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Can Technological Innovation and Financial Agglomeration Promote the Growth of Real Economy? Evidence from China

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Abstract: In the backdrop of China's evolving economic landscape, the real economy confronts a myriad of challenges, both domestically and on the global front. Technological innovation, characterized by its capital intensity and the unpredictable nature of its returns, stands as a pivotal force poised to rejuvenate nascent sectors and overhaul the existing industrial framework. Parallel to this, financial agglomeration emerges with a bifurcated function: it not only directly propels the real economic trajectory but also exerts an indirect influence via the channels of technological advancement. Delving deep into this interplay, our study dissected data collated from 30 major provinces and cities across mainland China, spanning the years 2011 to 2018. We employed the nuanced techniques of fuzzy matter–element analysis combined with the location entropy method. By anchoring our findings on a spatial econometric model, we uncovered the intricate dynamics of how technological ingenuity and financial clustering drive real economic growth, shedding light on the spatial reverberations that ripple across regions. Building on the tangible empirical evidence reflecting the trajectory of technological innovation and financial agglomeration within China, this article distills and presents the salient conclusions drawn from the investigation.

Keywords: technological innovation; financial agglomeration; real economy growth; space spillover effect

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1. Introduction

Amid evolving global economic dynamics, China's economic course has steadily entered a new phase. In this emerging economic landscape, the real economy stands as the backbone of the nation's financial fabric, critically influencing the overarching economic expansion (Cavalieri et al., 2021 [1]; Wang et al., 2023 [2]). Acting as the principal catalyst driving economic advancement and being central to the national economic structure, the real economy—particularly its manufacturing sector—remains crucial in the theater of international competition (He et al., 2021 [3]). Yet, China's real economy faces a myriad of both internal and international challenges that threaten its sustained and robust growth (Khan et al., 2021 [4]). Numerous studies have delved into the effects of technological innovation and financial evolution on economic growth, but detailed insights into their specific functions and synergy within China's present real economic surge are sparse.

In light of these dynamics, we propose the pivotal research inquiry: Do technological innovation and financial agglomeration have the potency to enhance the growth trajectory of China's real economy, and how do these elements intertwine? The objective of this article was to empirically probe into the distinct roles that technological innovation and financial agglomeration play in China's real economy evolution, highlighting their interconnected dynamics. Pursuing this, we undertook an exhaustive analysis of datasets from 30 provinces and municipalities in mainland China over the period 2011–2018. A standout aspect of our inquiry is our dual focus: we evaluated the influences of technological innovation and financial agglomeration on real economic ascendancy from a broad perspective while also diving deep into their diverse impacts across various sectors and geographical areas (Wang et al., 2023 [5]). Additionally, our investigation incorporated avant-garde methodologies, such as the fuzzy matter–element analysis and location entropy method, adding layers of innovation and academic depth to our findings.

2. Literature Review and Theoretical Mechanism Analysis

2.1. Research on the Growth of Real Economy

Different types of labor can influence an item's value differently. Labor that adds value is termed "productive labor", contrasting with "unproductive labor" (Laibman, 1996 [6]; Bernat, 1996 [7]; Mohun, 1996 [8]). This concept mirrors the broader real economy. Drucker (1958) differentiated between the real and symbolic economies, highlighting their intrinsic relationship [9]. Empirically, Hausmann et al. (2013) [10] posited that a nation's manufacturing complexity correlates with long-term economic growth, underlining the significance of the manufacturing-centric real economy for sustainable national economic progress.

2.2. The Impact of Technological Innovation on Economic Growth

Schumpeter laid the groundwork for innovation theory (Croitoru, 2008 [11]; Drucke, 2008 [9]), which subsequent scholars, like Lucas (1989) [12] and Romer (1994) [13], expanded upon, particularly emphasizing technological innovation's role in sustained economic growth. The consensus in both theory and empirical research is that technological innovation can enhance total factor productivity and drive economic growth (Bravo et al., 2011 [14]). Studies revealed its positive impact on countries like Mexico, Turkey, and those in Latin America, aided by the global diffusion of technological knowledge (Koh, 2007 [15]; Adak, 2015 [16]; Aali et al., 2016 [17]). However, through the empirical analysis of relevant data of developing countries from 2004 to 2011, scholars showed that technological innovation in developing countries is not conducive to economic growth in the short term (Feki and Mnif [18], 2016; Li and Ma., 2021 [19]).

2.3. The Impact of Financial Agglomeration on Economic Growth

The blossoming of new economic geography sparked interest in the correlation between industrial agglomeration and economic growth (Krugman, 1991 [20]; Fujita et al., 2001 [21]). Specifically, the phenomenon of financial agglomeration became a focal point. Theoretically, the concentration of financial entities can influence regional economic expansion (Greenwood and Jovanovic, 1990 [22]; Iyare and Moore, 2011 [23]), driven by its ability to bolster capital accumulation, foster technological innovation, and streamline financing processes, thereby reducing risks and transaction costs (Levine, 1996 [24]; Tadesse, 2002 [25]). Empirical studies have further endorsed the positive link and spatial spillover effects between financial agglomeration and regional growth (Bernat, 1996 [7]). Moreover, analyses leveraging panel data regression have cemented the idea that financial clusters spur economic growth (Hassan et al., 2011 [26]; Ottaviano, 2011 [27]). Furthermore, investigations into regions such as South Africa and Europe highlighted the enduring relationship between financial development and sustained economic expansion (Anwar and Cooray, 2012 [28]; Pradhan et al., 2016 [29]; Yuan et al., [30]).

2.4. Theoretical Mechanism Analysis

Innovation and credit are linchpins of economic advancement, with the former serving as the driving force and the latter ensuring its execution (Khan et al., 2023 [4]). This paper delves into the symbiotic relationship between technological innovation and financial agglomeration on the real economy's growth, drawing inspiration from economic development theories. Technological innovation boosts local real economic growth through creative destruction and benefit effects but can also impede it through cost effects. Notably, its knowledge spillover effect can generate a spatial spillover, influencing surrounding areas. Financial agglomeration spurs local real economic growth via agglomeration and financial function effects but may also act as a deterrent through its siphon effect. Its spatial diffusion can also ripple into surrounding areas, and intriguingly, its agglomeration effect can influence technological innovation, indirectly impacting real economic growth.

