

Promoting Sustainable and High-Quality Economic Development in China via Regional Innovation Poles

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Funding information: We acknowledge the support received from the National Social Science Foundation of China (18ZDA005), and the National Natural Science Foundation of China (71673033, 72203027, 72203028).

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Abstract: Using a panel data set comprising 284 prefecture-level and above cities in China during 2005-2018, this study develops a theoretical mechanism harnessing the spatial Durbin model (SDM) to accumulate evidence and explain how innovation affects China's economic growth. It is found that regional economic growth is facilitated by local innovation activities as well as the absorption capacity of innovation and technology spilled over from other regions. This study also identifies 12 regional innovation poles across the country, which are found to have played a significant role in promoting urban economic development within a physical distance range of 150 km of a given

region. This finding attests to the radiation effect from regional innovation poles in cultivating more such poles for China, to promote sustainable high-quality economic growth, suggesting a route for China to avoid the curse of the middle-income trap.

Keywords: middle-income trap, high-quality development, endogenous economic growth, regional innovation pole

JEL: O011 O031 O038 O047 O053

1. INTRODUCTION

Since the launch of reform and opening-up in 1978, China's GDP (gross domestic product) has been growing at an average annual rate of 9%. After more than 40 years of unbroken rapid growth, China has emerged from a poor agrarian country to be the world's second-largest economy as well as the largest manufacturer and exporter.¹ On October 18th, 2017, President Xi announced in the 19th National Party Congress that socialism with Chinese characteristics had entered a new era. The principal contradiction facing Chinese society has evolved into one between unbalanced and insufficient development and people's ever-growing demand and need for a better standard of living. At the present stage, China is directly facing the challenges of crossing the "middle-income trap" in developing into a high-income and developed economy.

Over the last fifty years, numerous middle-income countries have seemingly become deeply entrenched in the middle-income stage as they have been unable to actively develop themselves into high-income economies for a wide range of reasons (Gill & Kharas, 2007). According to the World

¹Source: China Statistical Yearbook 2020.

Bank's absolute income level criteria, countries with gross national income (GNI) per capita of less than or equal to \$1,025 are classified as low-income economies, countries with \$1,026-\$3995 as lower-middle-income economies, countries with \$3,996-\$12,375 as upper-middle-income economies, and countries with \$12,376 or more as high-income economies (The World Bank, 2018).² Zhang (2020) indicates that China's per capita gross national income (GNI) reached \$10,410 in 2019, making it an upper-middle-income economy. A more popular classifying criterion is the *catch-up index* based on relative income levels, which typically uses one (or more) developed country as the reference. In this paper, we follow Athukorala and Woo (2011) define the catch-up index (CUI) as the ratio between a country's per capita GDP and U.S.'s per capita GDP in the same year. The country is classified as a middle-income economy if its CUI lies between 20% and 55%. Some scholars have a broader range for middle-income economies. For example, Gong et al. (2017) set the range for middle-income economies as between 10% and 60%. In 2021, China's per capita GDP accounted for 32.95% of that of the United States and is still at the middle-income stage by this criterion.³

China is currently the largest middle-income country in the world, and it also has a large population of more than 1.4 billion. Crossing the middle-income trap into a high-income country remains a long-standing challenge for China. A “work report” of the government states that China's economy has shifted from the fast growth stage to the high-quality development stage.⁴ Low-quality development and the middle-income trap appear to comprise two sides of a coin. Countries

²Source: The World Bank. <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519>

³Source: Based on the Per adult GDP index of the WDI database. <https://wid.world/data/>

⁴Source: Report to the 19th CPC National Congress. http://www.xinhuanet.com/politics/19cpcnc/2017-10/27/c_1121867529.htm

that have crossed the middle-income trap are likely to fall back into it if the quality of economic growth development is low, as in the case of countries such as Argentina and Brazil. Promoting high-quality development is thus an essential requirement for successfully crossing the middle-income trap with a low probability of falling back again (Zhang et al., 2019). On the other hand, cities are the most dynamic part of the national economy, and their economic performance plays a key role in determining the pace and quality of the development of the whole country. The “herd of horses” theory proposed by Yao (2018) provides a theoretical basis for China to successfully cross the middle-income trap from a geo-economic development perspective. Yao uses running horses as an analogy for cities within a country and argues that more developed cities (leading horses) in China have already crossed the middle-income trap, while others (following horses) are still facing the challenge of crossing it. If crossed cities continue their economic growth and uncrossed cities grow faster, the country has two necessary conditions to cross the middle-income trap. This spurring on effect of cities with high levels of development on other cities is mostly referred to as the spillover effect in economic explanations.

In an early study of growth models, Romer (1986, 1990) argued that knowledge accumulation and spillover effects are the basis for endogenous growth in an economy. Lucas's (1988) framework argues that such spillovers are spatially localised as part of the urban growth process, and that advanced cities can drive national economic growth. In our study, cities are considered to be clustered together to form urban agglomerations (in the terms of the foregoing analogy – the multiple herds of horses) that are spatially linked, for example by transport, communications and networks. Clusters are usually made up of central cities, sub-central cities and other cities towns. Thus, many subsequent studies related to this point to one basic idea—cities may be viewed as the

engines of growth in an economy and the focus of knowledge spillovers (Henderson, 2007).

At present, unbalanced and inadequate urban economic development remains a prominent issue in China. Those cities that successfully crossed the middle-income trap are typically megacities, coastal or resource-based. This unbalanced and arguably inadequate economic structure is not conducive to forming a spatial geographical framework or pattern for high-quality economic development. How can underdeveloped cities narrow down the gap or even catch up with more developed cities? How can more developed cities be able to lead the following cities to cross the middle-income trap? Endogenous economic growth theory regards innovation and technological progress as a lasting driving force for growth. Based on the actual situation of China's economy, this study focuses on an endogenous mechanism and its path to promote overall economic growth through cities. Promoting local innovation or learning from external technology can, in principle, narrow the gap between developed cities. Innovation poles of regional economic growth, featuring high-level development and innovation ability, should, in principle, give scope to spillover effects, further promoting balanced regional development and helping to realise a more sustainable and “high-quality” regional economy.

In the extant academic literature, many studies have focused on economic growth and regional development through investment in both physical and human capital (Yao & Zhang, 2001; Yao & Wei, 2007; Jena & Sethi, 2021), but few have paid attention to how innovation clustered around the main cities may have a spurring on effect upon the surrounding cities to attain greater regional economic growth convergence. This study focuses on this latter issue and makes the following main contributions: (i) showing that urban economic growth is driven by local innovation and external innovation absorption; (ii) providing evidence that regional innovation poles have an economic

radiation effect; and (iii) indicating that the presence of an innovation pole within a 150 km range has a direct effect on the cities within the range, which also means that the cities receive more significant spillover effects from such innovation poles.

The remainder of this paper is structured as follows: Section 2 introduces the background of this paper with relevant literature. Section 3 provides a theoretical framework based largely on endogenous growth theory. Section 4 performs an empirical analysis using the Spatial Durbin Model to analyze the role of innovation in urban economic growth. Section 5 concludes and discusses the policy implications.

2. BACKGROUND

2.1: Middle-income trap in retrospect

The concept of middle-income trap has drawn broad global attention ever since it was proposed. Countries caught in the middle-income trap are mainly located in Latin America, Europe, Central Asia, East Asia, the Middle East, Southern Africa and North Africa (Zheng, 2011). Latin American countries, especially Brazil, Argentina, Mexico, and Venezuela, are the most typical and widely studied middle-income trapped economies (Agénor, 2017).

