



Can increasing technological complexity help strengthen regional economic resilience?

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Abstract

Improving regional economic resilience through technological innovation has always been a strategic focus of China, but the previous studies have paid little attention to the impact of structural characteristics of technological innovation on regional economic resilience. Based on the complexity of technology, this study studies the impact and mechanism of technological systems with more complex internal mechanisms on economic resilience. The main findings are as follows: (1) Higher technological complexity is conducive to technological innovation and can improve regional economic resilience; (2) technological complexity needs to be in the appropriate range, and its positive effect shows diminishing marginal effect; and (3) optimizing market competition and absorptive capacity plays a positive role in regulating the relationship between technological complexity and regional economic resilience. This study provides policy implications for implementing innovation-driven development strategy, formulating economic recovery plan, and medium- and long-term sustainable development strategy.

Keywords Technological complexity · Economic resilience · New technology · Market competition · Absorptive capacity

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1 Introduction

The world today is undergoing profound changes unseen in a century, and the evolution will accelerate. The complexity, uncertainty, and instability of the international economic environment have become the new normal. Improving the inherent resilience of the economic system is key to effectively responding to various risk challenges and achieving a dynamic balance between development and security (Martin and Sunley 2015; Courvisanos et al. 2016). When dealing with various acute shocks or chronic stress, regions with strong economic resilience can form stronger adaptive and self-reinforcing capabilities by virtue of their characteristics, such as dynamic balance, redundant buffering, and self-healing (Simmie and Martin 2010). As the core element of modern economic growth, technology is an important source of strengthening regional economic resilience. However, existing studies have paid more attention to the impact of the total technology scale and growth trends on regional economic resilience and have rarely mentioned the impact on technology structures. Based on this, this paper attempts to identify the origin of regional economic resilience from the perspective of technological complexity and is mainly guided by three questions: Can increasing technological complexity enhance the level of regional economic resilience, and is there a certain degree of regional heterogeneity? Is higher technological complexity better, and what is the marginal impact of technological complexity on regional economic resilience? Can a mature market environment play a positive role in regulating the relationship between technological complexity and regional economic resilience by strengthening market competition and absorptive capacity? Answering these questions will help to further understand the strategic value of optimizing the technological structure to strengthen the resilience of the regional economy and will provide a new policy perspective for the pursuit of high-quality development in an uncertain environment.

Strengthening economic resilience has always been a hot topic in academic circles and governments, and related research has increased rapidly since the COVID-19 pandemic. The research content mainly covers three aspects. The first is connotation analysis of regional economic resilience. Economic resilience is a key attribute for an economic system to achieve long-term and sustained improvement (Reggiano et al. 2002; Martin et al. 2016). It reflects the comprehensive ability of the regional economic system to reorganize its internal structure, such as the industry, technology, and system, when responding to external shocks, including the ability to resist shocks and absorb, restore, adapt, and create new paths (Breathnach 2015; Fingleton 2012; Pike et al. 2010). The second is the influencing factors of regional economic resilience. Most studies have focused on analysis based on the dimensions regional endowment, economic system characteristics, support conditions, and human environment (Lu et al. 2020; Zhang et al. 2019). These studies have shown that the larger the market size and the higher the population density, the stronger the economic resilience, and a diversified industrial structure can improve the stability of the economic system and strengthen regional economic resilience (Breathnach et al. 2015;

Daniela et al. 2018; Li et al. 2019). At the same time, a high-level service industry, a high-quality institutional environment, and governance capabilities are conducive to optimizing the market environment and improving the resilience of the regional economy (Liu et al. 2021; Xiao et al. 2018). The third is the effective path to green economic recovery. In the context of global warming and environmental degradation, how to achieve green economic recovery has also attracted wide attention. Among them, many studies explore effective paths for green economic recovery from the perspective of green transformation of financial industry, and find that green finance can increase investment in clean energy development projects (Abbas et al. 2020; Taghizadeh-Hesary 2022; Huang et al. 2022), reduce energy intensity, and improve energy efficiency (Huang et al. 2022; Guo et al. 2022) and energy poverty alleviation (Zhao et al. 2022) to achieve eco-friendly growth and promote green economic recovery.

In recent years, although few studies have focused on the impact of technological complexity on regional economic resilience, some scholars have explored the impact of technological complexity on sustainable economic growth, which provided the empirical inspiration for this research. Relevant studies have found that the overall innovation capability of a region is not only determined by the stock of technological knowledge but also affected by the technological composition structure (Balland and Rigby 2017; Mewes and Broekel 2020). The higher the technological complexity, the stronger the complex innovation ability (Bishop 2019; Sweet and Maggio 2015). However, the evolutionary path of technological complexity is not random; it is usually self-reinforcing at the original technological level and structure (Henrich 2004). New technologies are more likely to be generated in areas that are more closely related to existing technologies. Therefore, a region with a complex technological structure is more likely to achieve good technological innovation and gain a competitive advantage, manifesting as a resilient economy (Petralia et al. 2017; Rosiello and Maleki 2021).

Until now, empirical evidence of the relationship between technological diversity and economic resilience has been scarce and restricted to economic complexity, as measured by the product portfolio, while product is a small dimension of complexity. For the regional economic system, technological complexity is a more critical resource (Roman 1990). In this paper, this paper addresses this research gap by studying the impacts of technological diversity on regional economic resilience in 272 Chinese cities between 2004 and 2018. First, research hypotheses are proposed based on theoretical analysis. Secondly, an empirical model is designed based on the hypothesis, and the technological complexity and economic resilience of the sample cities are measured. Then, taking technological innovation as an intermediate process, this paper studies the direct and indirect effects of technological complexity on economic resilience, as well as the regional heterogeneity of such effects. Thirdly, the marginal effect of technological complexity on toughness and the improvement path exploration based on market competition and the regulatory effect of absorptive capacity are studied. Finally, based on the findings, specific recommendations are made to improve the economic resilience of Chinese cities.

The contributions of this paper are as follows: (1) Different from the previous studies that focused on the important role of technology scale characteristics

in economic resilience, the focus of this paper is the perspective of technology structure characteristics. With the construction of a two-stage production model and a marginal effect model, the relationship between economic complexity and regional economic resilience is described in depth, which provides a new perspective for exploring regional differences in economic resilience. (2) The existing estimates of regional technological structures are mostly based on industry or enterprise data. A regional technology relative advantage matrix is built by drawing on the technology dual-mode network and calculated based on micro-patent data of 650 subdivided technology categories in 272 cities. This can more objectively describe the regional technological complexity level. (3) This paper also examines the moderating effect of market competition and absorptive capacity on the relationship between technological complexity and economic resilience, providing a theoretical basis for optimizing market support policies. The conceptual framework of the paper is shown in Fig. 1.

