below threshold	–0.21 (–3.22)***	0.127 (2.85)***	–0.283 (–3.24)***	0.0192 (1.62)
Above threshold	–0.147 (–2.29)**	0.069 (1.15)	–0.199 (–2.73)***	0.175 (2.54)**

Note: Significant level at the α = 0.1, **at α = 0.05 and ***at α = 0.01.

4.6. Robustness test

We checked the sensitivity of the results using several methods. First, we replaced the R&D indicators in the regression model with R&D innovation as a proxy for the R&D expenditure per patent application (RDTS) and R&D density measured by R&D expenditure to GDP (RDEN). The results in Table 9 show that R&D density is positive but only significant in Model C, implying that R&D expenditure does not always improve economic performance when the overuse of inputs may cause a negative contribution. The coefficient of RDTS is negative and small, implying excessive R&D investment per patent application in China[9]. Second, we consider whether high or low GDP in the province affects the regression results differently. We classify provinces into the high GDP group when real GDP is above the national average and the low GDP group when real GDP is below the national average. As expected, the results change only marginally. The results are consistent with the main analysis.

Third, we also specify R&D efficiency as the distinction between R&D stocks and R&D expenditure. Following Cullmann et al. (2012) and Bai (2013), we measure R&D capital stock by PIM and calculate R&D inventory as

$$K_t = E_{t-1} + (1 - \delta)K_{t-1},$$

[9] We also apply the conventional DEA model to evaluate overall technical efficiency as a proxy for R&D efficiency and reestimate Eq. (6). The results are consistent with Section 4.2. These results are omitted here for brevity but are available on request from the authors.

where K_t and K_{t-1}indicate R&D inventories at time t and t – 1, respectively[10]. δ is the R&D depreciation rate, which, as in Cullmann (2012), is 15%. E_{t-1} indicates the real R&D expenditure at time t–1[11]. We find that two models have a similar result, especially in terms of the efficiency value change trend and ranking, which is consistent with Cullmann et al. (2012). This is an unsurprising result due to the high correlation between stocks and flows (Cullmann et al., 2012).

Table 9. Results of robustness test

	LNGDP	LNGDP	LNGDP	LNGDP
$LNGDP_{t-1}$	0.982 (112.15)***	0.979 (35.850)***	0.968 (19.89)***	0.988 (30.85)***
SEVRS	0.439 (3.77)***	0.247 (3.19)***	0.284 (2.38)**	–0.210 (2.76)***
SECRS	–0.626 (–4.48)***	–0.410 (–4.34)***	–0.500 (–3.16)	–0.367 (–4.66)***
RDTS	–0.000068 (–0.740)	–0.00023 (–3.22)***	–0.000114 (–1.160)	–0.000242 (–3.600)***
RDIN	0.021 (0.700)	0.032 (1.090)	0.046 (1.86)*	0.027 (0.890)
HCI		0.952 (2.47)**	0.795 (1.72)*	0.944 (2.630)***
FIND		–0.014 (–0.560)	–0.009 (–0.210)	–0.024 (–0.900)
CAGGL		–0.030 (–0.740)	0.029 (0.460)	–0.032 (–0.740)
INDUP		0.00026 (0.480)	–0.001 (–0.520)	0.00036 (0.530)
DVE		–0.021 (–1.170)		
DVM			0.004 (0.090)	
DVW				0.009 (0.450)
Cons.	0.382 (4.27)***	0.400 (3.16)***	0.394 (2.11)**	0.385 (2.68)***
Obs.	403	403	403	403
AR(1)	–3.680	–3.840	–3.630	–3.810
P-value	0.000	0.000	0.000	0.000

[10] We assume the inventory growth rate is the same as the R&D capital growth rate.; thus, the starting period of capital inventory is

$$K_0 = \frac{E_0}{(g+\delta)},$$

where K_0 indicates the initial inventory, E_0 indicates initial R&D investment, and g indicates the mean R&D capital growth Rate.

[11] Following Zhu and Xu (2003) converted the nominal R&D investment into the 2012 value of the R&D price index. We measure the R&D price index as (0.55 × consumer price index) + 0.45 × fixed asset investment price index), though this index represents fixed-asset investment only for 2012–2019 using data from the *China Statistical Yearbooks*. We use the three-year moving-average to estimate the 2020 price index for fixed-asset investment.