Many Latin American countries are rich in natural resources. In the middle of the last century, many of these countries entered the middle-income stage, and some of them even crossed the lowest threshold of high-income economies briefly. Examples include Argentina, Mexico, Brazil, and Venezuela. However, these countries could not maintain sustainable economic growth and were caught in the middle-income trap again. Argentina and Brazil were among the first Latin American countries that entered the middle-income or even high-income stage. However, those countries

found it difficult to provide a lasting impetus for their industrial upgrading and economic growth due to the complexity of innovation-driven industrial chains, among other reasons. Consequently, these countries typically saw periodical ups and downs and multiple crises in the process of economic development. They typically failed to sustain their presence in the group of high-income economies (Wu & Zhang, 2012). Li et al. (2013) demonstrates that whether the middle-income trap can be crossed or not, 74% of the probability is explained by a country's conversion ability of the product hierarchy and 26% by the country's strategic choice. Keijiro et al. (2017) argue that the middle-income trap is not caused by an economic slowdown but a failure of the government or private sector response to the transition from rapid growth to moderate growth in some countries, such as Malaysia and Thailand. These two countries became middle-income economies during the mid to the late 20th century. They failed to climb up because their industrial and export structures did not successfully respond to changes in the international product market at that time (Agénor, 2017). Jiménez et al. (2012) find that education affects economic development and that the economic slowdown in Malaysia and Thailand is a result of their relatively low levels of education. Education has a more positive direct contribution to the economies of less developed countries, while for upper-middle-income countries it seems to require a contribution to economic development through the interaction generated by urbanization (Zhang et al., 2018).

It is unrealistic to expect China, which is already an upper-middle income economy, to cross the middle-income trap simply by continuing its fast economic growth pace. The requirements of high-quality development in the background of the new era must arguably also address the problem of internal imbalance. China has faced income inequality and the wealth gap problems. Compared with middle-income families, the solidification phenomenon of low-income and top-rich families in

China has become increasingly apparent. The solidification problem of income groups between urban and rural areas has also been severe (Zhang, 2017). Guo and Yan (2017) argue that public policies can help to reduce income inequality and promote sustained economic growth through the adequate as well as high-quality provision of social pensions and education. Apart from policies, many countries have made important contributions to the process of economic development by using industries with comparative advantages as their leading industries. However, long-term reliance on industries with comparative advantages will lead to a slowdown in the process of scientific and technological innovation, which in turn will affect the upgrading of industrial structures and ultimately lead to a decline in international competitiveness (Lu & Ye, 2019). Comparative advantage and increasing economies of scale have been the main driving forces of China's industrial upgrading over the past few decades, which has weakened since this century (Yu & Wang, 2014). China faces the dilemma that the contribution of resource redistribution to economic growth is shrinking. Therefore, there is a need to rely more on innovation and human capital in future economic development (Storesletten & Zilibotti, 2016). Many empirical studies have demonstrated the importance of innovation and technology in economic development. Paus (2012) argues that only technological capacity can sustain economic growth, industrial transformation, and upgrading. Zhang (2013) indicates that reform and original technological progress are the main sources of economic growth. Chen (2018) shows that innovation is the driving force behind high-quality development in China's new era. Liu et al. (2019) confirms that the driving force of national innovation has a positive effect on high-quality economic development.

It can be seen from the above research perspective that, for developing countries, crossing the middle-income trap is a practical problem that must be faced to achieve sustainable and high-quality

economic development. The driving forces of sustained economic growth in the future are technological progress, human capital accumulation, and institutional innovation. The relevant studies are at both the national and the city levels (Martin, 2012; Ponds et al., 2010; Storper & Scott, 2009; Rocchetta et al., 2021). The country consists of economic activity units such as provinces, cities, counties (townships), and villages, level by level. The development of economic activity units determines whether a country can achieve sustainable and high-quality economic development after crossing the middle-income trap. Based on urban development, this study explores the connection mechanism of the urban economy in its growth process. Using endogenous economic growth theory, we analyze a possible pathway beyond the middle-income trap from an urban perspective to promote sustainable and high-quality economic development. This is an important contribution to the existing literature and theories of development economics.

2.2: Unbalanced urban economic development

This study uses per capita GDP data from 2001 to 2018 (in the empirical analysis, the sample period is restricted to 2005-2018 due to many missing values of some important variables in 2001-2004 at the city level) in 284 prefecture-level and above cities with continuous data in the statistics.⁵As shown in Figure 1, low-income and lower-middle-income cities accounted for most Chinese cities before 2011. Since 2011, upper-middle-income and high-income cities have accounted for more than 50%. Since then, many upper middle-income and high-income cities have increased and progressively occupied the main position. In 2018, this percentage reached 92%. According to the

⁵ We use per capita GDP as the measure of the total output of the national economy. And GDP per capita converted to US\$ according to the World Bank Atlas algorithm. <https://wid.world/data/>

World Bank's high-income level of \$12,375 in 2018, 62 cities entered the high-income rank, accounting for 21.83% of all the sample cities. This means that more than one-fifth of the cities had crossed the middle-income trap by 2018.

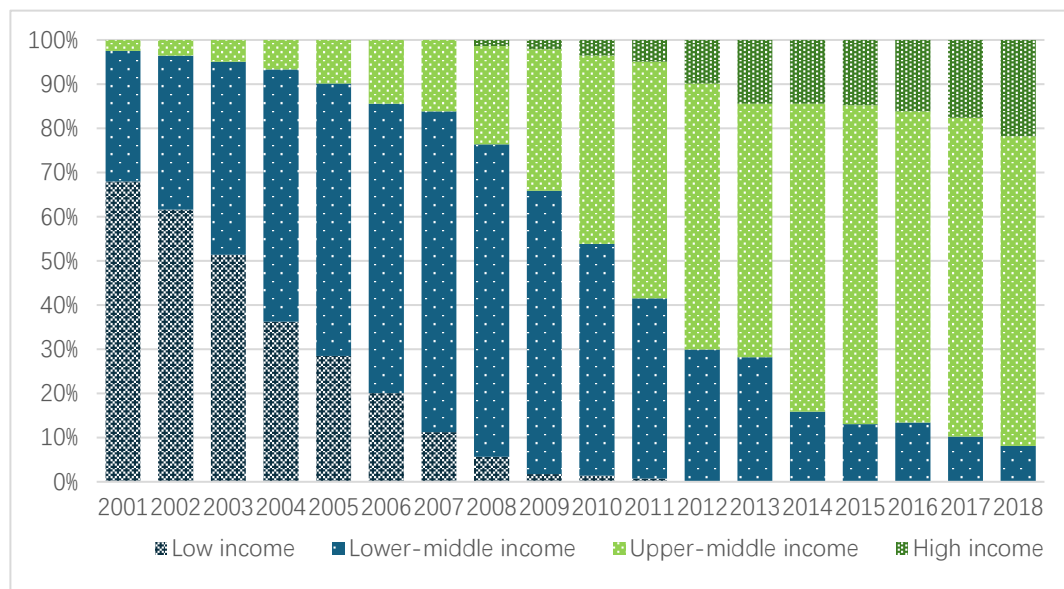


FIGURE 1 Proportion of cities by income level in China (2001-2018, %)

Source: composed and calculated by authors based on *China City Statistical Yearbook* (2002-2019)

In the process of cities crossing the middle-income trap, location advantage itself seems to determine the initial unbalanced state of economy. Figure 2 shows the proportion of crossed cities in the coastal and inland areas. The *China Marine Statistical Yearbook* defines coastal areas as cities at the prefecture level along the coastline. Among the 284 sample cities, 53 were coastal, with the others being characterised as inland. As shown in Figure 2, the proportion of coastal cities crossing the middle-income trap is significantly higher than that for their inland counterparts. However, in 2008, the proportion of crossed-trap inland cities was higher than that of the crossed-trap coastal

areas. Of the few cities that had crossed the middle-income trap in 2008, they were mainly the inland resource-based cities. By 2011, the proportion of crossed-trap cities was similar for both the inland and coastal city groups. From 2012 to 2013, the proportion of crossed-trap cities in the coastal regions increased significantly, whereas the proportion of crossed-trap cities in the inland areas increased slowly. The proportion of crossed-trap cities in the coastal regions increased from 0% in 2008 to 43% in 2018, and the proportion of crossed-trap cities in inland areas rose from 2% to 17% over the same period. It shows that the growth rate of coastal cities with geographical advantages is higher than that of inland cities. However, the total number of inland cities in China is far greater than that of the coastal cities. Therefore, inland cities must become the main driving force of growth for the country to cross the middle-income trap in aggregate.