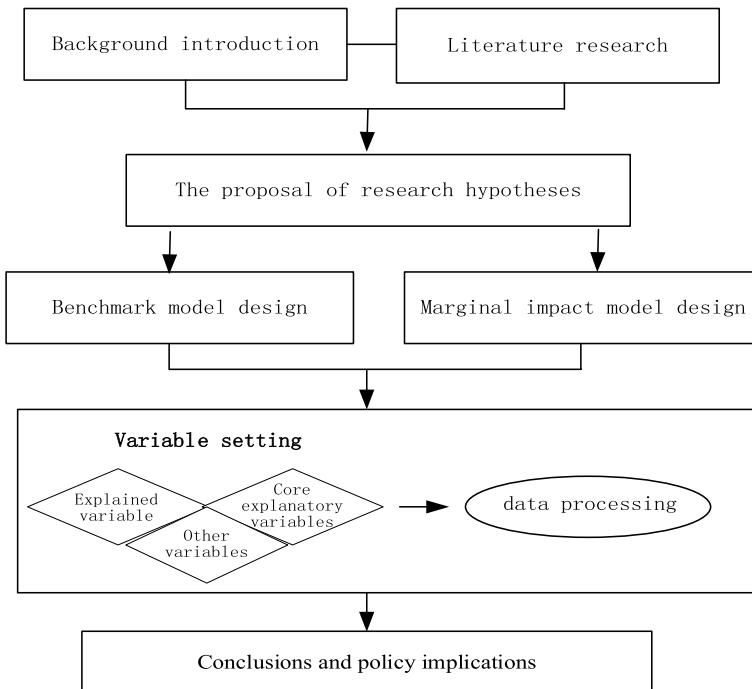


Fig. 1 The conceptual framework of the paper

2 Research design

2.1 Research hypothesis

2.1.1 Technological complexity and regional economic resilience

Regional technological complexity refers to the degree of diversification of regional technological reserves, which is the behavior of enriching the technological structure and improving the development capability of existing technologies in the region by continuously extending the depth and breadth of the technological knowledge fields (He and Chen 2012). A technological structure with higher complexity is more conducive to integrating technological resources, generating new technologies, and realizing the synergy and expansion of technologies in multiple industrial fields. In the face of sudden changes in the external environment, it can make timely adaptive adjustments and lead the economy into a new round of growth, thus showing stronger economic resilience. The social economy has entered the stage of collective production; thus, traditional linear or chain technology transmission can no longer meet development requirements, which are necessary to form a more complex networked technology structure, organically integrate various technologies, continuously learn, integrate, and apply widely to realize the emergence of complex innovations through the inherent mechanism of self-organization (Ca et al. 2020; Sun and Sun 2017). This kind of complex technological structure with self-organizing characteristics can strengthen the interaction and correlation of technology in different industrial fields, generate newer technologies and emerging industries, enable the economy to form a more diversified industrial structure (Bristow and Healy 2018), realize industrial restructuring faster amid risks and fluctuations, and then show a stronger ability to stabilize, adapt, transform, and upgrade (Koren and Silvana 2013; Su and Xu 2015). Therefore, the following hypothesis is proposed:

Hypothesis 1: Increasing technological complexity has a positive effect on economic resilience.

Although technological complexity has a positive impact on economic resilience, higher technological complexity is not always better. Excessive technological complexity may rapidly increase innovation costs, reduce technology spillover efficiency and overall factor allocation efficiency, and further weaken its positive impact on economic resilience. First, a technology portfolio with higher complexity may obtain higher monopoly profits but requires more investment in technological R&D personnel and capital. The longer the technology development cycles, the higher the costs and risks of the technology developments (Yayavaram and Chen 2015). Second, an increase in technological complexity also increases the learning difficulty of the innovation subject. Therefore, the increase may reduce the efficiency of technology absorption, spillover, and diffusion (Pintea and Thompson 2007). Third, an increase in technological complexity leads to diversified industrial allocation. Although an increase can disperse risks to a certain extent, the correlation effect of various industries may not be strong due to

the lack of close technological connections, and the allocation of factors among various industries will be distorted, leading to a decline in the marginal output of factor inputs. As a result, the overall factor allocation efficiency of the economy gradually deviates from the optimal state (Liu et al. 2017). In the face of external shocks, the distortion of factor allocation makes the economy less able to evolve to a new path, and the level of economic resilience also declines (Mewes and Broekel 2020). Thus, the following hypothesis is proposed:

Hypothesis 2: The positive effect of technological complexity on economic resilience shows a marginal decreasing trend.

As an intrinsic attribute of the economic system, technological complexity changes resource allocation through a series of market behaviors, optimizes regional economic resistance, recovery, and evolutionary capabilities, and ultimately affects regional economic resilience (Deng and Sun 2022). Therefore, the development of the market environment inevitably affects the relationship between technological complexity and economic resilience. The impact of market development is analyzed from two perspectives: market competition level and absorptive capacity. Existing studies have shown that technological exchanges and cooperation differ from explicit knowledge dissemination. Technological cooperation can only be fully mastered and exert its economic value through in-depth practical activities (Nelson 1985), and moderate market competition is an important guarantee for the realization of this practice. High-complexity technologies require continuous R&D investment. Too high market competition will prevent microeconomies from accumulating market power, so they cannot generate monopoly profits and continue to invest in innovation activities. However, an excessive monopoly may reduce the vitality of technology development (Rosiello and Maleki 2021). Therefore, moderate market competition is more conducive to the orderly evolution of the technological structure to complexity. Absorptive capacity has always been considered the comprehensive capacity of an economy to carry out technological learning, cooperation, and transformation. The stronger the absorptive capacity, the more conducive it is to playing the advantage of technology spillovers and re-innovation, which has a positive effect on the improvement of economic resilience (Chatzistamoulou et al. 2022; Feng et al. 2020). Thus, the following hypothesis is proposed:

Hypothesis 3: The level of market competition and absorptive capacity positively moderates the relationship between technological complexity and economic resilience.

2.2 Model design and variable description

2.2.1 Benchmark model

To empirically test the impact of technological complexity on regional economic resilience, it is necessary to consider the self-renewal of the regional technology pool. To reduce endogeneity, the part of the role that generates new technologies

and reacts to the regional economic system is separated. Therefore, a two-stage production model from technological complexity to new technology generation and then to regional economic resilience is constructed.

The first stage is new technology production; the model is based on the Cobb–Douglas production function. New patent authorization is used as the output, and regional technological complexity (TCI) is added as the new input factor, in addition to the capital input (K) and the labor input (L). As there is a time lag in the process from input to output, all input elements are delayed for one period. The new technology generation equation in the first stage is as follows:

$$\text{Tech}_{c,t} = \alpha K_{t-1} + \beta L_{t-1} + \gamma \text{TCI}_{t-1} + \varepsilon_{c,t}, \tag{1}$$

The second stage is the improvement in regional economic resilience, the process of technological complexity acting on regional economic resilience by generating new technologies.

$$\text{RES}_{c,t} = \alpha_0 \text{TCI} + \beta_1 \widetilde{\text{Tech}}_{c,t-1} + \mathbf{AX} + \varepsilon_{c,t} \tag{2}$$

RES stands for regional economic resilience, $\widetilde{\text{Tech}}_{c,t-1}$ is the predicted value based on the estimated results of the new technology generation stage, \mathbf{X} is the vector representing other control variables, and $\varepsilon_{c,t}$ is the random disturbance term.