In essence, the pivotal roles that technological innovation and financial agglomeration play in spurring economic growth are incontrovertible (Wen et al., 2023 [31]). Yet, there is an observable gap in the current body of research that presents two primary shortcomings. Firstly, recognizing the dual function of financial agglomeration—its capacity to directly amplify economic growth and to indirectly modulate it via its effects on technological innovation—it becomes imperative to holistically examine these tripartite elements under a unified theoretical lens. This comprehensive approach not only aligns more closely with real-world dynamics but also offers a more robust understanding of their interplay. Secondly, in the backdrop of the financial industry's marked shift towards "decoupling from the tangible economy," the once central role of financial agglomeration in servicing the real economy appears to be waning. Against this evolving landscape, a pressing question emerges: How does the nexus between financial agglomeration and tangible economic expansion compare with traditional theoretical predictions? Through a meticulous analysis, this paper endeavored to shed light on these salient concerns, providing a renewed perspective in an ever-evolving economic discourse.

3. Measurement of Technological Innovation and Financial Agglomeration

3.1. Measurement of Technological Innovation

The accurate quantification of China's technological innovation level is pivotal for strategic planning and policy implementation. This study employed the fuzzy matter–element analysis complemented by the entropy method, aiming for a more comprehensive and precise measurement of China's technological innovation magnitude. The fusion of these methodologies provided a robust framework that captured the multifaceted aspects of innovation while also addressing potential uncertainties inherent in traditional measurements. This approach ensured a holistic understanding of China's innovation landscape, shedding light on areas of strength and potential opportunities for growth.

3.1.1. Fuzzy Matter–Element Analysis Method

Fuzzy matter–element analysis is based on thing M, feature C, and its corresponding magnitude x_{ij} (i = 1, 2, ..., m; J = 1, 2, ..., n). These three basic elements describe the research problem, and the matter elements in the research problem can be denoted as $R = (M, C, x_{ij})$. Its basic idea is to analyze the quantity value corresponding to different characteristics of different things on the basis of fully considering the incompatibility between multiple influencing factors of things, that is, to solve the problem of numerous and fuzzy incompatibilities of indicators faced in the evaluation of things.

If matter–element R contains m things $M_1, M_2, \ldots M_m$, and things M_i (i = 1, 2, ..., m) correspond to n features $C_1, C_2, \ldots, C_n$, then the matter element R has a total of $m \times n$ magnitude values x_{ij} (i = 1, 2, ..., m; J = 1, 2, ..., n), which can be called the n-dimensional complex element of m things, namely:

$$R_{m\times n} = \begin{array}{c c} & \begin{array}{ccc} C_1 & \ldots & C_n \end{array} \\ \begin{array}{c} M_1 \\ \vdots \\ M_m \end{array} & \begin{bmatrix} x_{11} & \ldots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \ldots & x_{mn} \end{bmatrix} \end{array} \tag{1}$$

In modern research, the task of accurately determining the weight of different indices becomes critical, especially when the nature of data is complex and multi-dimensional. This paper introduces an innovative approach to this problem by applying the fuzzy matter–element analysis underpinned by the entropy method. Such a methodology is not only adept at capturing the intrinsic value of each index but also ensures that the weight assigned is a reflection of the true importance and variability of the data. Through this method, biases associated with conventional weighting approaches are minimized, and the calculated weights become more representative of the real-world scenarios. This paper elucidates the detailed procedure and justifies the superiority of this combined technique over traditional methods.

3.1.2. Index Selection and Data Source

Building on prior research, this paper gauged the technological innovation level across 30 Chinese provinces and cities, encompassing the production, commercialization, and economic input stages of innovation. Given the abstract index of the variables under study, we opted to use indicators as proxies, potentially introducing some level of uncertainty. Measurements consider three dimensions: patent output (reflected in the number of patents granted in ten thousand CNY), technology market transactions (in ten thousand CNY), and the revenue from scientific and technological achievements, indicated by new product sales revenue (in ten thousand CNY). Given that the latter two are nominal variables, they were adjusted using the GDP deflator and PPI to the 2011 base year to account for inflation.

Post-deflation, the weights for these three indicators within the technological innovation measurement system were determined using Formula (1). The measurement system of technological innovation index and the weights of each index are shown in Table 1.

Table 1. Index system of technological innovation.

Secondary Index	Indicator Description	Data Sources	Weights
Patent output levels	Number of patents granted	Wind Database	0.2917
Technical market transaction	Technology market turnover/GDP deflator after fixed basis	Wind Database World Bank	0.4269
Income from scientific and technological achievements	New product sales income/PPI after fixed base	National Bureau of Statistics	0.2814

3.1.3. The Evaluation and Evolution Characteristics of China's Technological Innovation Level Based on the Measurement Results

In Figure 1, based on the data from measurement result, we present an average line chart depicting the technological innovation level (*INNO*) across 30 Chinese provinces and cities from 2011 to 2018. The chart reveals a consistent growth in China's average *INNO*, ascending from 0.0531 in 2011 to 0.1287 in 2018, reflecting a geometric annual average growth rate of 13.46%. This steady rise underscores the effectiveness of China's technology-driven strategies, emphasizing a consistent enhancement in its innovation capabilities.

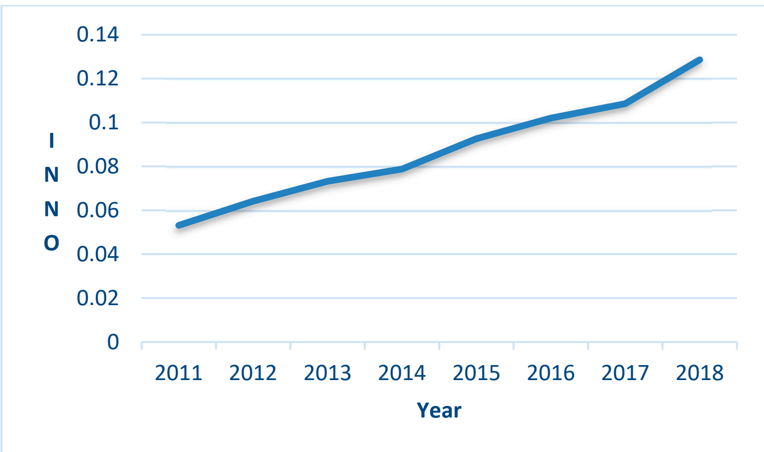

Figure 1. Average technological innovation level.

Figure 2 showcases the geographical distribution of the technological innovation level (*INNO*) across Chinese provinces and cities, utilizing the evaluation results from measurement results. For clarity and space constraints, only the evaluation maps for the initial and terminal years of the study period, specifically 2011 and 2018, are depicted.