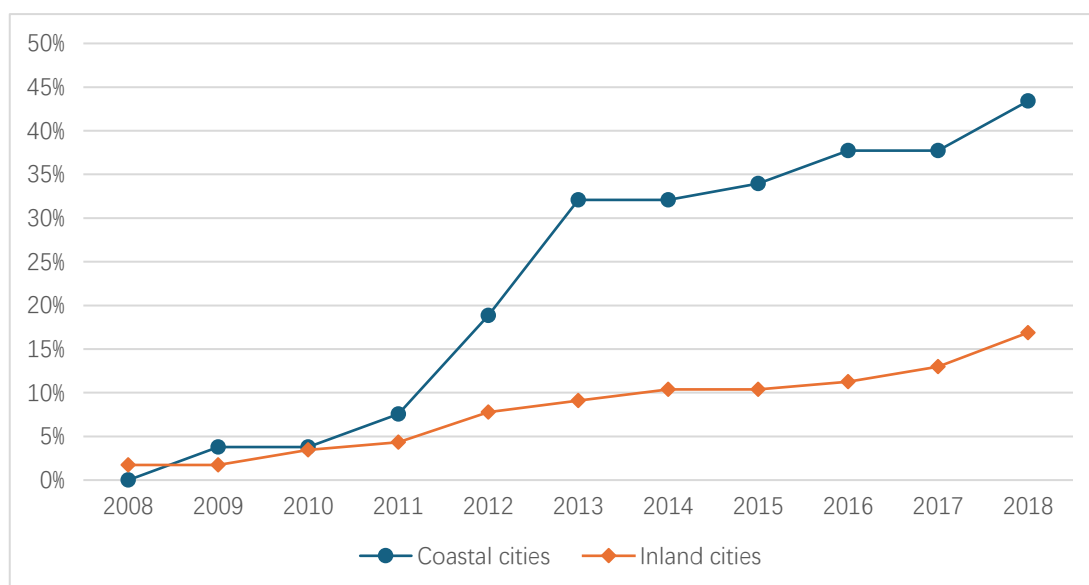


FIGURE 2 Proportion of crossed-trap cities in different areas in China (2008-2018, %)

Source: composed and calculated by authors based on *China City Statistical Yearbook* (2009-2019)

Four cities leading the way in crossing the middle-income trap were Dongying, Suzhou, Ordos,

and Karamay in 2008. Besides Suzhou, three other cities have inherent location or endowment advantages. As shown in Figure 3, from 2008 to 2011, high-income cities were primarily resource-based. From 2012 to 2016, the number of cities crossing the middle-income trap was much higher in coastal and inland (non-resource-based) cities than in resource-based cities and increasingly intertwined with each other. After 2017, the number of crossed-trap cities in inland areas were significantly higher than that of coastal cities. Among the 62 cities that entered the high-income ranks in 2018, 24 were coastal, 6 were resource-based, and 32 were inland (non-resource-based). Inland cities (non-resource-based) exceeded the total number of coastal and resource-based cities.

While the location advantages can be significant in the early stages of economic development, they cannot be a lasting driver of the economy. Most inland cities in China do not have these advantages and are numerous. With the development of cities, it seems that the unbalanced advantage of quantity can compensate for the unbalanced disadvantages of location.

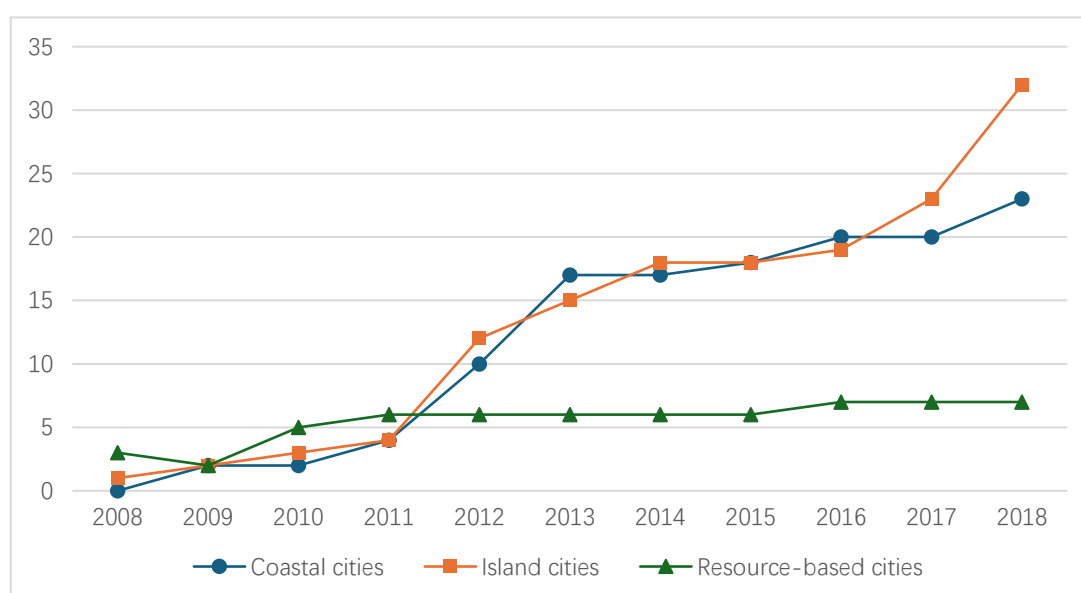


FIGURE 3 Changes of High-income Cities in China (2008-2018, number of cities)

Source: composed and calculated by authors based on China City Statistical Yearbook (2009-2019)

To lead those underdeveloped cities to cross the middle-income trap, the more developed cities that have already crossed need to continue economic growth. Further, the left-behind cities needed to grow faster than the more developed ones so that the national economy could escape the middle-income trap. Using GDP growth rate as the measure of the growth rate of the national economy, Figure 4 shows that the growth rate of more developed cities was lower than that of the less developed cities, with less uplift in the number of crossed-trap cities in 2009. Economic growth in non-crossed-trap cities was higher than that in crossed-trap cities, with the latter experiencing a significant increase in growth from 2010 to 2014. Crossed-trap cities had higher economic growth rates than uncrossed-trap cities, with a significant reduction in crossed-trap city growth in 2015, 2016 and 2017. The relationship between the growth rate and uplift in the number of crossed trap cities in 2018 differed from before. Although the growth rate of uncrossed-trap cities was lower than that of crossed-trap cities, the incremental rate still increased significantly. This change was due to the slow downward trend of growth in crossed-trap cities, while the growth rate of cities which have not crossed the trap showed a decreasing and then increasing trend from 2015 to 2018. This indicates that uncrossed-trap cities were actively contributing to the acceleration in economic growth, and thus, the number of crossed-trap cities had increased significantly.