2.2.2 Marginal impact model

To test the marginal impact of regional technological complexity on regional economic resilience, regional economic resilience (RES) is simplified into a Cobb–Douglas production model that includes only technological sectors (T) and non-technological sectors (F): $\text{RES} = R(T, F)$. After taking the logarithm, the model is simplified to $R = T + F$. The following assumptions are made: (1) Technological parameters include technology scale parameters and technological complexity (TCI). (2) The technological sector and non-technological sector both satisfy general production function assumptions: the input of labor (L) and capital factor (K). (3) The development of technology will have an impact on the non-technological sector.

$$T = T(L_T, K_T)$$

$$F = F(L_F, K_F, T, \text{TCI}) \tag{3}$$

L_T and K_T stand for the labor input and the capital input of the technological sector, respectively; L_F and K_F represent the labor input and the capital input of the non-technological sector, respectively, and $L = L_T + L_F$, $K = K_T + K_F$. Then, the differential of economic resilience with respect to the factor input of technology, the output of technology sector, and the technological complexity can be expressed as follows:

$$\begin{aligned}
 dR &= dT + dF \\
 &= \frac{\partial T}{\partial L_T} dL_T + \frac{\partial T}{\partial K_T} dK_T + \frac{\partial F}{\partial L_F} dL_F + \frac{\partial F}{\partial K_F} dK_F \\
 &\quad + \frac{\partial F}{\partial T} dT + \frac{\partial F}{\partial TCI} dTCI \\
 &= - \left(\frac{\partial F}{\partial L_F} dL_T + \frac{\partial F}{\partial K_F} dK_T \right) + \left(1 + \frac{\partial F}{\partial T} \right) dT + \frac{\partial F}{\partial L_F} dL \\
 &\quad + \frac{\partial F}{\partial K_F} dK + \frac{\partial F}{\partial TCI} dTCI \\
 &= - \left(\frac{\partial F}{\partial L_F} \frac{\partial L_T}{\partial T} \frac{\partial T}{\partial L_T} dL_T + \frac{\partial F}{\partial K_F} \frac{\partial K_T}{\partial T} \frac{\partial T}{\partial K_T} dK_T \right) + \left(1 + \frac{\partial F}{\partial T} \right) dT + \frac{\partial F}{\partial L_F} dL \\
 &\quad + \frac{\partial F}{\partial K_F} dK + \frac{\partial F}{\partial TCI} dTCI \\
 &= - \left(\frac{\partial F / \partial L_F}{\partial T / \partial L_T} \cdot \frac{\partial T}{\partial L_T} dL_T + \frac{\partial F / \partial K_F}{\partial T / \partial K_T} \cdot \frac{\partial T}{\partial K_T} dK_T \right) + \left(1 + \frac{\partial F}{\partial T} \right) dT + \frac{\partial F}{\partial L_F} dL \\
 &\quad + \frac{\partial F}{\partial K_F} dK + \frac{\partial F}{\partial TCI} dTCI
 \end{aligned} \tag{4}$$

$\frac{\partial F / \partial L_F}{\partial T / \partial L_T}$ and $\frac{\partial F / \partial K_F}{\partial T / \partial K_T}$ are the ratio of the marginal output of non-technological departments to that of technological departments, which are about T/R increasing. $\frac{\partial F / \partial L_F}{\partial T / \partial L_T} = \frac{\partial F / \partial K_F}{\partial T / \partial K_T} = \lambda$, $\frac{\partial F}{\partial L_F} = a$, $\frac{\partial F}{\partial K_F} = b$ isset, and then, the original equation can be simplified as follows:

$$dR = \left(\frac{\partial F}{\partial T} + 1 - \lambda \right) dT + adL + bdK + \frac{\partial F}{\partial TCI} dTCI. \tag{5}$$

Furthermore, the marginal effect of T on R is simplified to a linear model; the size of λ and $\frac{\partial F}{\partial T}$ is related to the technology component of resilience. That is, $\frac{\partial F}{\partial T} + 1 - \lambda$ is a linear equation about T/R , the marginal effect of TCI on F is simplified to a linear model, and $\frac{\partial F}{\partial TCI}$ is a linear equation about TCI. Therefore, the equation above can be transformed into the following:

$$dR = \alpha + \beta_1 dTCI + \beta_2 dT + \beta_3 \frac{T}{R} dT + adL + bdK. \tag{6}$$

The final empirical model for the diminishing marginal effect of technological complexity is set as follows:

$$\begin{aligned}
 dRES &= \alpha + \beta_0 dTCI + \beta_1 TCI dTCI + \beta_2 dTech + \beta_3 \frac{Tech}{RES} dTech \\
 &\quad + adL + bdK + AX + D_c + \varepsilon_{c,t},
 \end{aligned} \tag{7}$$

where RES, TCI, and Tech are consistent with those above. dRES, dTCI, dTech, dL, and dK stand for the differential of regional economic resilience, technological complexity, technological innovation, labor input, and capital input, respectively, and X

stands for a series of control variables. A is the coefficient matrix corresponding to the control variables, D_c represents the unobserved individual effect, and $\varepsilon_{c,t}$ is the random disturbance term.

2.2.3 Moderation test model

To further test the regulating effect of the degree of market competition and absorptive capacity, the interaction term between the proxy variable of the mechanism and the core explanatory variable is added to the model. The test model is as follows:

$$RES = \alpha_0 + \beta_0 \widetilde{Tech} + \beta_1 \widetilde{Tech} * channel + \beta_2 \widetilde{Tech} * channel^2 + \beta_3 channel + AX + \varepsilon_{c,t}, \quad (8)$$

$$RES = \alpha_0 + \beta_0 TCI + \beta_1 TCI * channel + \beta_2 TCI * channel^2 + \beta_3 channel + \beta_4 \widetilde{Tech} + \varepsilon_{c,t} (TCI > 0.6). \quad (9)$$

Equation (8) is used to test the regulating effect of market competition and absorptive capacity on the negative impact of new technological innovation on economic resilience based on stock technological complexity. Equation (9) is used to test the regulating effect of market competition and absorptive capacity on the negative impact of high technological complexity on economic resilience found in the previous nonlinear relationship study. Channel stands for the mechanism variable: market competition degree (MCI) and absorptive capacity (ACI), respectively. Considering that the main body of complex technology transformation and application is mainly enterprises, the sales revenue of listed companies in the region is used to measure the Herfindahl index, and the average value is taken to measure the degree of market competition in the region. The smaller the MCI, the higher the degree of market competition; the larger the MCI, the higher the degree of market monopoly. Second, for absorptive capacity, it is generally believed that the higher the level of human capital, the stronger the ability to absorb and transform technology. Human capital is used to describe a region's absorptive capacity for technology. Considering the double-edged sword effect of the degree of market competition, the interaction term between the secondary term of market competition and the core explanatory variable is added.

2.3 Variable setting and data processing

Due to the lack of data for some cities, 272 prefecture-level cities in China from 2004 to 2018 are selected as the research objects. Data on the core explanatory variables technological complexity and the number of patents granted are obtained from national patent offices, and the rest of the explained variables and control variables are from the China City Statistical Yearbook over the years. The range is the data for the entire city. To eliminate the influence of inflation in different years, some data are deflated and adjusted with 1978 as the base period. In addition, the data intervals used for the core explanatory variables and the explained variables are between 0

and 1. To facilitate analysis and comparison, STATA 16 is used to standardize data with large dimensional gaps.