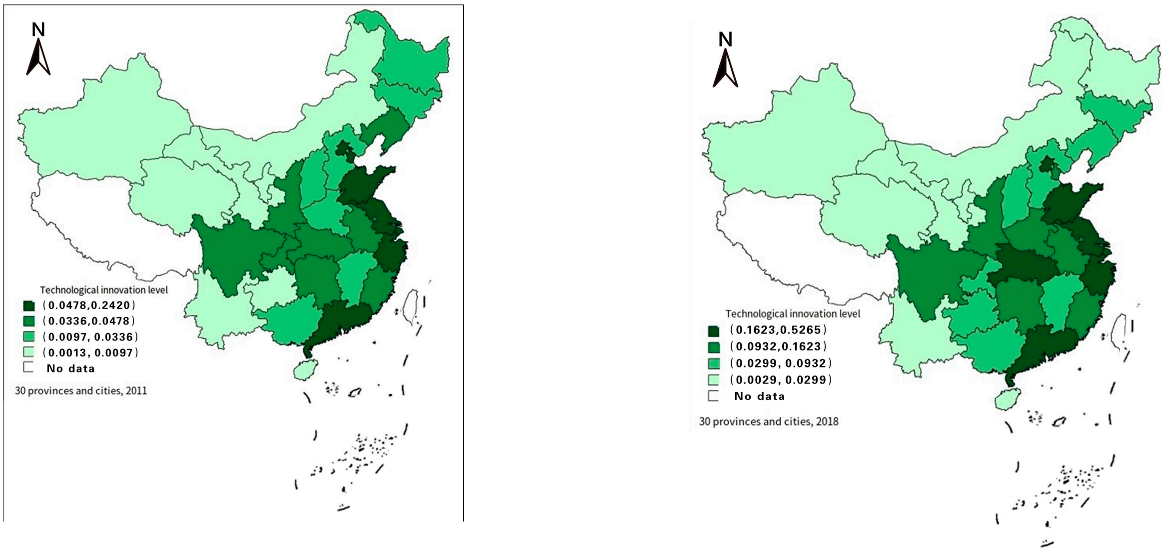

Figure 2. Technology innovation level in 2011 (**left**) and 2018 (**right**).

In the maps, a loci classification method is employed to segment the *INNO* of each province and city into four distinct tiers. A gradient color scheme represents these tiers, with deeper shades signifying higher levels of technological innovation. This visualization method allows for an intuitive understanding of the innovation landscape and its evolution over the span of the study.

Figure 2 illustrates the regional disparities in the technological innovation level (*INNO*) of the 30 provinces and cities in China for the year 2011. The clear gradient and clustered distribution from east to west underline the knowledge spillover effects inherent in technological innovation.

The eastern coastal regions, with their strategic location and mature economic foundations, form the vanguard in *INNO*. They have magnetized a wealth of technological innovation resources. Among these, the provinces of Shandong, Jiangsu, Shanghai, and Zhejiang stand out for their pronounced innovation clusters. However, areas like Beijing, Tianjin, and Guangdong, while being in the east, do not showcase the same level of clustered innovation as their counterparts.

The second and third tiers span across the central regions, with provinces like Hubei, Hunan, Sichuan, Chongqing, and Shaanxi revealing a distinct cluster distribution. Contrarily, Jiangxi province contrasts with its neighbors, indicating a pronounced negative spatial correlation in innovation.

Lastly, the trailing tier is predominantly in the western part of the country.

Comparing the two timelines in Figure 2, it becomes evident that the national *INNO* distribution in 2018 remained largely consistent with that in 2011, still exhibiting a pronounced gradient distribution pattern. This suggests that, while innovation may have grown, the fundamental regional disparities in innovation capabilities have been retained over the years.

3.2. The Measurement of Financial Agglomeration

3.2.1. The Measurement Method of Financial Agglomeration

The location entropy index, as suggested by Haggett (1977) [32], is an analytical tool used to measure the spatial concentration or dispersion of an activity or phenomenon across different locations or regions. When applied to financial agglomeration, this index can be instrumental in understanding the concentration of financial activities in various provinces and cities (Pandit et al., 2001 [33]).

Using the extended version of the location entropy index allows for a more nuanced analysis, adapting the original concept to better suit the specifics of financial agglomeration. By employing this formula, we can determine which provinces or cities in China serve as major hubs for financial activity and which ones are less concentrated. The specific formula is shown in Equation (2).

$$Efinance_{i,t} = \frac{E_{i,t}/P_{i,t}}{E_t/P_t} \quad (2)$$

In the numerator of Equation (2), $E_{i,t}$ represents the industrial resource index of province i in year t, and $P_{i,t}$ represents the permanent population of province i at the end of year t. In the denominator, E_t represents the nationwide industrial resource index in year t, and P_t represents the national permanent population at the end of year t. That is, the index reflects the ratio of the per capita industrial resources of a certain province to the per capita industrial resources of the country. The larger the index is, the larger the per capita scale of industrial resources in the region is in the national industrial scale, and the higher the degree of industrial agglomeration.

3.2.2. Evaluation and Evolution Characteristics of China's Financial Agglomeration Level Based on the Measurement Results

Figure 3 plots the financial agglomeration level (*FINA*) of 30 Chinese provinces and cities from 2011 to 2018. The trend reveals a fluctuating growth in China's financial agglomeration. After a slowing growth from 2011 to 2014, there was a notable dip in 2015. Post-2015, the growth stabilized and continually rose, going from 0.9851 in 2011 to 1.1683 in 2018, representing a 2.47% geometric average annual growth rate. This underscores the evolving concentration of China's financial resources amidst the robust expansion of its financial sector.

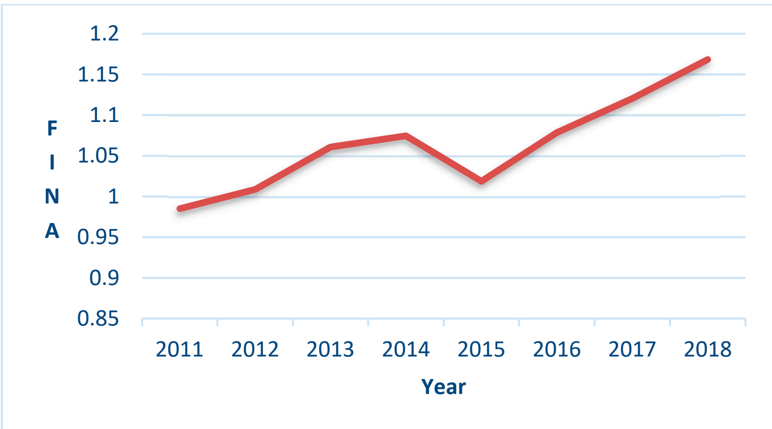

Figure 3. Average level of financial agglomeration.