End of Table 9

	LNGDP	LNGDP	LNGDP	LNGDP
AR(2)	–0.080	–1.450	–1.360	–1.560
P-value	0.934	0.148	0.174	0.119
Hasen test	26.070	28.620	28.100	28.930
P-value	0.037	0.537	0.565	0.469

Note: *α = 0.1 significant at the 10% level, **α = 0.05 significant at the 5 % level, ***α = 0.01 significant at the 1% level.

Fourth, to test the sensitivity of dynamic panel data model results, we repeat the analysis using a subsample that excludes the least developed provinces, and consequently, the number of observations. This analysis excludes thereby excludes the provinces with the lowest GDP: Ningxia, Qinghai, and Tibet. As expected, the results change slightly and align with the main analysis[12].

Finally, we check the sensitivity of the results of the panel threshold model, which uses the financial development indicator for different threshold variables. Following Levine (1997) and Hassan et al. (2011), we use the ratio of outstanding loans of domestic financial institutions to GDP (LDGDP) as an indicator of financial development. The results in Table 10 indicate only one threshold, but it remains consistent with the main conclusion that R&D efficiency significantly affects economic growth in highly financially developed provinces.

Table 10. Results of panel threshold regression: robustness test

	Threshold variable: LDGDP	
	Model I	Model J
SEVRS	–0.331 (–1.40)	
SECRS		0.762 (2.93)***
HCI	–2.133 (–1.69)*	–2.3 (–1.81)*
CAGGL	–0.023 (–0.24)	–0.024 (–0.25)
INDUP	0.0034 (0.96)	0.004 (1.00)
	Regime–dependent variable: SECRS	Regime–dependent variable: SEVRS
LNFDL < 1.1936	0.45 (1.68)*	–0.553 (–2.33)**
LNFDL ≥ 1.1936	1.094 (4.14)***	–0.026 (–0.11)
R^2	0.0417	0.051

Note: *α = 0.1 significant at the 10% level, **α = 0.05 significant at the 5 % level, ***α = 0.01 significant at the 1% level.

[12] These results are omitted here for brevity but are available on request from the authors.

5. Conclusions

This study aims to determine whether threshold effects exist in the innovation–economic growth nexus in China from 2008 to 2020. We conduct the main analysis using dynamic and static panel threshold estimation techniques and find a threshold effect of R&D efficiency on economic growth. That is, R&D efficiency is not always positively associated with economic growth in China. Though R&D efficiency is poor, R&D investment still enhances economic growth due to considerable R&D investment. This finding suggests that it is not appropriate to increase R&D investment mindlessly. In the future, the focus should be on making full use of R&D resources and improving R&D efficiency.

We confirm a nonlinear effect of R&D efficiency on economic growth due to the dynamic and static threshold effects of financial development and R&D expenditure after dividing all provinces into three threshold regimes. We find no direct effect of financial development on economic growth, but an indirect effect through R&D efficiency. However, R&D efficiency does not significantly improve economic growth in low or middle-financial development provinces. This finding implies that the positive effect of R&D efficiency on China's economic growth mainly comes from provinces with high financial development.

We also find that R&D investment prompts economic growth using a dynamic GMM regression, confirming the general consensus among economists. However, the results of threshold estimation show that the effect of R&D efficiency on economic growth will gradually decline with the increase in R&D investment, implying that R&D investments only generate excess returns in provinces in which sufficient R&D investment improves productivity; otherwise, R&D resources will be wasted, even if they have a negative contribution.

From the policy perspective, the findings offer some suggestions and implications for improving the R&D efficiency and economic growth of China's provinces. First, uncertainty around how to improve R&D scale inefficiency is affecting the improvement of China's R&D efficiency. It is necessary to ensure that R&D funding provides reasonable performance and that resource allocation to innovation at the national level is efficient. Second, the results suggest that innovation policies and R&D plans must have solid regional features in each province – regional socio-economic characteristics will affect R&D efficiency through the capacity to transform R&D investment and R&D activities will ultimately indirectly promote economic growth. Third, the results suggest that it is necessary to significantly change the R&D input target; it is not enough to simply call for more R&D input and set a myopic numerical target in China. For example, the R&D strategy should be switched from R&D investment-based to R&D efficiency-based plans. In light of this, future research could investigate these aspects using a dynamic DEA or network DEA model with different input–output variables to evaluate R&D efficiency and how digital finance (green economic) affects economic growth.

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