2.3.1 The explained variable

Regional economic resilience (RES): In terms of measuring economic resilience, existing studies mainly included three methods: the actual expected deviation method, which uses the deviation of the actual value from the expected value to measure resilience; the index system method; and the use of a single indicator proxy, such as the employment rate. This paper refers to Martin et al. (2016) to divide economic resilience into resistance and resilience, measured by the deviation between actual values and expected values. Then, the resistance (Resi) and recovery (Recov) of the regional economy can be defined as follows:

$$\text{Resi}_c = \frac{\Delta E_C^{\text{recession}} - (\Delta E_C^{\text{recession}})^{\text{expectation}}}{\left| (\Delta E_C^{\text{recession}})^{\text{expectation}} \right|}$$

$$\text{Recov}_c = \frac{\Delta E_C^{\text{recovery}} - (\Delta E_C^{\text{recovery}})^{\text{expectation}}}{\left| (\Delta E_C^{\text{recovery}})^{\text{expectation}} \right|} \quad (10)$$

For resistance (Resi), which is measured by the deviation between the actual decline and the expectation, the smaller the value, the stronger the resilience. For recovery (Recov), which is measured by the deviation between the actual growth and the expectation, the larger the value, the stronger the resilience. To make the economic resilience values of the whole sample period comparable, the growth rate of the real gross domestic product (GDP) is used as the growth value. At the same time, referring to the practice of most existing studies, 2008 is selected as the cutoff point for external shocks. Based on this, the actual growth rate of urban GDP in 2008 is used as the expectation, and the extremum method is used to standardize the indexes. Then, the measured regional economic resilience is between 0 and 1. The closer it is to 1, the stronger it is, and the closer it is to 0, the weaker it is.

2.3.2 Core explanatory variables

Technological complexity (TCI): This paper draws on the practice of Hidalgo and Hausmann (2009) and Balland and Rigby (2017) to construct a bimodal network with a region technique $c \times p$ and establish a matrix $X_{c,p}$. c stands for the region, and p stands for the technology. The technology category is identified according to the International Patent Classification (IPC) three-quantile code. The elements in $X_{c,p}$ stand for the technology stock of technology p in region c , which refers to the cumulative number of invention patents granted. Then, the relative technological advantage matrix $M_{c,p}$ of the region is calculated on this basis to reflect whether region c has a relative technological advantage (RTA) in technology p . The calculation method is as follows:

$$RTA = \begin{cases} 1, & \text{if } \frac{X_{c,p} / \sum_p X_{c,p}}{\sum_c X_{c,p} / \sum_c \sum_p X_{c,p}} \geq 1 \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

$T_{c,0}$ represents the number of technology categories with RTAs in a region, and $T_{p,0}$ stands for the number of cities with RTAs in a specific technology category. The bimodal degree centrality of the two groups of nodes above in the comprehensive regional technological knowledge network is constructed as follows:

$$T_{c,0} = \sum_p M_{c,p}, \tag{12}$$

$$T_{p,0} = \sum_c M_{c,p}, \tag{13}$$

$$T_{c,n} = \frac{1}{K_{c,0}} \sum_p M_{c,p} T_{p,n-1}, \tag{14}$$

$$T_{p,n} = \frac{1}{T_{p,0}} \sum_c M_{c,p} T_{c,n-1}. \tag{15}$$

The iterations continue until $T_{c,n} = T_{c,n-2}$ ends. Substituting (15) into (14), the formula is

$$T_{c,n} = \frac{1}{T_{c,0}} \sum_p M_{c,p} \frac{1}{T_{p,0}} \sum_{c'} M_{c',p} T_{c',n-2} = \sum_{c'} \tilde{M}_{c,c'} T_{c',n-2}, \tag{16}$$

where $\tilde{M}_{c,c'} = \sum_p \frac{M_{c,p} M_{c',p}}{T_{c,0} T_{p,0}}$, and c' represents region c and cities other than c . \vec{T} is set as the second eigenvector of the matrix $\tilde{M}_{c,c'}$, and the technological complexity of each region can be obtained after each element in \vec{T} is standardized. The technological complexity of each region standardized by the extremum method is between 0 and 1, and the larger the value, the higher the technological complexity.

2.3.3 Other variables

The variables involved in the estimation process of new technology generation and the marginal effect test include technological innovation (Tech), talent supply (L), capital investment (K), and the technological complexity of the previous period (ITCI). Technological innovation is represented by the number of patents granted, talent supply is represented by the number of students in general colleges and universities, and capital investment is represented by science and technology expenditures.

Control variables: Economic resilience is the inherent ability of regional economy to resist risks and achieve sustainable growth. Relevant studies have also mentioned the impact of regional basic conditions on economic resilience, such as labor,

Table 1 lists the symbols and descriptive statistics of the variables used

	Variables	Variable names	Index
The variables involved in the generation of new technologies	RES	Resilience	
	TCL	Technological complexity	
	ITCI	Technological complexity of the previous period	
	Tech	Technological innovation	The number of patents granted
	K	Capital investment	The science and technology expenditures
	L	Talent supply	The number of students in general colleges and universities
	MCI	Market competition degree	The mean value of the Herfindahl index measured by the sales revenue of listed companies
Control variables	ACI	Absorptive capacity	Human capital
	Variables	Variable names	Index
	People	Labor supply	The number of students in general colleges and universities
	Fin	Financial development level	The proportion of the balance of financial institutions to the GDP at the end of the year
	Gov	Government governance	The proportion of government fiscal expenditure in the GDP
	Man	Proportion of manufacturing industry	The logarithm of the proportion of employees in the manufacturing industry
	GE	Educational level	Per capita educational expenses
	FTD	Foreign trade dependence	The ratio of total imports and exports to the GDP

capital, government governance, industrial structure, and education level. Combined data availability, the following control variables are selected for this paper: The labor supply (People) is represented by the number of students in general colleges and universities, educational level (GE) is represented by per capita educational expenses, financial development level (Fin) is represented by the proportion of the balance of financial institutions to the GDP at the end of the year, government governance (Gov) is represented by the proportion of government fiscal expenditure in the GDP, the proportion of manufacturing industry (Man) is represented by the logarithm of the proportion of employees in the manufacturing industry, and foreign trade dependence (FTD) is represented by the ratio of total imports and exports to the GDP. The symbols and descriptive statistics of the variables Showed in Table [1].