Figure 4 illustrates the financial agglomeration levels across Chinese provinces and cities using evaluation maps from 2011 and 2018. Due to space constraints, only these two years, marking the start and end of our study period, are depicted. Using the loci classification, each province and city's financial agglomeration level is categorized into four tiers; the darker the shade, the higher the level of financial agglomeration.

From Figure 4's left diagram, the 2011 financial agglomeration levels across China's 30 provinces and cities highlight a clustered distribution with clear polarization. Predominantly, the first tier is evident in the eastern coastal regions, such as Beijing, Tianjin, Jiangsu, Zhejiang, Shanghai, and Guangdong. Their geographical perks combined with an export-driven industry structure magnetized a significant portion of financial resources. Notably, Chongqing, the central region's transportation nexus, also attracted immense financial resources. This first-tier concentration drew resources from neighboring provinces, relegating areas like Henan, Anhui, Jiangxi, Hunan, and the Guangxi Zhuang Autonomous Region to the fourth tier. Meanwhile, the second and third tiers are interspersed across the central and western zones. Contrasting the two diagrams from 2011 to 2018, it is evident that by 2018, China's financial agglomeration had begun to depict a trickle-down effect.

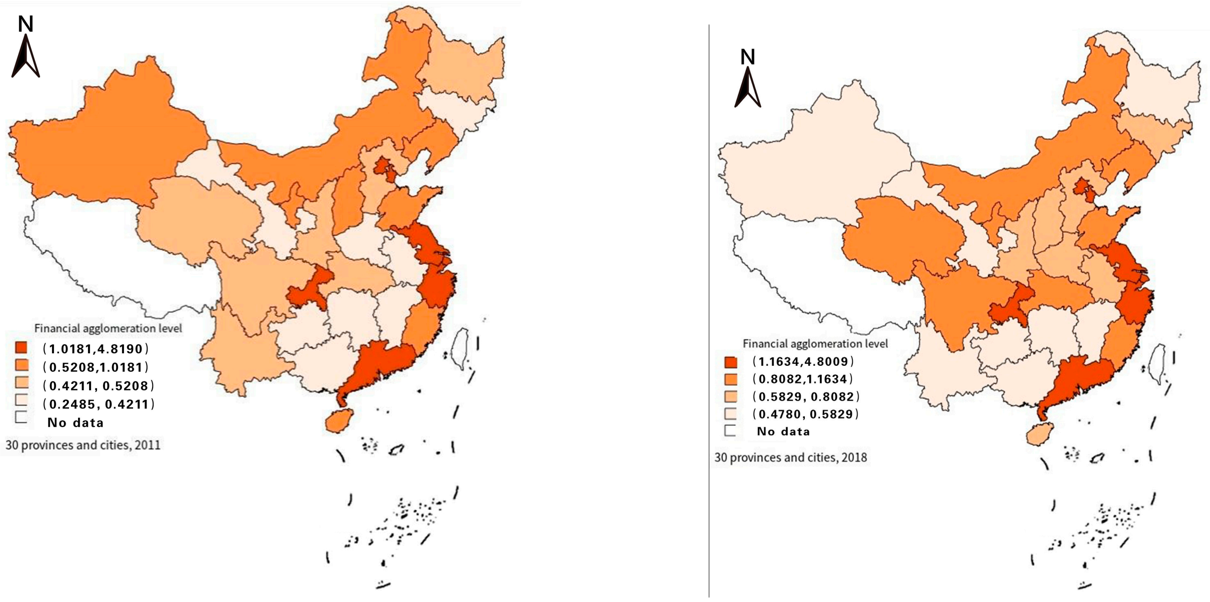

Figure 4. Distribution of the financial agglomeration level in 2011 (**left**) and 2018 (**right**).

3.3. The Comparison of Technological Innovation and Financial Agglomeration

Utilizing the data we gathered previously, it is imperative to conduct a comprehensive comparison of both the technological advancements and financial performance across some of the primary provinces in China. This comparative analysis not only sheds light on the regional disparities but also highlights areas that are leading in innovation and economic growth. By understanding these key indicators, policymakers and stakeholders can make informed decisions and strategize better for future developments in these regions. To illustrate this point, as shown in Figure 5, the radar chart effectively displays the relationship, with the left picture depicting the relationship of INNO and FINA in 2011 and the right picture depicting the relationship of INNO and FINA in 2018.

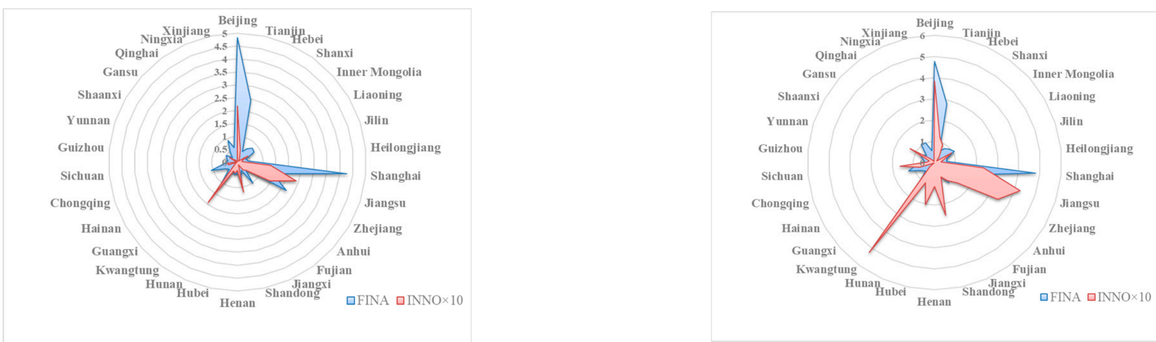

Figure 5. The radar chart of *INNO* and *FINA* in 2011 (**left**) and 2018 (**right**).

Significantly, in 2011, regions such as Shanghai, Beijing, and Guangxi stood out with a pronounced dominance in the technology innovation level metric. However, by 2018, Shanghai, Beijing, Zhejiang, and Jiangsu saw a notable uptick in their technology innovation level scores. This trend is paralleled in the financial agglomeration level metric. While 2011 heavily emphasized Shanghai, Beijing, and Guangxi, by 2018, Zhejiang and Jiangsu began to rise to prominence. Consistently, Shanghai and Beijing maintained their stature as leading figures in both metrics throughout this period. Additionally, provinces like Fujian, Henan, Hubei, Guangdong, and Yunnan exhibited stability, showing only minor variations in their values. The shift from 2011 to 2018 highlights a palpable transition in the economic and innovative potentials of these regions, with Zhejiang and Jiangsu emerging as budding centers of innovation. Additionally, while Shanghai and Beijing continue to exert significant influence, there is a clear realignment in their individual financial and innovative roles. In essence, these charts offer a comprehensive view into the intertwined dynamics of innovation and finance across China's key provinces over an eight-year span, acting as an invaluable resource for identifying regional fortes, projecting growth trajectories, and guiding future policy and investment strategies.