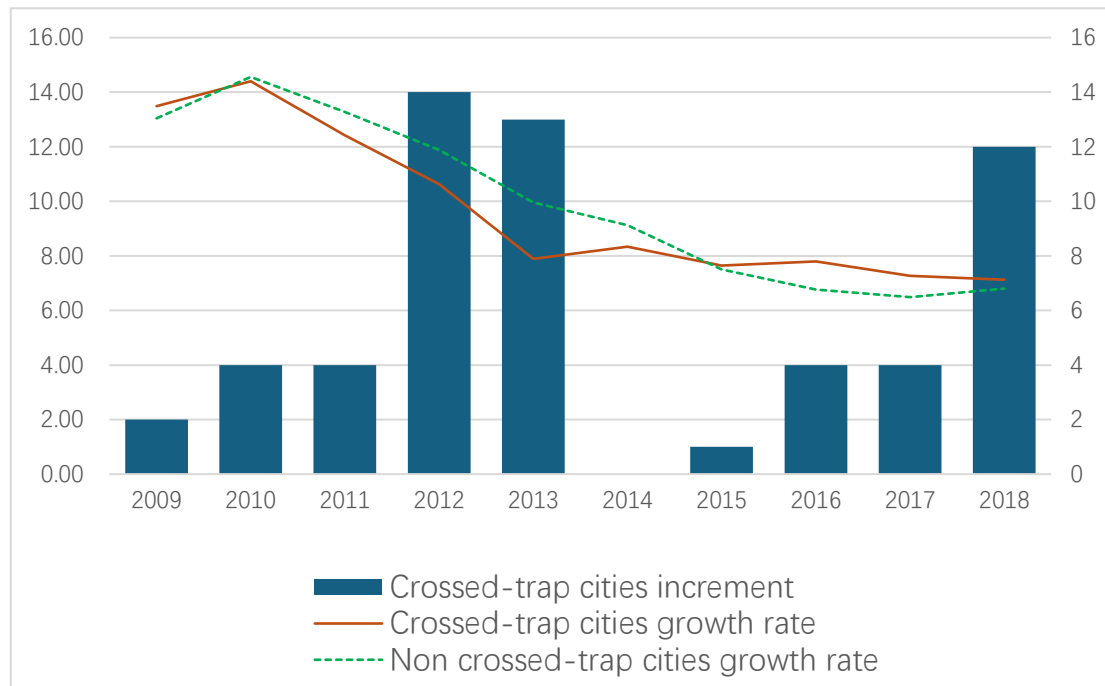


FIGURE 4 Growth rate and number of crossed cities (2009-2018, % and number of cities)

Source: composed and calculated by authors based on China City Statistical Yearbook (2010-2019)

2.3: Urban Innovation and Economic Development

Although urban economic development is unbalanced, as carriers of innovation activities, cities are an important foundation for promoting regional economic growth. Innovation and entrepreneurship do not only occur in cities, but they cannot exist without the carriers of cities (Florida et al., 2017). From an internal perspective, innovative enterprises and startups are more willing to concentrate in regions or large cities with high innovation capabilities during their initial period (Adler & Florida, 2021), so cities have become a direction. For the external areas of the city, it is significant to be spatially close to innovative sources. Early studies have pointed out that the diffusion process of innovation in space follows the central city, sub-central city, and sub-central surrounding areas (Pred, 1977). Research on innovation geography has shown that spillover effects are an important feature of innovation and spatial integration (Anselin et al., 1997; Greunz, 2003). The impact of regional

innovation activities on surrounding areas weakens with increasing spatial distance. Economic entities closer to the innovation pole have better innovation performance compared to other economic entities far from the innovation pole (Feldman, 1999). The attenuation effect at this distance indicates that spillovers are not low-cost (Moreno et al., 2005; Sonn & Storper, 2008).

Innovative regions or cities have positive externalities for the economic development of surrounding regions. This externality is the Jacobian externality and is usually associated with the location of a region or city, involving different companies, industries, and regional cross-sectoral types. The output, functional transformation, or upgrading of these entities will change with the introduction of new technologies, leading to diversity and a positive impact on the economy (Cooke, 2008; Desrochers & Leppala, 2011; Cainelli et al., 2015; Baltzopoulos et al., 2016). In open economies, some specific clusters with high cognition⁶ and low level of specialisation may also informally release Jacobian externality and promote technological exchange and progress (Francesco et al., 2022). Meanwhile, Jacobian externalities will also improve a city's competitive environment. This will likely lead to a decrease in the survival rate of enterprises, accelerating the exit of inefficient enterprises (Tsvetkova et al., 2020; Conroy & Deller, 2023). However, for entrepreneurial enterprises, the higher the "relevant diversity" between the region where the startup company is located and the company, the higher the company's chances of survival (Tavassoli & Jianwatcharamongkhol, 2016). The powerful economic effect produced by the Jacobian knowledge externality has reduced the cost of knowledge which is used for input and output. It helps to generate

⁶ By cognition we mean a cluster exhibiting some capacity for understanding, learning and comprehending the external environment. It also implies that such clusters have some awareness of their limitations and actively engage in discovering and learning about new technologies.

new local knowledge. The composition of local knowledge is closely related to further innovative development (Antonelli et al., 2017). As an innovation incubator, cities have both output and spillover functions. These functions can effectively promote regional economic development and provide a possible path to overcome the "middle-income trap".

3. URBAN ECONOMIC GROWTH PATHS: A THEORETICAL FRAMEWORK

From the neoclassical to the new economic growth theory, economic growth lies in the endogenization of technological progress, which explains the growth of the developed economies. In the neoclassical growth framework represented by the Solow model, the marginal productivity of capital diminishes toward zero, and the long-run economic growth rate is determined by exogenous technological progress. Romer (2000) separate the R&D sector from the production sector, where the allocation of production factors between sectors is proportionally exogenous but technical progress is endogenous.

The model of this paper is primarily based on Romer's (2000) endogenous growth model where technological innovation is endogenized. There are still two sectors in the economy, the R&D sector and the production sector. The only difference is that we consider that the economy comprises of two cities for simplification purpose.

3.1: Dynamics of the national economy

Suppose the production function of an economy is:

$$Y(t) = F(K(t), A(t)L(t)) \quad (1)$$

Where Y represents the total output of the economy; A represents the technical level. K and L

represent the capital and labor inputs respectively; and t represents the time. The production function

F satisfies the following conditions:

$$F(\lambda K, \lambda L) = \lambda F(K, L), \quad \forall \lambda > 0 \quad (2a)$$

$$F_1 > 0, F_{11} < 0; F_2 > 0, F_{22} < 0 \quad (2b)$$

$$F(0, L) = F(K, 0) = 0 \quad (2c)$$

$$\lim_{x_i \rightarrow 0} F_i(x_1, x_2) = +\infty, \quad \lim_{x_i \rightarrow +\infty} F_i(x_1, x_2) = 0, \quad i = 1, 2 \quad (2d)$$

The economy is assumed to be comprised of two cities (denoted as 1 and 2 in the above derivative functions), and its aggregate productivity level is determined by the city-specific productivity levels of City 1 and City 2. The dynamics of the economy's productivity is assumed to take the following form:

$$\dot{A}(t) = A(t)^\theta G(A_1(t), A_2(t)), \quad 1 > \theta > 0 \quad (3)$$

Where $\dot{A}$ is the derivative of A with respect to time, or the increment of A with one unit of time.