3 Results and discussion

3.1 Technological complexity and economic resilience

Before the estimation outcomes is discussed, descriptive results regarding the technological complexity and economic resilience of 272 Chinese cities are discussed. The formula for technological complexity in Sect. 2 is used to calculate the technological complexity level of 272 cities in China based on the patent data of 650 subdivided technological categories. The results are shown in Fig. 2. As can be seen from the figure, the average number of patent applications granted and invention patents granted in cities showed a steady upward trend, especially in 2015. The rate of ascent increased significantly, while the average technological complexity of cities showed greater volatility from 2004 to 2020. From 2003 to 2015, the average technological complexity of cities fluctuated frequently between 0.2 and 0.8, indicating that a large number of cities experienced fluctuations in technological status, and that the dominant technology was unclear. After 2015, the average technological

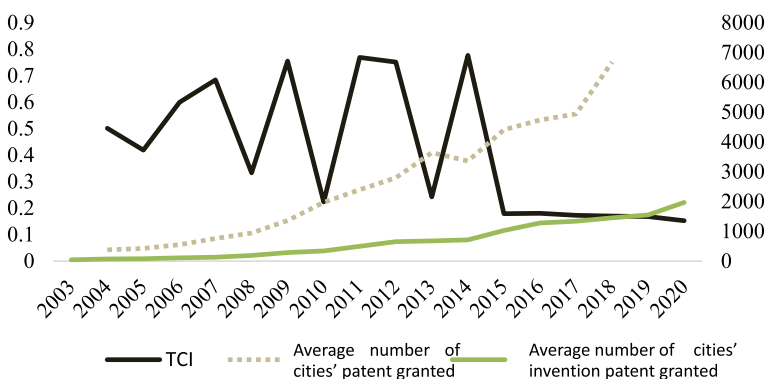


Fig. 2 Changes in the city-level TCI and patent (unit: item)

complexity of cities was basically stable between 0.15 and 0.20, and showed a slight decline. During this period, the number of patent applications granted and invention patents granted increased rapidly, but the patents were distributed in different industries, which, in turn, leads to the technological complexity of a city being lower than that in the previous stage.

The average of the urban technological complexity in 2004–2008 and 2009–2018 is taken, and ArcGIS is used to draw the urban technological complexity distribution map (as shown in Fig. 3). As can be seen from the figure, before 2008, there was no obvious gap in the technological complexity of Chinese cities, and the technological complexity of most cities was at the upper–middle level. However, after 2008, the technological complexity of coastal cities and cities in the three major urban circles increased significantly and showed a certain degree of agglomeration. This confirms that the self-reinforcing process of technology will further accelerate the generation and complexity of new technologies, and that the technological complexity between cities shows a more obvious imbalance.

The economic resilience measurement method in Sect. 2 is used to calculate the economic resilience of 272 cities in China from 2001 to 2019, and the average value is taken. The results are shown in Fig. 4. In general, the level of urban economic resilience and the GDP growth rate show a downward trend. From 2004 to 2011, the average GDP growth rate of Chinese cities showed large fluctuations. Therefore, fluctuations in economic resilience are also obvious. After 2011, the fluctuation range of the average urban GDP growth rate is smaller, and the average value of urban economic resilience also stabilizes and continues to decline.

Figure 5 shows the distribution map of the economic resilience of Chinese cities before and after 2008, drawn with ArcGis. On the whole, the economic resilience of northern cities is lower than that of southern cities, regardless of whether it was before or after 2008. Most of the high-resilience cities in China are concentrated in the Chengdu–Chongqing urban agglomeration, the urban agglomeration in the middle areas of the Yangtze River, and the urban agglomeration in the Yangtze River Delta. Although the average economic resilience of all cities in China has decreased,

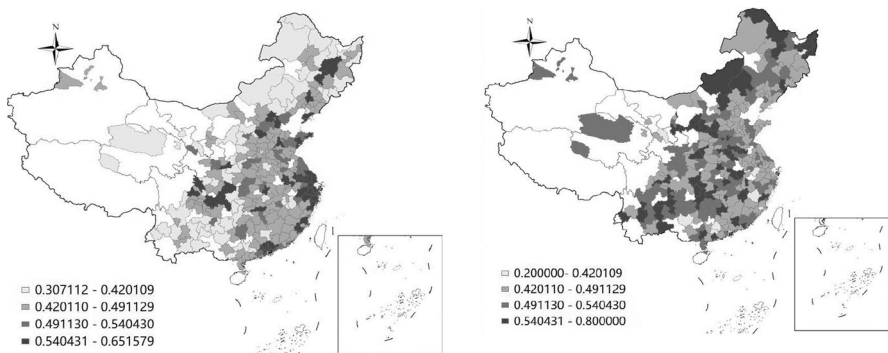


Fig. 3 Distribution of city TCI. *Note:* The picture on the left is before 2008, and the picture on the right is after 2008. To retain the technological categories to the greatest extent, only the technological complexity of 272 cities is calculated, and the white areas in the picture are the uncalculated cities

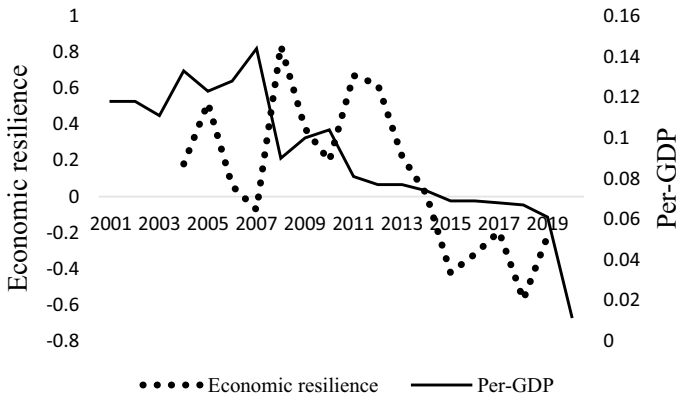


Fig. 4 Temporal evolution of national average economic resilience

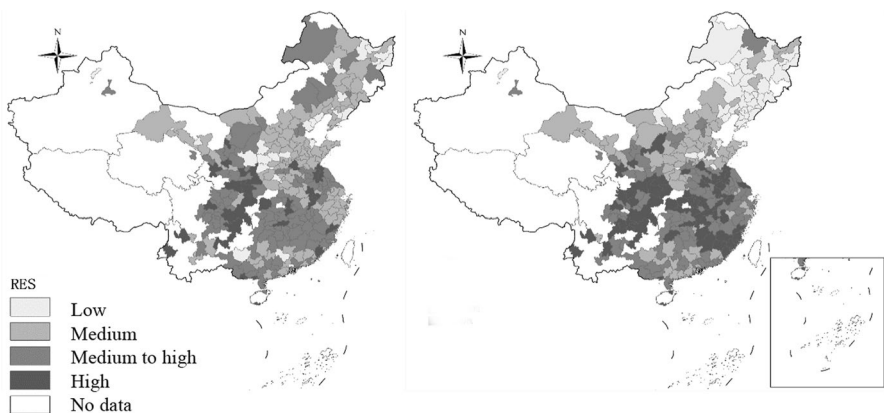


Fig. 5 Map of economic resilience

the number of high-resilience cities has increased significantly since 2008. Most of the low-resilience cities in the Central Plains have been upgraded to medium-resilient regions, and only the northeast region has a concentration of lower-resilience cities (Table 1).