4. Analysis of the Spatial Spillover Effect of Technological Innovation and Financial Agglomeration on Economic Growth

4.1. Construction of Spatial Econometric Model

Technological innovation and financial agglomeration are spatially correlated in boosting real economic growth. To ensure that our empirical research mirrored real-world dynamics, it was imperative to integrate New Economic Geography insights. Employing a spatial econometric model then effectively elucidated the relationship among these factors.

Firstly, the generalized nested space model of static panel data was constructed as follows:

$$\begin{gathered} y_{it} = \rho w_i' y_t + x_{it}' \beta + d_i' X_t \delta + u_i + \gamma_t + \varepsilon_{it} \\ \varepsilon_{it} = \lambda m_i' \varepsilon_t + v_{it} \end{gathered} \tag{3}$$

where $\rho w_i' y_t$ represents the spatial lag of the explained variable, $x_{it}'\beta$ represents the explanatory variable and its regression coefficient, $d_i' X_t \delta$ represents the spatial lag of the explanatory variable, and $\lambda m_i' \varepsilon_t$ represents the spatial lag of the random disturbance term. w_i', d_i' , and m_i' represent the i row of the corresponding spatial weight matrix, ρ is the spatial autoregressive coefficient, δ is the spatial hysteresis coefficient of the explanatory variable, and λ is the spatial correlation coefficient of the disturbance term. u_i and γ_t are individual effects and time effects, respectively. By adding different constraints to Equation (3), the generalized nested space model can be simplified to special spatial econometric models.

If the spatial correlation coefficient λ is 0, then the spatial Durbin model (*SDM*) is obtained, as shown in Equation (4):

$$y_{it} = \rho w_i' y_t + x_{it}' \beta + d_i' X_t \delta + u_i + \gamma_t + \varepsilon_{it} \tag{4}$$

If the Spatial lag coefficient of the explanatory variable δ is 0, then the spatial autocorrelation model (SAC) is obtained, as shown in Equation (5):

$$\begin{gathered} y_{it} = \rho w_i' y_t + x_{it}' \beta + u_i + \gamma_t + \varepsilon_{it} \\ \varepsilon_{it} = \lambda m_i' \varepsilon_t + v_{it} \end{gathered} \tag{5}$$

If the spatial correlation coefficient λ and the spatial lag coefficient of explanatory variables δ are both 0, then the spatial autoregression model (*SAR*) is obtained, as shown in Equation (6):

$$y_{it} = \rho w_i' y_t + x_{it}' \beta + u_i + \gamma_t + \varepsilon_{it} \tag{6}$$

If the spatial autoregressive coefficient ρ and the spatial lag coefficient of explanatory variable δ are both 0, then the spatial error model (*SEM*) is obtained, as shown in Equation (7):

$$\begin{gathered} y_{it} = x_{it}' \beta + u_i + \gamma_t + \varepsilon_{it} \\ \varepsilon_{it} = \lambda m_i' \varepsilon_t + v_{it} \end{gathered} \tag{7}$$

In the process of empirical research, the likelihood ratio (*LR*) test can be used to choose between the above models.

4.2. Index Selection and Data Source

Owing to data constraints, this study utilized panel data from 30 provinces and cities across mainland China spanning from 2011 to 2018. The XiZang Autonomous Region was excluded because of data unavailability. We define the variables as follows.

4.2.1. Dependent Variable

This study employed the per capita real economic GDP (PGDP) of each province and city as a measure for the real economic growth of each region. Specifically, the calculation deducted the added values of the financial and real estate sectors from the GDP, yielding the real economy. With 2011 as the base year, we adjusted the GDP using the GDP deflator, then normalized it by the end-of-year population. All data regarding China's GDP, financial and real estate sectors, and population were sourced from the National Bureau of Statistics. The GDP deflator is referenced from the World Bank's database.

4.2.2. Primary Explanatory Variables

This encompasses technological innovation (*INNO*) and financial agglomeration (*FINA*).

4.2.3. Control Variables

Based on prior research, we incorporated the following control variables:

1. Government intervention (*GOV*) is defined as the local public finance expenditure's proportion to the GDP of the respective provinces and cities. Data were sourced from the Wind database.
2. Fixed asset investment intensity (*INV*) was quantified by the ratio of the adjusted total fixed asset investment to the adjusted GDP, which used the 2011-based GDP deflator. The fixed asset investment and its associated price index were referenced from the National Bureau of Statistics.
3. Infrastructure (*FRU*) was represented by the combined railway and road mileage relative to the provincial land area. The data for both mileages were derived from the National Bureau of Statistics, while land area statistics were from the Yearbook of China Regional Economic Statistics.
4. Urbanization level (*URB*) was measured by the urban population's ratio to the year-end permanent residents of each province or city, with data sourced from the National Bureau of Statistics.
5. Labor force intensity (*LAB*) was determined by the ratio of urban unit employees to the year-end permanent residents in each province or city. Data were obtained from the National Bureau of Statistics.
6. Foreign trade intensity (*TRAD*) was defined by the business unit location's total import and export volume's ratio to the GDP of each province and city. It is noteworthy that this metric was computed in USD. To mitigate the influence of exchange rate volatility, we first discerned the annual exchange rate from 2011 to 2018 by dividing the RMB-based national GDP by the USD-based one. We then converted the USD-valued total imports and exports using this rate. The resulting value's proportion to the provincial GDP quantified foreign trade intensity. The USD-based national GDP data were sourced from the World Bank. The panel data descriptive statistics of the above variables are shown in Table 2.

Table 2. Description of the panel data descriptive statistics of variables.