G is the production function of technology that satisfies the following conditions:

$$G_1 > 0, G_{11} < 0, G_2 > 0, G_{22} < 0 \quad (4a)$$

$$G(0, A^2) = G(A^1, 0) = 0 \quad (4b)$$

$$\lim_{x_i \rightarrow 0} G_i(x_1, x_2) = +\infty, \quad \lim_{x_i \rightarrow +\infty} G_i(x_1, x_2) = 0, \quad i = 1, 2 \quad (4c)$$

The savings rate and population growth rate are exogenous and assumed to be s and n , respectively. Depreciation is not considered here for simplification. The dynamics of capital accumulation and population growth are:

$$\dot{K}(t) = sY(t), \quad \dot{L}(t) = nL(t) \quad (5)$$

$\dot{K}$ and $\dot{L}$ are the increments of capital and labor respectively. The growth rate of capital can be expressed as $g_K = \dot{K}(t)/K(t)$. Incorporating equation (1) with equation (5) to derive g_K :

$$g_K = \frac{\dot{K}(t)}{K(t)} = \frac{sY(t)}{K(t)} = \frac{sF(K(t), A(t)L(t))}{K(t)} = sF(1, A(t)L(t)/K(t)) \quad (6)$$

From equation (6), we have:

$$\dot{g}_K / g_K = \varepsilon_{FL}(g_A + n - g_K) \quad (7)$$

Where $\varepsilon_{FL} = ALF_2/F$ is labor output elasticity in the production function.

$\dot{A}$ is the increment of technology. The growth rate of technology can be expressed as $g_A = \dot{A}(t)/A(t)$. Incorporating equation (3) into g_A such that,

$$g_A = \frac{\dot{A}(t)}{A(t)} = \frac{A(t)^\theta G(A_1(t), A_2(t))}{A(t)} = A(t)^{\theta-1} G(A_1(t), A_2(t)) \quad (8)$$

From equation (8), we have:

$$\dot{g}_A / g_A = (\theta - 1)g_A + \varepsilon_{GA_1}g_{A_1} + \varepsilon_{GA_2}g_{A_2} \quad (9)$$

Where $\varepsilon_{GA_1} = G_1 A_1 / G$ is the innovation output elasticity of City 1 in the technology production function with respect to the technology level of the economy, and $\varepsilon_{GA_2} = G_2 A_2 / G$ indicates the innovation output elasticity of City 2 in the technology production function with respect to the technology level of the economy. The value of ε is between (0, 1). G_1 represents the first term derivative of function G, and G_2 represents the second term derivative of function G.

3.2: Urban economic dynamics

Assume that cities 1 and 2 have the following production functions:

$$\begin{cases} Y_1(t) = F((1 - a_K)K(t), A_1(t)(1 - a_L)L(t)) \\ Y_2(t) = F(a_K K(t), A_2(t)a_L L(t)) \end{cases} \quad (10)$$

Where $(1 - a_K)$ and $(1 - a_L)$ represent the proportions of city 1's capital and labor as part of the aggregate capital and labor, respectively. a_K and a_L represent the proportions of city 2's capital and labor as part of the aggregate capital and labor, respectively. It is assumed that these proportions are exogenous and fixed.

The urban innovation function draws on the learning-by-doing theory (Arrow, 1962). Innovation is a function of capital, which is embedded in production activities. Arrow's theory emphasizes the production's learning effect of new capital. The technical production functions of cities 1 and 2 are expressed as:

$$\begin{cases} A_1(t) = B_1((1 - a_K)K(t))^{\frac{1}{\varphi_1}} \\ A_2(t) = B_2(a_K K(t))^{\frac{1}{\varphi_2}} \end{cases} \quad (11)$$

Where B and $1/\varphi$ represent the conversion coefficient and innovation scale respectively. Both B and φ are greater than zero. There is a slight change in the power function here, but it does not affect the interpretation of the scale effect.

From equation (10), we can see that the urban output is in the same form as the overall economic output. Therefore, we can obtain the following equation:

$$\dot{g}_K / g_K = \varepsilon_{FL,1}(g_{A_1} + n - g_K) = \varepsilon_{FL,2}(g_{A_2} + n - g_K) \quad (12)$$

Where $\varepsilon_{FL,1} = A_1 L F_2 / F$ and $\varepsilon_{FL,2} = A_2 L F_2 / F$ are the labor output elasticities of the production function in city 1 and city 2 respectively.

According to formula (11), we have:

$$\begin{cases} g_{A_1} = \dot{A}_1(t) / A_1(t) = g_K / \varphi_1 \\ g_{A_2} = \dot{A}_2(t) / A_2(t) = g_K / \varphi_2 \end{cases} \quad (13)$$

3.3: Dynamic relationship of economic growth

The urban economy is an integral part of the overall economy and therefore technological progress in each city jointly determines the level of innovation in the overall economy. The relationship between the technological progress in each city and the rate of capital growth and technological progress of the overall economy can be obtained through equations (7) and (9). Combining the rate

of capital growth and the rate of technological progress of the overall economy enables the dynamic behavior of economic growth to be observed.

Equation (13) is substituted into equation (9) while reducing the scale payment of urban innovation to α_{A_1} and α_{A_2} , with $\alpha = 1/\varphi$. When $\dot{g}_A = \dot{g}_K = 0$:

$$g_K = g_A + n \quad (15)$$

$$(\alpha_{A_1}\varepsilon_{GA_1} + \alpha_{A_2}\varepsilon_{GA_2})g_K = (1 - \theta)g_A \quad (16)$$

The solution that puts the economy in equilibrium is:

$$\begin{cases} g_A^* = \frac{n(\alpha_{A_1}\varepsilon_{GA_1} + \alpha_{A_2}\varepsilon_{GA_2})}{1 - \theta - (\alpha_{A_1}\varepsilon_{GA_1} + \alpha_{A_2}\varepsilon_{GA_2})} \\ g_K^* = \frac{n(1 - \theta)}{1 - \theta - (\alpha_{A_1}\varepsilon_{GA_1} + \alpha_{A_2}\varepsilon_{GA_2})} \end{cases} \quad (17)$$

Figure 5 shows the dynamics of equations (15) and (16), where the capital growth rate and technological progress rate remain constant. As can be seen in the figure, when $1 > (\alpha_{A_1}\varepsilon_{GA_1} + \alpha_{A_2}\varepsilon_{GA_2} + \theta)$, wherever the economy would eventually converge to the equilibrium point (g_A^*, g_K^*) of continuous growth; when $1 < (\alpha_{A_1}\varepsilon_{GA_1} + \alpha_{A_2}\varepsilon_{GA_2} + \theta)$, the equilibrium point is at less than zero and the economy will experience negative growth, the economy converges to a state of constant growth only if the initial value (g_A, g_K) is not less than zero; when $1 = (\alpha_{A_1}\varepsilon_{GA_1} + \alpha_{A_2}\varepsilon_{GA_2} + \theta)$, any combination of points (g_A, g_K) will cause the economy to converge to a state of sustained growth.