3.2 Benchmark model regression

The estimated results of the new technology generation process in the first stage are shown in Table 2. Column (1) in Table 2 shows the results for the contribution of technological complexity to the generation of new technologies. The complexity of new technologies in each period (ITCI) is calculated and added to the new technology production model. Column (2) in Table 2 shows the results of the contribution

Table 2 The first stage: the new technology generation process

Explained variable: technological innovation	(1)	(2)	(3)
TCI	0.25*** (6.55)		0.28*** (7.22)
ITCI		0.16*** (2.81)	0.25*** (4.12)
<i>K</i>	1.20*** (71.93)	1.19*** (70.74)	1.20*** (71.58)
<i>L</i>	0.03*** (4.19)	0.03*** (4.12)	0.03*** (3.89)
Constant term	67*** (-30.55)	-0.62*** (-21.24)	-0.79*** (-21.18)
Observations	3472	3472	3472
R^2	0.68	0.68	0.69
<i>F</i>	2503	2467	1890

T-values are in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

of the complexity of new technology innovation in period $T-1$ to the production process of new technologies in the current period. In column (3) of Table 2, the results for the technological complexity of phase $T-1$ and the complexity of new technologies in phase $T-1$ are included in the model, and the coefficients are still significant. In the whole process of generating new technologies, whether it is the technological complexity of the entire regional technology pool accumulated over a long period of time or the complexity of the latest generation of technology, regional technological innovation can be significantly promoted. In addition, the coefficient of technological complexity in column (1) of Table 2 is greater than that of new technologies in column (2) of Table 2. When both are included in column (3) of the model, the coefficient of technological complexity is still greater than that of new technologies, indicating that long-term complex technology reserves are more conducive to the generation of new technologies than new complex technologies.

The regression results for the second stage are shown in Table 3. In column (1) of Table 3, only the results for the regression of technological complexity and regional economic resilience are shown. The results show that increasing technological complexity has a positive impact on regional economic resilience. The control variables are added to column (1) in Table 3, and the results are shown in column (3) of Table 3; they are robust. Therefore, hypothesis 1 is supported.

In columns (2) and (4) of Table 3, the results for the new technology generation stage are shown. The results show that although technological complexity can effectively generate new technologies, the new technologies generated have a certain negative effect on economic resilience. To further explore whether this negative effect is really caused by this part of new technology, two methods are used. First, the empirical tests above are repeated by replacing technological complexity with the complexity of the new technologies in $t-1$. The results show that the coefficient of

Table 3 The second stage: the process of improving economic resilience

Variables	(1)	(2)	(3)	(4)
TCI	0.25*** (14.72)	0.27*** (16.52)	0.12*** (7.24)	0.17*** (9.64)
Tech		−0.14*** (−20.10)		−0.16*** (−8.49)
Gov			−0.13*** (−15.52)	0.01 (0.77)
People			0.03*** (9.26)	0.04*** (9.75)
Man			−0.002 (−0.25)	0.005 (0.61)
Fin			−0.06*** (−9.53)	−0.05*** (−8.83)
GE			−0.04*** (−9.37)	−0.04*** (−9.21)
FTD			−0.04*** (−8.85)	−0.05*** (−9.70)
Constant term	0.31*** (34.67)	0.39*** (41.56)	0.33*** (22.26)	0.43*** (23.03)
Observations	3720	3720	3720	3720
R ²	0.055	0.147	0.220	0.234
F	216.6	322.0	150.4	143.2

T-values are in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ITCI is positive and significant but smaller than that of TCI. When both are included in the model, the coefficient of ITCI is still smaller than that of TCI, which indicates that the performance of new technologies in improving economic resilience is not as good as that of long-term accumulated technologies. Then, the mediation effect test of stepwise regression is used, and the same results are obtained. The overall effect of technological complexity on economic resilience is positive, but the emergence of new technologies in the short term will reduce the level of regional economic resilience to a certain extent. This may be because this part of technological innovation cannot generate positive economic benefits within a short period due to its absorption and transformation ability and the lag of application.

3.3 Robustness test

First, the proxy variable is replaced. Considering the depreciation of technological knowledge as an asset, based on the original technological complexity calculation, the technological stocks are depreciated at a rate of 15% based on the perpetual inventory method, and the calculated technological complexity is used as a supplement for the original technological complexity index. Column (1) in Table 4 shows

Table 4 Robustness test results

Variables	(1) Replace TCI	(2) Replace RES	(3) 3/10 Quantile	(4) 7/10 Quantile	(5) Lag TCI by one period	(6) IV: lag TCI by one period	(7) IV: lag TCI by two periods
TCI	0.36***	0.29***	0.16***	0.21***	0.10***	-0.09***	0.17***
ITCI	-8.56	-15.33	-7.39	-7.52	-6.71	(-4.26)	-4.83
	0.02						
	-0.32						
<u>Tech</u>		-0.17***	-0.11***	-0.24***	-0.27***		
		(-8.83)	(-3.84)	(-6.30)	(-16.59)		
K	1.20***						
	-71.82						
L	0.03***						
	-3.68						
People		0.03***	0.03***	0.04***	0.04***	-0.06***	-0.04***
		-8.78	-5.46	-5.36	-10.96	(-5.81)	(-4.64)
Gov		0.02	0.01	0.08***	0.12***	-0.15***	-0.13***
		-0.89	-0.33	-2.78	-8.3	(-12.58)	(-12.32)
Man		0.001	-0.001	0.02	-0.01*	0.03**	0.04***
		-0.16	(-0.17)	-1.24	(-1.67)	-2.12	-3.56
Fin		-0.05***	-0.02***	-0.07***	-0.05***	-0.07***	-0.04***
		(-7.50)	(-4.31)	(-11.44)	(-9.96)	(-12.29)	(-8.56)
GE		-0.03***	-0.02***	-0.06***	-0.02***	-0.02***	-0.01***
		(-8.35)	(-3.18)	(-7.34)	(-5.05)	(-8.88)	(-4.38)
FTD		-0.06***	-0.06***	-0.04***	-0.03***	-0.07***	-0.04***
		(-13.20)	(-9.96)	(-5.30)	(-7.70)	(-15.07)	(-8.91)

Table 4 (continued)

Variables	(1) Replace TCI	(2) Replace RES	(3) 3/10 Quantile	(4) 7/10 Quantile	(5) Lag TCI by one period	(6) IV: lag TCI by one period	(7) IV: lag TCI by two periods
Constant term	-0.70*** (-23.03)	0.40*** -21.93	0.22*** -8.89	0.60*** -17.08	0.47*** -28.21	1.27*** -17.46	0.91*** -15.09
Observations	3472	3720	3720	3720	3472	3472	3224
R ²	0.687	0.258			0.257	0.718	0.783

T-values are in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

the regression results of the first stage of the benchmark regression model of technological complexity calculated after depreciation, and the original conclusions are still valid. Furthermore, the sensitivity index calculated by the employment rate is used as a proxy variable of regional economic resilience to test the second stage of resilience improvement. Column (2) in Table 4 shows the regression results of the benchmark regression model after resilience is replaced with the employment rate sensitivity index in the second stage. The regression results show that the effect of technological complexity on resilience is still significantly positive, and the new technology coefficient produced by improving technological complexity is significantly negative, which is consistent with the original conclusion.

Second, the influence of singular values is excluded. Considering that the deviation in the measurement of macro-variables may have an adverse effect on the results, a regression is performed after all variables are tailed. Furthermore, the estimation results above are all the conditional mean values of the city's technological complexity affecting its economic resilience, which is easily affected by outliers. Therefore, panel quantile regression is used to estimate the different quantiles of the regional economic resilience level, which is regressed to the 0.1, 0.3, 0.5, 0.7, and 0.9 quantiles, in turn. The coefficients of TCI are all positive and significant, and the coefficients of $\widehat{\text{Tech}}$ are all negative and significant. The original conclusion is robust.