Variables	Categories	Mean Value	Standard Deviation	Minimum	Maximum	Observed Value
PGDP	Overall	4.3417	1.7923	1.5119	9.5438	N = 240
	Between		1.7261	2.1943	8.5302	n = 30
	Within		0.5659	2.7874	6.1107	T = 8

Table 2. *Cont.*

Variables	Categories	Mean Value	Standard Deviation	Minimum	Maximum	Observed Value
	Overall		0.1032	0.0012	0.5265	N = 240
INNO	Between	0.0877	0.0991	0.0019	0.3351	n = 30
	Within		0.0334	0.0494	0.2812	T = 8
	Overall		1.0253	0.2485	4.8190	N = 240
FINA	Between	1.0643	1.0333	0.3874	4.5982	n = 30
	Within		0.1216	0.6481	1.7225	T = 8
	Overall		0.1030	0.0458	0.6274	N = 240
GOV	Between	0.2460	0.1022	0.1237	0.5935	n = 30
	Within		0.0216	0.0809	0.3003	T = 8
	Overall		0.2583	0.2296	1.5066	N = 240
INV	Between	0.8264	0.2230	0.2603	1.2389	n =30
	Within		0.1358	0.3925	1.1902	T = 8
	Overall		0.0047	0.0009	0.0194	N = 240
FRU	Between	0.0094	0.0047	0.0011	0.0168	n =30
	Within		0.0006	0.0070	0.0122	T = 8
	Overall		0.1230	0.3497	0.8961	N = 240
URB	Between	0.5711	0.1216	0.4112	0.8864	n =30
	Within		0.0280	0.5095	0.6352	T = 8
	Overall		0.0587	0.0690	0.3804	N = 240
LAB	Between	0.1309	0.0584	0.0809	0.3582	n = 30
	Within		0.0118	0.0651	0.1637	T = 8
	Overall		0.3121	0.0168	1.5488	N = 240
TRAD	Between	0.2747	0.3072	0.0355	1.1923	n = 30
	Within		0.0763	0.0951	0.7228	T = 8

Note: N represents sample size; n represents sample size in the dimension of province; T represents sample size in the dimension of time.

4.3. Panel Unit Root Check

The LLC test and ADF-based Fisher type test were used to perform a unit root test on panel data. The test results are shown in Table 3.

Table 3. Panel data unit root check.

Variables	LLC Test	Fisher Type Test				Smoothness
	Adj-t * Statistic	P Statistic	Z Statistic	L * statistic	Pm Statistics	
PGDP	13.3879 *** (0.0000)	108.1377 *** (0.0001)	2.9261 *** (0.0017)	3.0758 *** (0.0012)	4.3944 *** (0.0000)	Smooth and steady
INNO	23.8554 *** (0.0000)	85.5163 ** (0.0169)	1.7125 ** (0.0434)	1.7969 ** (0.0372)	2.3293 *** (0.0099)	Smooth
FINA	11.4934 *** (0.0000)	145.8741 *** (0.0000)	6.9268 *** (0.0000)	6.8433 *** (0.0000)	7.8392 *** (0.0000)	Smooth
GOV	30.1765 *** (0.0000)	103.4039 *** (0.0004)	4.3320 *** (0.0000)	4.1405 *** (0.0000)	3.9622 *** (0.0000)	Smooth
INV	7.4903 *** (0.0000)	147.4878 *** (0.0000)	6.4990 *** (0.0000)	6.5015 *** (0.0000)	7.9865 *** (0.0000)	Smooth
FRU	8.6623 *** (0.0000)	128.5222 *** (0.0000)	4.9756 *** (0.0000)	5.1003 *** (0.0000)	6.2552 *** (0.0000)	Smooth
URB	13.5586 *** (0.0000)	87.2865 ** (0.0123)	2.1589 ** (0.0154)	2.1005 ** (0.0187)	2.4909 *** (0.0064)	Smooth
LAB	37.0871 *** (0.0000)	222.3900 *** (0.0000)	9.3152 *** (0.0000)	10.6654 *** (0.0000)	14.8241 *** (0.0000)	Smooth
TRAD	11.5037 *** (0.0000)	117.9598 *** (0.0000)	5.2625 *** (0.0000)	5.0328 *** (0.0000)	5.2910 *** (0.0000)	Smooth

Note: *p* values in parentheses; ***, **, * indicates significant at the 1%, 5%, 10% significance level, respevtively.

The findings presented in Table 4 confirm that each panel data variable is stationary and is therefore suitable for subsequent empirical evaluations.

Table 4. Global Moran's I index.

	2011	2012	2013	2014	2015	2016	2017	2018
PGDP	0.284 *** (2.913)	0.269 *** (2.772)	0.257 *** (2.657)	0.238 ** (2.475)	0.236 ** (2.451)	0.241 ** (2.505)	0.281 *** (2.875)	0.279 *** (2.850)
INNO	0.000 (0.627)	0.003 (0.574)	0.004 (0.506)	0.004 (0.631)	0.022 (0.713)	0.009 (0.570)	0.034 (0.853)	0.065 (1.055)
FINA	0.213 ** (2.522)	0.218 ** (2.554)	0.212 ** (2.498)	0.205 ** (2.435)	0.178 ** (2.179)	0.172 ** (2.123)	0.175 ** (2.155)	0.167 ** (2.070)

Note: Z-values in parentheses; ***, ** are significant at the significance level of 1%, 5%, respectively.

4.4. Empirical Analysis Based on Spatial Econometric Model

4.4.1. Global Spatial Autocorrelation Test

The Global Moran's I test assessed the overall spatial correlation of sample variables. Fundamentally, the Global Moran's I index, typically ranging between −1 and 1, calculated the product of the deviations between two regional observations. A result greater than 0 suggested positive interregional correlation, indicating spatial clustering. Conversely, a value less than 0 signified negative interregional correlation, pointing to spatial dispersion. If the value was near 0, it implied negligible spatial correlation. The formula for the Global Moran's I index is provided in Equation (8):

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (8)$$

where n is the sample size, x_i is the observed value of variable x in region i, $\overline{x}$ is the sample mean, S^2 is the sample variance, and w_{ij} is the spatial weight matrix. In this paper, the 0–1 spatial weight matrix was used for calculation. Since there is no province bordering Hainan Province, Guangdong Province and Guangxi Zhuang Autonomous Region were set as the neighboring provinces of Hainan Province.

Initiating our analysis, we applied the bilateral global Moran test to three pivotal variables: real economy growth (*PGDP*), technological innovation (*INNO*), and financial agglomeration (*FINA*). This study incorporated data sourced from 30 distinct provinces and cities across China, spanning the years 2011–2018. Detailed outcomes of this examination are tabulated in Table 4.