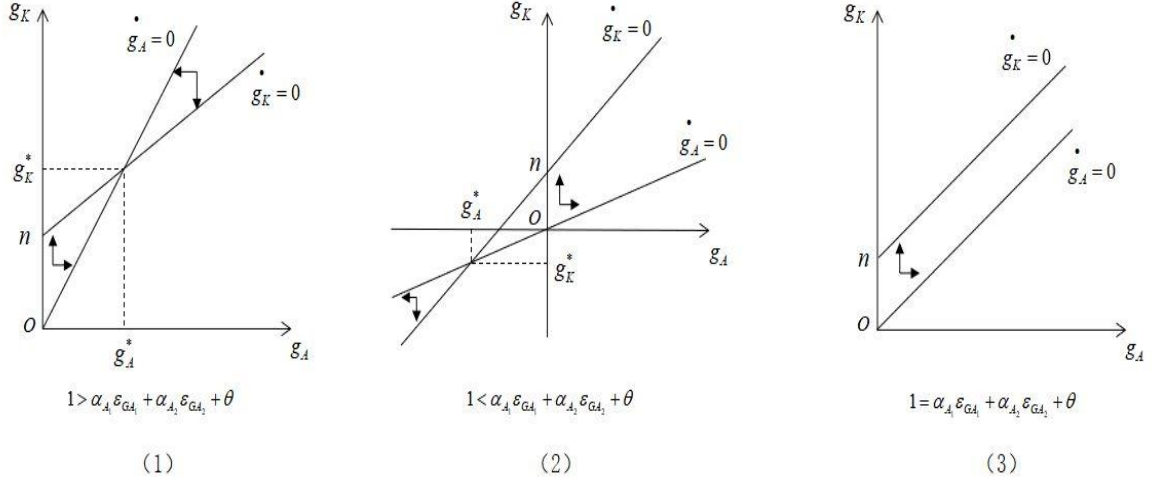


FIGURE 5 Dynamic characteristics of economic growth

3.4: Cities promote the overall economic growth path

The endogenous economic growth mechanism described above suggests that under certain conditions, the elasticity of urban innovation concerning overall technological output and the payoffs to scale of urban innovation are satisfied. Endogenous economic growth mechanisms can contribute to sustained overall economic growth in urban development. China's urban development and innovation are uneven, and cities with high innovation levels must play a leading role in driving urban development in the surrounding areas. Here, we propose a path for urban innovation to promote sustainable and high-quality development under the endogenous economic growth mechanism. Specifically, we express the urban output with the C-D function as:

$$Y(t) = K(t)^\alpha [A(t)L(t)]^{1-\alpha}, \quad 0 < \alpha < 1 \quad (18)$$

The relationship between innovation and capital can be expressed by a power function as:

$$A(t) = BK(t)^{\frac{1}{\varphi}}, \quad B > 0, \quad \varphi > 0 \quad (19)$$

Where B indicates the conversion coefficient and $1/\varphi$ represents the scale compensation for innovation. Substituting the inverse function $K(t) = (A(t)/B)^\varphi$ of $A(t)$ into (18) yields

$$Y(t) = B^{-\alpha\varphi} \cdot A(t)^{1+\alpha(\varphi-1)} \cdot L(t)^{1-\alpha} \quad (20)$$

Taking the logarithm on both sides of equation (20) and then finding the derivative of its time t , an expression for the growth rate can be obtained:

$$\frac{(\ln Y(t))'}{Y(t)} = [1 + \alpha(\varphi - 1)] \cdot \frac{(\ln A(t))'}{A(t)} + (1 - \alpha) \frac{(\ln L(t))'}{L(t)} \quad (21)$$

Defining the growth rate as $g = (\ln F(X))' / F(X)$, the relationship between the growth rates of output (g_y), innovation (g_a), and labor (g_l) in equation (21) can be expressed as:

$$g_{y,t} = [1 + \alpha(\varphi - 1)]g_{a,t} + (1 - \alpha)g_{l,t} \quad (22)$$

Assuming that there are no technical barriers within the same economy, the economic growth power of cities depends on the local innovation, external innovation absorption, and external innovation spillover levels. We represent the innovation function of city i in period t as

$$A_{i,t} = \begin{cases} \frac{\lambda_i}{d_{pole}^{min} - d_i} A_{pole,t-1} + \eta_i A_{i,t-1} & , \Delta d \leq d_0 \\ \eta_i A_{i,t-1} & , \Delta d > d_0 \end{cases} \quad (23)$$

Where η_i represents the autonomous innovation capacity of the i -th city and λ_i represents the external innovation absorption ability. d_i represents the location of the i -th city, d_{pole}^{min} indicates the nearest regional innovation pole (city or city clusters), and d_0 indicates the effective radiation distance, where $\Delta d = d_{pole}^{min} - d_i$, representing the physical distance of the i -th city from the nearest regional innovation pole. The closer this distance, the greater the effect of the innovation pole on radiation, where $1/(d_{pole}^{min} - d_i)$ can be explained as the level of external innovation spillover. When the extreme distance between the city and the regional innovation pole is less than or equal to the effective radiation distance d_0 , the urban local economic growth power comes from the radiation effect of independent innovation and the regional innovation pole. When the distance between the city and regional innovation pole is greater than the effective radiation distance d_0 , the economy relies entirely on local independent innovation to provide an impetus for growth.

We use $\gamma = A_{i,t-1}/A_{pole,t-1}$ to represent the innovation gap between the i-th city and its closest regional innovation pole. The innovation rate of city i in period t is:

$$g_{i,a,t} = \frac{A_{i,t}}{A_{i,t-1}} = \frac{\lambda_i}{d_{pole}^{min} - d_i} \cdot \frac{A_{pole,t-1}}{A_{i,t-1}} + \eta = \frac{\lambda_i}{\gamma(d_{pole}^{min} - d_i)} + \eta_i \quad (24)$$

For a simple analysis, assuming that the labor growth rate is zero, substituting formula (24) into formula (22) yields the key expression of this study:

$$g_{i,y} = \frac{[1+\alpha(\varphi-1)] \cdot \lambda_i}{\gamma} \cdot \frac{1}{(d_{pole}^{min} - d_i)} + [1 + \alpha(\varphi - 1)] \cdot \eta_i \quad (25)$$

According to equation (25), the urban economic growth path can be expressed as shown in Figure 6: (1) when other conditions are unchanged, the growth rate is inversely proportional to the distance between the regional innovation pole and the city; the closer the distance is, the faster the growth; (2) when the distance is certain, the growth rate can be increased by improving the external innovation absorption capacity(λ_i); (3) when the distance is certain, the growth rate can be increased by improving the independent innovation ability (η_i).

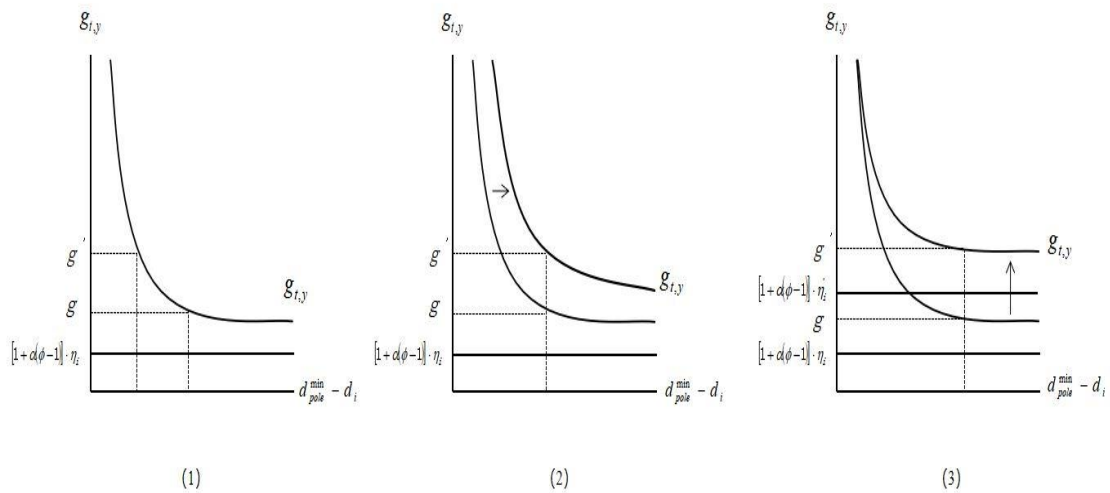


FIGURE 6 Urban economic growth path

The above growth path can explain the economic link between regional innovation poles and

other cities. When the cities are far away from their closest regional innovation poles, it is challenging to promote local economic growth through obtaining the spillover of the regional innovation poles, and the local innovation ability mainly determines the economic growth power. When the distance is reduced to a specific range, the spillover effect of the innovation pole and learning from local external innovation can play a more potent role. This growth path shows that, in addition to promoting economic growth through local innovation, broader regional economic growth can also be promoted by developing regional cities or clusters of cities with innovative capabilities that have a radiating economic effect on their nearby regions or cities. Therefore, our study suggests two hypotheses based on the earlier theoretical analysis. Whether these positions uphold in the Chinese cities is a key research question that will be answered in the following sections focusing on empirical analysis with real city level data.