Third, endogenous problems could be an issue. To rule out the problem of reverse causality, the core explanatory variables are lagged by one period. The results, shown in column (5) in Table 4, are consistent with the original conclusions. Furthermore, considering the endogeneity problem caused by omitted variables, the instrumental variable method is adopted, and the one lag period and the two lag periods of the core explanatory variables are taken as instrumental variables. The results in columns (6) and (7) in Table 4 show that the coefficients are still significantly positive, indicating that after considering the endogeneity problem caused by omitted variables, the conclusions of this paper are still robust.

3.4 Regional heterogeneity analysis

The 272 cities were divided into eastern, central, western, top 100 cities, and non-top 100 cities according to their geographic distribution and development levels. The empirical results are shown in Table 5. Among the eastern, central, and western regions, the direct effect of technological complexity on economic resilience does not differ much. The direct effect of technological complexity in the eastern and central regions is similar, and the effect is significantly lower in western cities than in eastern and central cities. However, the effect of new technologies generated by technological complexity is significantly higher in eastern and central regions than in western regions. Classified according to the level of urban development, the promotion effect of technological complexity on economic resilience is more significant in the top 100 cities, but similarly, the negative effects of new technologies generated by technological complexity in the top 100 cities are also significantly higher than those in non-100 cities. This strengthening effect of providing technological

Table 5 The results of the regional heterogeneity test

	(1)	(2)	(3)	(4)	(5)
	Eastern	Central	Western	Top 100 cities	Non-top 100 cities
TCI	0.15*** (5.10)	0.16*** (5.49)	0.13*** (3.96)	0.12*** (3.55)	0.07*** (2.61)
$\widehat{\text{Tech}}$	-0.17*** (-6.78)	-0.16*** (-3.24)	-0.08* (-1.75)	-0.14*** (-6.38)	0.07 (1.24)
Gov	0.035 (1.56)	-0.181*** (-3.34)	-0.103** (-2.46)	0.016 (0.85)	-0.592*** (-8.17)
People	0.032*** (5.82)	0.049*** (7.68)	0.061*** (7.17)	0.026*** (6.43)	-0.010 (-0.51)
Man	0.002 (0.16)	-0.037*** (-2.93)	0.060*** (3.13)	0.024* (1.69)	-0.018* (-1.85)
Fin	-0.05*** (-4.92)	-0.04*** (-4.46)	-0.06*** (-4.97)	-0.06*** (-5.91)	-0.02** (-2.27)
GE	-0.02*** (-2.86)	-0.05*** (-7.57)	-0.06*** (-6.84)	-0.01 (-1.53)	-0.05*** (-8.71)
FTD	-0.06*** (-7.65)	-0.03*** (-3.24)	-0.05*** (-5.24)	-0.06*** (-7.76)	-0.04*** (-7.19)
Constant term	0.45*** (16.74)	0.31*** (8.52)	0.44*** (10.18)	0.48*** (17.38)	0.19*** (4.93)
Observations	1635	1290	795	1440	2280
R^2	0.22	0.30	0.28	0.25	0.31
F	56.97	70.74	39.20	59.38	127.9

T-values are in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

complexity on economic resilience is significantly higher in more competitive cities in eastern and central regions and the top 100 cities than in the slightly weak cities in western regions and the non-top 100 cities. However, the negative effects of new technologies generated by technological complexity on regional economic resilience are the opposite. This may be because eastern and central cities and the top 100 cities have richer technology stocks and technology categories, and regional development tends to rely on original technologies, making new technologies difficult to absorb and transform within a short period of time.

3.5 Marginal impact model regression

The empirical regression results of the marginal impact model are shown in Table 6. First, the impact of technological complexity on regional economic resilience is nonlinear. In other words, increased technological complexity is not always better. When it exceeds a certain threshold, its effect on improving economic resilience will decrease. Specifically, the effect of increasing technological complexity on

Table 6 The results of the marginal impact test

Explained variables dRES	(1)	(2)	(3)	(4)
	OLS (ordinary least squares)		Fixed effect model	
dTCI	0.65*** (12.93)	0.54*** (10.28)	0.80*** (14.69)	0.56*** (9.54)
TCI*dTCI	-1.01*** (-10.45)	-0.89*** (-8.99)	-1.32*** (-12.50)	-0.99*** (-9.06)
dTech	0.00004*** (6.04)	0.00003*** (5.38)	0.00004*** (6.63)	0.00004*** (5.67)
$\frac{\text{Tech}}{\text{RES}} \text{dTech}$	0.00002*** (2.74)	0.00001** (2.46)	0.00002*** (3.04)	0.00002*** (2.87)
dL	0.05*** (2.97)	0.04*** (2.86)	0.05*** (3.27)	0.04** (2.32)
dK	-0.06*** (-3.52)	-0.08*** (-4.24)	-0.06*** (-3.41)	-0.09*** (-4.78)
FTD		0.00001 (1.41)		0.00001 (0.31)
fin		-0.07*** (-9.02)		-0.10*** (-9.60)
man		-0.04*** (-3.76)		-0.04 (-1.53)
gov		0.02** (1.97)		0.02 (0.99)
GE		0.01* (1.92)		0.01** (2.03)
Constant term	-0.24*** (-17.90)	-0.31*** (-12.19)	-0.24*** (-17.47)	-0.31*** (-5.71)
Observations	3472	3472	3472	3472
R ²	0.08	0.11	0.11	0.14
F	51.70	37.61	65.44	47.03

T-values are in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

economic resilience is $0.65 \times \text{dTCI} - 1.01 \times \text{TCI} \times \text{dTCI}$, and the marginal effect is $0.65 - 1.01 \times \text{TCI}$. In other words, when TCI is less than 0.66, the effect of technological complexity on economic toughness is positive, and the closer it is to 0.66, the smaller the effect. When TCI is greater than 0.66, the effect of technological complexity on toughness is negative, and the closer it is to 1, the more unfavorable it is.

To test the robustness of this result, the control variables are included, and the conclusion remains basically unchanged. In addition, the square term of technological complexity is included in the resilience improvement model of the benchmark regression model. The results show that the primary term is positive, and the quadratic term is negative; that is, the effect of technological complexity on economic

resilience presents an inverted *U* shape, which further verifies that when technological complexity exceeds a certain value, its marginal effect on the improvement of regional economic resilience is decreasing. Thus, hypothesis 2 is supported.