Table 5's analysis reveals that, from 2011 to 2018, there existed a pronounced spatial positive correlation between China's real economy growth (PGDP) and its financial agglomeration (FINA). Both metrics achieved significance in the global Moran's I test at the 5% level. Such results suggest that, if a specific province experiences growth in its real economy and financial agglomeration, neighboring provinces are likely to be positively influenced, highlighting a potential trickle effect. In contrast, the spatial correlation for technological innovation (INNO) appeared negligible during the same period.

Table 5. Estimation results of the spatial econometric model.

Variables	SDM	SAR	SAC	SEM
INNO	3.7127 *** (0.7327)	3.5048 *** (0.7280)	3.7354 *** (0.7360)	3.0961 *** (0.8035)
FINA	0.1086 (0.1452)	0.0209 (0.1459)	0.0837 (0.1501)	0.0030 (0.1490)
GOV	3.4832 *** (0.7918)	3.4224 *** (0.8126)	3.3240 *** (0.7989)	3.6438 *** (0.8546)
INV	0.4877 *** (0.1577)	0.5149 *** (0.1617)	0.4997 *** (0.1595)	0.5245 *** (0.1662)
URB	2.3404 (1.7415)	2.7579 (1.7728)	2.3232 (1.7220)	3.3027 * (1.8916)

Table 5. *Cont.*

Variables		**SDM**	**SAR**	**SAC**	**SEM**
LAB		5.6902 *** (1.7606)	5.4400 *** (1.7809)	4.7686 *** (1.7667)	5.9587 *** (1.8605)
TRAD		1.9850 *** (0.3196)	1.9343 *** (0.3208)	1.8719 *** (0.3121)	2.0318 *** (0.3406)
FRU		18.8158 (37.2926)	20.4876 (36.9260)	11.1092 (36.9141)	45.8038 (37.7292)
*W*INNO*		5.9224 *** (1.3904)	-- --	-- --	-- --
*W*FINA*		0.9467 *** (0.3562)	-- --	-- --	-- --
rho		0.2100 *** (0.0754)	36.9260 *** (0.0595)	0.4550 *** (0.0714)	-- --
Lambda		-- --	-- --	0.2183 * (0.1313)	0.3549 *** (0.0889)
Log-likelihood		31.9518	22.5785	23.8530	12.1935
Area effect		Control	Controls	Controls	Controls
Time effect		Control	Controls	Controls	Controls
Hausman check	chi2(8)	19.25 **	17.42 **	--	25.76 ***
	p value	0.0136	0.0260	--	0.0012
	Model selection	Fixed effect model	Fixed effect model	Fixed effect model	Fixed effect model
LR test		SDM vs. SAR		LR chi2(2) = 18.75 ***	
		SDM vs. SAC		LR chi2(1) = 16.20 ***	
		SDM to SEM		LR chi2(2) = 39.52 ***	

Note: Standard deviation in parentheses; ***, **, and * are significant at the significance level of 1%, 5%, and 10%, respectively.

Observing the temporal shifts in the global Moran's I index, we noted a stark decline in the spatial correlation of real economy growth between 2011 and 2014. This correlation plateaued from 2015 to 2016, only to surge in 2017 and stabilize in 2018. Overall, the fluctuations in this index remained within the range of 0.23 to 0.29, showcasing relative consistency. Interestingly, the spatial relationship of financial agglomeration has been on a decline since 2014, suggesting a diminishing spatial spillover effect on proximate regions.

4.4.2. Local Spatial Autocorrelation Test

To delve deeper into the spatial distribution nuances of real economic growth and financial agglomeration across China's provinces and cities, we utilized the local Moran test. This examination was undertaken for the years 2011 and 2018 across 30 provinces and cities. The local Moran's I test elucidated the spatial correlation dynamics of the sample variables for individual regions. Equation (9) details the mathematical representation of the local Moran's I index:

$$\mathrm{I}_i = \frac{(x_i - \overline{x})}{S^2} \sum_{j=1}^{n} w_{ij}\left(x_j - \overline{x}\right) \tag{9}$$

Given the spatial autocorrelation patterns observed in China's real economic growth and financial agglomeration, this study employed a spatial econometric model. This approach aimed to provide a nuanced understanding of how technological innovation and financial agglomeration influence real economic growth.

4.4.3. The Model Estimation Results and Analysis

This study utilized the maximum likelihood estimation (*MLE*) for regression estimations of the following various spatial models: the spatial Durbin model (*SDM*), spatial autoregressive model (*SAR*), spatial autocorrelation model (*SAC*), and spatial error model (*SEM*). Notably, the *SDM* focused solely on the spatial lag of the core explanatory variables, *INNO* and *FINA*. The outcomes of these regressions can be viewed in Table 5.

Table 6's empirical results indicate that the four models' fitting outcomes were consistent, confirming model robustness. Notably, the spatial autoregressive coefficient ρ stood at 0.2100 and was 1% significant, highlighting a distinct spatial positive autocorrelation in the real economy's growth. The LR test established the *SDM*'s superior fit over other models, making it our primary analysis framework.

Table 6. Decomposition of spatial effects based on the spatial Durbin model.

Variables	Direct Effects	Indirect Effects	Total Effect
INNO	4.0825 *** (0.7316)	8.2264 *** (1.3325)	12.3089 *** (1.6111)
FINA	0.1543 (0.1456)	1.2013 *** (0.4504)	1.3556 *** (0.5215)
GOV	3.4446 *** (0.7612)	0.8560 ** (0.3917)	4.3006 *** (0.9495)
INV	0.4927 *** (0.1538)	0.1238 * (0.0665)	0.6165 *** (0.1969)
URB	2.3912 (1.7384)	0.6086 (0.5535)	2.9998 (2.2019)
LAB	5.8545 *** (1.7726)	1.4890 * (0.8093)	7.3435 *** (2.3303)
TRAD	1.9959 *** (0.3240)	0.5073 ** (0.2388)	2.5032 *** (0.4650)
FRU	19.9701 (36.3143)	4.6665 (9.8359)	24.6366 (45.3201)

Note: Standard deviation in brackets; ***, **, and * are significant at the significance level of 1%, 5%, and 10%, respectively.