Hypothesis 1: Local innovation and external innovation absorption can promote urban economic growth.

Hypothesis 2: Regional innovation poles have an economic radiation effect so that their innovation activities can propel the urban economic growth of surrounding cities.

4. EMPIRICAL ANALYZES

4.1: Spatial correlation test

To analyze the spatial connection of cities, we first test the spatial association of cities. The global Moran's I index is derived and used to examine the spatial dependence of city clusters as shown in equation (26).

$$Moran's\ I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})^2} \quad (26)$$

Where x_i and x_j represent the attribute values of different cities or regions, n represents the number of cities (or regions), and w represents the spatial weight matrix. Moran's I belongs to $[-1, 1]$. When Moran's I is close to 1, it implies a strong positive correlation. When it is close to -1, it implies a strong negative correlation. When it is equal to 0, it implies no correlation. The relationship between urban economic growth shows that rapidly developing cities can drive cities that grow slowly, and the driving effect varies with the distance between cities. Therefore, we used the inverse distances as elements in the spatial weight matrix. The global Moran's I index of urban GDP from 2005 to 2018 was calculated based on the growth rate. Table 1 shows the results. The global Moran's I index is greater than 0 in all years, and the p -value is significant at the 1% level. It indicates that the spatial correlation of GDP growth is positive in the sample cities. From 2005 to 2009, the spatial correlation gradually increased. From 2010 to 2015, volatility increased slightly, and the highest spatial correlation reached 0.716 in 2016. From the change of Moran's I index, the spatial relevance of cities shows a fluctuating upward trend over the sample period. Moran's I index is positive and significant, indicating that the residuals of ordinary least squares (OLS) are spatially correlated. OLS regression cannot reflect this spatial reality, and a panel model estimate that reflects spatial properties should be adopted.

TABLE 1 Global Moran's I index of urban GDP growth rate

Year	Moran's I	Z-value	P-value
2005	0.283	6.810	0.000
2006	0.213	5.133	0.000
2007	0.235	5.671	0.000
2008	0.318	7.578	0.000
2009	0.359	8.564	0.000
2010	0.232	5.566	0.000
2011	0.283	6.761	0.000
2012	0.332	7.942	0.000

2013	0.220	5.312	0.000
2014	0.394	9.607	0.000
2015	0.364	8.713	0.000
2016	0.716	17.193	0.000
2017	0.536	12.779	0.000
2018	0.368	8.740	0.000

4.2: Model setting and variable selection

The basic model of this study adopts the general form of the Spatial Durbin Model (SDM), which can degenerate into a spatial autoregressive model (SAR) and a spatial error model (SEM) under certain conditions, and the WALD and LR tests can be used to determine whether degradation will occur. First, the basic form of SDM is shown in equation (27).

$$y_{it} = \beta_0 + \rho \sum_{j=1}^N w_{ij} y_{jt} + \beta x_{it_0} + \theta \sum_{j=1}^N w_{ij} x_{jt_0} + u_{it} \quad (27)$$

Where y_{it} represents the output of city i in period t , β_0 is the intercept term, x_{it_0} is a set of indicators affecting the output of the $K \times 1$ order, and β is the corresponding K -dimensional parameter. When the initial conditions and space overflow are controlled, the error terms (u_{it}) are uncorrelated. w_{ij} is an element of the $N \times N$ order row random non negative spatial weight matrix W . ρ represents the degree of spatial autocorrelation, where $\rho \in (-1, 1)$. θ are regression parameters for the spatial lag term. The Spatial Durbin Model nests most models commonly used in the spatial econometrics literature (Lesage & Pace, 2009). This type of specification can clarify the complex relationship between output growth and influencing factors. According to the fourth part of the growth path analysis, the regression equation can be set as

$$g_{it} = \beta_0 + \rho \sum_{j=1}^N w_{ij} g_{jt} + \beta_1 \ln pat_{it} + \beta_2 \ln h_{it} + \beta_3 x_{it} + \theta_1 \sum_{j=1}^N w_{ij} \ln pat_{jt} + \theta_2 \sum_{j=1}^N w_{ij} \ln h_{jt} + \theta_3 \sum_{j=1}^N w_{ij} x_{jt} + u_{it} \quad (28)$$

$$g_{it} = \beta_0 + \rho \sum_{j=1}^N w_{ij} g_{jt} + \beta_1 \ln pat_{it} + \beta_2 \ln h_{it} + \beta_3 pole_{it} + \beta_4 x_{it} + \theta_1 \sum_{j=1}^N w_{ij} \ln pat_{jt} +$$

$$\theta_2 \sum_{j=1}^N w_{ij} \ln h_{jt} + \theta_3 \sum_{j=1}^N w_{ij} pole_{jt} + \theta_4 \sum_{j=1}^N w_{ij} x_{jt} + u_{it} \quad (29)$$

Where $\ln pat_{it}$ represents independent innovation ability, $\ln h_{it}$ represents the absorption capacity for innovation, and x_{it} is a set of control variables.

The specific definitions of the explanatory variables and the main explanatory variables are as follows: g_{it} represents the economic growth rate, and GDP is the most important statistical indicator for measuring macroeconomic growth. In this study, the GDP growth rate was calculated using the constant price in 2004 as the explained variable to measure the economic growth situation. $\ln pat_{it}$ represents urban innovation ability, and many scholars have used patents to measure innovation levels (Jaffe, 1989; Bottazzi & Peri, 2003; Wu, 2006; Wei et al., 2010). Wu (2006) and Wei et al. (2010) used the number of patent licenses to measure each province's innovation output or innovation intensity. We use the number of patents granted per 10,000 people to measure innovation ability. $\ln h_{it}$ represents the innovation absorption ability and reflects the region's ability to learn from external innovation. Li et al. (2010) believed that improving human capital can enhance obtaining and using knowledge, technology, and other information. Yao et al. (2020) assumed that the dynamic process of human capital accumulation is similar to material capital accumulation; human capital is defined as the ratio of the number of students to the population. Zhao and Wang (2020) used the number of university students in higher education as a proportion of the total urban population to measure the level of urban human capital. Considering data acquisition and as much urban coverage as possible, the ratio of the total number of students to the total population to reflect the human capital level is selected as a proxy variable of innovation absorption ability.