3.6 Moderating effect test

The results in columns (1), (2), and (3) in Table 7 focus on the impact of market competition and absorptive capacity in the process of new technologies improving economic resilience caused by complexity. Although it has been found that this part of technological innovation has a negative effect on economic resilience, according to the results in columns (1) and (2) of Table 7, the negative effect of Tech on economic resilience decreases with an increase in market monopoly. However, there is a threshold for this adjustment effect of MCI, and the excessive degree of market monopoly will also exacerbate the negative effect of Tech on economic resilience. Specifically, the marginal effect of Tech on economic resilience is $-0.45MCI^2 + 0.60MCI - 0.26$, which means that in a market competition within an appropriate

Table 7 The results of the adjustment mechanism test

Variables	Adjustment to the negative effect of new technologies caused by complexity			Variables	Adjustment to the negative effect of high complexity	
	(1)	(2)	(3)		(4)	(5)
\widehat{Tech}	-0.23*** (-6.70)	-0.27*** (-7.75)	-0.13*** (-7.12)	TCI	0.22*** (6.95)	-0.56*** (-6.57)
$\widehat{Tech} * MCI$	0.17*** (4.34)	0.60*** (6.97)		$TCI * MCI$	0.22** (2.27)	
$\widehat{Tech} * MCI^2$		-0.45*** (-5.62)		$TCI * MCI^2$	-0.16* (-1.68)	
$\widehat{Tech} * ACI$			0.02*** (7.81)	$TCI * ACI$		0.15** (1.96)
MCI	-0.10*** (-4.99)	-0.10*** (-4.72)		MCI	-0.07*** (-2.74)	
ACI	0.04*** (10.15)	0.03*** (8.80)	0.01* (1.70)	ACI		-0.089* (-1.66)
Control variables	Yes	Yes	Yes	\widehat{Tech}	-0.14*** (-19.50)	-0.19*** (-11.93)
Constant term	0.53*** (22.06)	0.52*** (21.50)	0.49*** (26.13)	Constant term	0.43*** (24.46)	0.99*** (15.18)
Observations	3720	3720	3720	Observations	3720	1303
R^2	0.222	0.229	0.229	R^2	0.150	0.167
F	117.6	109.9	138.1	F	131.5	65.06

T-values are in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

range, technological complexity can improve economic resilience by generating new technologies. According to the results in column (3) of Table 7, with the increase in absorptive capacity, the negative effect of Tech on economic resilience is decreasing, specifically $0.02 \text{ ACI} - 0.13$, which indicates that when the absorptive capacity is sufficient to realize the transformation and absorption of new technologies and turn them into power to improve economic resilience, technological complexity can still indirectly promote improvement in economic resilience by generating new technologies.

The marginal effect of technological complexity on economic resilience is decreasing, and high technological complexity has a negative impact on resilience improvement. Therefore, a regression under the condition of $\text{TCI} > 0.6$ is performed, and the test results are shown in columns (4) and (5) in Table 7. From the perspective of the coefficient of the interaction term, the adjustment in market competition and absorptive capacity due to the role of high-tech complexity is similar to that of new technology induced by technological complexity. Under market competition within a certain range, the effect of technological complexity on economic resilience is positive, and being too low or too high is not conducive to economic resilience. With the increase in absorptive capacity, technological complexity has a positive impact on the marginal effect of resilience. Therefore, hypothesis 3 is supported.

4 Conclusions and policy implications

4.1 Conclusions

Combining the current uncertain and unstable realistic background and the strategic requirements for coordinating development and security, the impact of increasing technological complexity on regional economic resilience was explored. The following conclusions can be drawn from the results. First, on the whole, increasing technological complexity can strengthen regional economic resilience. In stages, increasing technological complexity is conducive to the emergence of new technologies, but new technologies generated in the short term cannot effectively strengthen regional economic resilience. The heterogeneity results show that in more competitive cities, such as those in eastern and central regions and the top 100 cities, technological complexity has a more significant role in improving regional economic resilience. Second, the positive effect of technological complexity on economic resilience is not linear. With the continuous improvement in technological complexity, its impact on regional economic resilience will decrease marginally. Excessive technological complexity is not conducive to improvement in economic resilience. Third, the degree to which technological complexity affects regional economic resilience is affected by market maturity. Optimizing market competition and absorptive capacity can effectively strengthen the positive impact of technological complexity on regional economic resilience.

The contribution of technological complexity to the generation of new technologies while the technological complexity of phase $T-1$ and the complexity of

new technologies in phase $T-1$ are still significant. The technological complexity of the entire regional technology pool accumulated over a long period of time or the complexity of the latest generation technology, regional technological innovation can be significantly promoted. With regard to absorptive capacity, it is generally believed that the higher the level of human capital, the stronger the ability to absorb and transform technology. The results emphasize the impact of market competition and absorptive capacity on the process of new technologies improving economic resilience caused by complexity. However, there is a threshold for this adjustment effect of MCI, and an excessive degree of market monopoly will also exacerbate the negative effect of $\widetilde{\text{Tech}}$ on economic resilience.

The marginal effect of technological complexity on economic resilience is decreasing, and high technological complexity has a negative impact on resilience improvement, whereas the coefficient of the interaction term, the adjustment of market competition and absorptive capacity on the role of high-tech complexity, is similar to that of new technology induced by technological complexity. The strengthening effect of providing technological complexity on economic resilience is significantly higher in more competitive cities in eastern and central regions and the top 100 cities than in slightly weak cities in western regions and the non-top 100 cities. The regression results of the first stage of the benchmark regression model of the technological complexity were calculated after depreciation, and the original conclusions are still valid. The regression results show that the effect of technological complexity on resilience is still significantly positive, and the new technology coefficient produced by improving technological complexity is significantly negative, whereas the quantile regression to estimate the different quantiles of the regional economic resilience level regressed to the 0.1, 0.3, 0.5, 0.7, and 0.9 quantiles, in turn.

4.2 Policy implications

First, we should strengthen the forward-looking consciousness of economic resilience construction. At present, the uncertain and unstable factors of the world economy continue to increase, and the economic pattern at home and abroad is constantly changing. It is necessary to take the construction of "economic resilience" as a long-term strategy for cities to achieve high-quality development, strengthen top-level design, and focus on the internal technical structure of the regional economic system. We should formulate and improve relevant policies, measures and action plans for the promotion of economic resilience, and guide enterprises, universities, and research institutions in the economic system to actively adjust their development concepts and models, further strengthen the core driving force of technological innovation, and work together to explore the path of economic resilience construction.

Second, we should strengthen the innovation incentives, promote the technological linkages between industries, and improve the level of technological complexity orderly. The research affirms the positive effect of technological complexity on economic resilience, it is necessary to further strengthen innovation

incentives, cultivate new technologies, develop complex technologies, and transform into competitive advantage. However, the development of complex technology needs the support of various factors, so the formation process of complex technology is different in the regions with different factor endowments. Therefore, it is necessary to give full play to the characteristic industrial advantages of different cities. Compared with the western or non-top 100 cities, the eastern central or top 100 cities have larger and more complex technology reserves, can obtain highly complex technologies at a lower cost, and become the forerunners of innovation and development.

Third, we should further strengthen the construction of innovation system and enhance the effect of urban technological complexity on economic resilience. On the one hand, we should pay attention to avoid market monopoly, it will lead to higher industry barriers and restrain market vitality, it is necessary to balance economies of scale and market competition vitality among different industries to form an appropriate scale. On the other hand, we should improve the ability of technology absorption and transformation, promote the agglomeration of innovative elements and the transformation of technological achievements, strengthen the local financial support for the development of science and technology, especially the relevant technologies of high value-added new economic sectors, strengthen the support of technological incubation, break down the obstacles to the transformation of new technological achievements, and encourage the high-tech enterprises to innovate, digest, apply, and re-innovate superior cutting-edge technologies. Strengthen the joint efforts of the government, universities, enterprises and talents to promote technological innovation and strengthen the resilience of the regional economy.

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Data availability The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no financial or non-financial interests that are directly or indirectly related to the work submitted for publication.

Ethical approval We confirmed that this manuscript has not been published elsewhere. Ethical approval and informed consent do not apply to this study.

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