1. Technological innovation (*INNO*) significantly bolsters real economic growth. Directly, as an economic production input, it enhances societal productivity and real economic operations. Indirectly, it fosters high-tech entrepreneurship, facilitating China's industrial structural upgrade, thus optimizing market resource allocation.
2. Regarding financial agglomeration (*FINA*), while it theoretically enhances real economic growth by streamlining financial resource allocation, its coefficient is not statistically significant. Excessive financial agglomeration might dilute this effect due to its inherent siphon effect.
3. Government intervention (*GOV*) poses a notable dampening effect on real economic growth. Driven by societal equity goals, such intervention may "crowd out" real economy operations, resulting in growth impediments.
4. Fixed asset investment (*INV*) showed a robust positive relationship with real economic growth, underlining its pivotal role in fostering sustainable societal development.
5. Urbanization level (*URB*) potentially drives real economic growth, though its p-value is not significant.
6. Labor force level (*LAB*) is a significant enhancer for real economic growth as an integral operational input.
7. Foreign trade level (*TRAD*) exhibits a pronounced negative correlation with real economic growth. Given escalating trade protectionism and growing anti-globalization sentiments, China's foreign trade faces unprecedented challenges, impacting real economic growth.
8. Infrastructure development (*FRU*)'s correlation with real economic growth is not statistically robust.

From a spatial perspective, technological innovation's spatial lag (*W*INNO*) notably propels real economic growth, implying that surrounding regions' innovation boosts a region's economy through knowledge spillovers. Furthermore, financial agglomeration's spatial lag (*W*FINA*) has a 1% significance level, suggesting that adjacent provinces' financial agglomeration can amplify a province's real economic growth via trickle effects. These spatial spillovers underline the growth pole's potential in bridging regional economic disparities.

4.4.4. Spatial Spillover Effect Decomposition

The partial differential decomposition, based on the spatial Durbin model's estimation results, offers insights into the direct and indirect effects each variable exerts on real economic growth. The detailed outcomes are elucidated in Table 6.

In light of the detailed breakdown presented in Table 6, we can surmise the following pivotal points.

1. Technological Innovation (*INNO*)

The direct, indirect, and cumulative effects of technological innovation on real economic growth are palpably positive. Intrinsically, technological advancements augment a region's industrial structure and real economy's efficiency, catalyzing its economic progression. Externally, due to regional economic integration and the knowledge spillover effect, a particular region's technological strides can permeate surrounding areas. This essentially allows adjacent regions to benefit from these innovations without having to expend equivalent resources, resulting in a "free rider" effect. Hence, the growth impetus derived from neighboring regions' technological advancements supersedes the direct benefits.

2. Financial Agglomeration (*FINA*)

Directly, financial agglomeration does not render a statistically significant impact on real economic growth. Contrarily, financial agglomeration in proximate areas can amplify the growth of the local real economy, likely due to the trickle-down effect and the interconnected financial network.

3. Government Intervention (*GOV*)

Both local and external government interventions curtail the real economic growth of a province. The domestic ramifications, especially due to the "crowding out effect," are markedly pronounced.

4. Fixed Asset Investment (*INV*)

Investments in fixed assets, be it within the province or in surrounding provinces, substantially bolster the province's real economic growth. Local investments, in particular, exhibit a salient amplifying effect.

5. Urbanization Level (*URB*)

While urbanization tends to exert positive direct and indirect influences on real economic growth, the effects are statistically inconclusive.

6. Labor Force Level (*LAB*)

The significance of the labor force on real economic growth is evident both directly within the province and indirectly from surrounding regions, substantiating the integral role labor plays in economic dynamism.

7. Foreign Trade Level (*TRAD*)

Both directly and indirectly, foreign trade exhibits a dampening effect on real economic growth, significant at the 5% level. This suggests that external trade dynamics, perhaps influenced by global protectionist sentiments, adversely impact regional economic performance.

8. Infrastructure Development (*FRU*)

Infrastructure investments appear to correlate negatively with real economic growth both directly and indirectly, though these results are not statistically robust.

These insights provide a comprehensive understanding of the multifaceted interactions at play in shaping the real economic growth of a region, taking into account both intrinsic and extrinsic factors.

5. Conclusions

5.1. Research Summary

The findings and conclusions derived from this comprehensive research shed light on the intricate interplay of technological innovation, financial agglomeration, and other macroeconomic variables in shaping the trajectory of China's real economy in the "new normal" phase, summarizing the crucial takeaways.

1. Dual roles of technological innovation (*INNO*) and financial agglomeration (*FINA*)

Both technological innovation and financial agglomeration can be a boon or bane to the real economy. While the former invigorates the economy through creative destruction and income effects, it may simultaneously act as a drag due to the associated cost effects. Similarly, financial agglomeration, though it is a bedrock by offering resources through agglomeration and financial function effects, can have a reverse siphoning effect. Financial agglomeration also indirectly influences the real economy by modulating technological innovation, and both these pillars influence neighboring regions due to the knowledge spillover and spatial diffusion effects.

2. Predominance of technological innovation

Technological innovation stands out as a major propellant for the growth of China's real economy, exhibiting strong direct and indirect positive influences. Financial agglomeration, although instrumental, is not a cardinal driver. Its spatial spillover effects, however, reinforce the importance of interconnected growth among provinces and cities.

3. Investment (*INV*) and Labor (*LAB*) Remain Integral

Fixed asset investments and labor levels continue to be pivotal for China's real economic growth. Meanwhile, urbanization and infrastructure levels are not bottleneck factors anymore, reflecting China's progress in these domains.

4. Diminishing government intervention (*GOV*) and foreign trade level (*TRADE*) concerns

Over-reliance on government interventions and the challenges in the foreign trade arena (especially in the light of global trade frictions) could be counterproductive. China must steer towards more market-led reforms and bolster its endogenous growth engines for sustainable, high-quality economic evolution.

In essence, as China traverses its "new normal" phase, the emphasis should be on harnessing technological innovations as the lynchpin for high-quality economic growth. While financial agglomeration is vital, its role is complementary, necessitating a recalibration of strategies across financial sectors. Additionally, a shift towards more market-centric reforms that focuses on endogenous growth factors will be pivotal in navigating the evolving economic landscape.

5.2. Limitations and Future Research

5.2.1. Limitations

While this paper conducts a comprehensive theoretical and empirical examination of the influence of technological innovation and financial agglomeration on real economic growth under the guidance of Schumpeter's theory of economic development and offers policy recommendations tailored to the Chinese context, there are certain limitations due to constraints on research timeframe, data availability, scope, and the author's expertise. These shortcomings, however, illuminate potential avenues for future investigations.

5.2.2. Future Research

This paper emphasizes the significance of refining data indicators for technological innovation and financial agglomeration, pointing out possible gaps due to oversights. While the focus is predominantly on provincial dynamics, the diverse economic interactions between adjacent provinces, shaped by varying scales, industries, and roles, call for more granular research. Additionally, the intertwined nature of China's economy with global cycles necessitates examining the fluctuating relationships in innovation, financial congregation, and economic growth. These insights not only pave the way for richer academic exploration but also provide a foundation for more informed policy-making.

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