Other control variables, such as material capital, technological progress rate, natural population growth rate, and depreciation rate, are usually considered in the process of economic growth (Yao

& Zhang, 2001; Yao et al., 2020; Jena & Sethi, 2021). This study incorporates these factors in the economic growth processes into the control variables. lnk_{it} represents the investment rate (fixed asset investment/GDP). $(n+\gamma+\delta)$ is the sum of the natural population growth, technological progress, and depreciation rates, assuming 10% for the combined value of the last two rates (Yao et al., 2020). lny_{it-1} represents the lagging period GDP per capita and g_{it-1} represents the lagged GDP growth rate. se_{it} (output of the secondary industry/GDP) represent industrial structure. Liu and Li (2001) show that changes in industrial structure are closely related to economic development. Liu and Zhang (2008) compared changes in the industrial structure and the contribution of technological progress to the economy. fdi_{it} (foreign direct investment/GDP) is the proportion of foreign direct investment, and investment and economic growth have been widely studied by scholars (Yao & Wei, 2007). pf_{it} is the proportion of public fiscal expenditure (public fiscal expenditure/GDP). The level of fiscal expenditure is usually negatively related to economic growth (Guo et al., 2003; Ma & Sun, 2005). For the availability of some data, the basic regression data of each variable were determined from the 2005-2018 panels, mainly from the CNRDS database. Missing data were supplemented by the China Urban Statistics Yearbook, local statistics yearbooks, and local statistics bureaus.

TABLE 2 Statistical characteristics of the sample variables

Variable	Sample	Mean	Standard error
g_{it}	3976	0.105	0.039
$lnpat_{it}$	3976	0.596	1.618
lnh_{it}	3976	-1.969	0.281
lny_{it-1}	3976	10.014	0.816
lnk_{it}	3976	-0.433	0.935
$ln(n+\gamma+\delta)_{it}$	3976	-2.247	0.050

g_{it-1}	3976	0.109	0.039
fdi_{it}	3976	0.020	0.110
se_{it}	3976	0.483	0.020
pf_{it}	3976	0.173	0.102

4.3: Results and analysis

First, we test the first proposition of this study: that urban economic growth power comes from local innovation and external innovation absorption. By running a regression on the total sample data, we obtain the estimates in Table 3. Both the WALD and LR tests are significant at the 1% level, indicating that the model does not degenerate into a spatial autoregressive model (SAR) or a spatial error model (SEM), and the Spatial Durbin Model (SDM) is appropriate. The Hausman test results showed that the null hypothesis of random effect could be rejected, so the Spatial Durbin Model (SDM) with fixed effect was used for regression on equation (28). Individual and temporal double-fixed models were used for the model estimation. The model estimates in Table 3 show that the coefficient symbols are all significant and consistent with expectations for the main explanatory variables ($lnpat_{it}$) and local innovation absorption capacity (lnh_{it}). Both R^2 and likelihood values indicated a good model fit. The spatial autoregressive coefficient of 0.334 is significant at the 1% level, indicating a pronounced spatial effect.

TABLE 3 Panel data regression (Spatial Durbin Model) results of innovation ability among China's 284 prefecture-level and above cities (2005-2018)

DV= g_{it}	SDM_fe
$lnpat_{it}$	0.002(1.94)*
lnh_{it}	0.009(2.61)***
lny_{it-1}	-0.087(-18.28)***
lnk_{it}	-0.001(-2.78)***

$\ln(n+\gamma+\delta)_{it}$	0.022(1.88)*
g_{it-1}	0.290(19.86)***
se_{it}	0.105(11.93)***
fdi_{it}	0.078(2.70)***
pf_{it}	-0.006(-0.91)
$W \times \ln pat_{it}$	0.002(1.66)*
$W \times \ln h_{it}$	0.003(0.60)
$W \times \ln y_{it-1}$	0.023(3.05)***
$W \times \ln k_{it}$	-0.001(-1.78)*
$W \times \ln(n+\gamma+\delta)_{it}$	0.010(0.55)
$W \times g_{it-1}$	0.031(1.51)
$W \times se_{it}$	-0.022(-1.62)
$W \times fdi_{it}$	0.062(1.34)
$W \times pf_{it}$	0.015(0.96)
ρ	0.334(20.22)***
σ^2_e	0.000(44.13)***
R^2	0.6300
Log-lik	9975.36
Time-fixed	Yes
City-fixed	Yes
Hausman test	223.30***
Wald spatial lag test	21.16***
LR spatial lag test	22.38***
Wald Spatial error test	222.20***
LR spatial error test	90.57***

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; fe indicates a fixed effect; the t-values are in parentheses.

The variable regression coefficients obtained by the SDM do not accurately reflect the interpretation of the independent variables, and it is usually necessary to calculate the direct, indirect, and total effects of the explanatory variables on the explained variables. As the results in Table 4 show, the local independent innovation ability variables ($\ln pat_{it}$) and innovation absorption capacity ($\ln h_{it}$) as the main explanatory variables are significant and positive at the 5% and 1% level, respectively. This shows that local independent innovation capacity and the absorption of external

innovation are conducive to local economic growth. Still, the independent innovation capacity coefficient is 0.002, less than 0.009 of the innovation absorption capacity. In the indirect effects, the independent innovation capacity in the growth path studied here ($lnpat_{it}$) is significant at 5%, whereas the local innovation absorption capacity (lnh_{it}) is not significant. The indirect effect reflects the spillover effect in other regions. The significant capacity for autonomous innovation shows that improving innovation capacity promotes growth and positively affects the surrounding regions. Innovation absorption ability is mainly reflected in the city, so the indirect effect is not significant. The remaining explanatory variables were also largely significant, as expected. The total effect is consistent with the direct effect results, which show that improving local innovation and external innovation absorption capacity is a viable path for urban economic growth for all cities. Whether in the direct or total effects, the coefficient of independent innovation ability is less than the innovation absorption capacity coefficient. To a certain extent, this indicates that the dynamics of economic growth in cities rely more on the absorption and learning of external innovation and that the contribution of local independent innovation is relatively weak.

TABLE 4 Panel data regression (Spatial Durbin Model) results showing direct, indirect and total effects of innovation ability among China's 284 prefecture-level and above cities (2005-2018)

DV= g_{it}	Direct effect	Indirect effect	Total effect
$lnpat_{it}$	0.002(2.32)**	0.004(2.31)**	0.007(3.52)***
lnh_{it}	0.009(2.91)***	0.009(1.22)	0.018(2.36)**
lny_{it-1}	-0.087(-19.39)***	-0.008(-0.85)	-0.095(-9.11)***
lnk_{it}	-0.002(-3.24)***	-0.003(-2.64)***	-0.004(-3.68)***
$ln(n+\gamma+\delta)_{it}$	0.024(2.16)**	0.025(1.09)	0.049(1.99)**
g_{it-1}	0.303(21.60)***	0.178(6.95)***	0.481(17.65)***
se_{it}	0.106(12.03)***	0.019(1.10)	0.125(6.99)***
fdi_{it}	0.086(3.15)***	0.132(2.16)**	0.218(3.27)***
pf_{it}	-0.004(-0.65)	0.017(0.77)	0.013(0.53)

Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively; the t-values are in parentheses.

Next, we test the second proposition: the regional innovation pole has an economic radiation effect. A regional innovation pole within a specific range can promote urban economic growth in its surrounding areas. At present, the academic community has not yet uniformly defined the concept of innovation pole. The consideration of the regional innovation pole is based on its scientific and technological level and includes political, financial, education, transportation, culture, and other comprehensive environmental conditions. In this paper, 12 national central cities are selected as regional innovation poles. The selection is primarily based on the 2020 National Central Cities Index report released by the Center for Urban and Competitiveness of the Chinese Academy of Social Sciences. The report measured index data from 25 major cities in China. The comprehensive index obtained from the unique index of ten special functions, such as political and financial, is the national comprehensive central index. This reflects the extensive functions of national central cities. Figure 7 shows the average innovation capacity of national central cities (number of patents authorised per 10,000 people) and the average innovation capacity of other cities. We can see that the innovation capacity of innovation pole cities is much higher than that of the other cities. Thus, these 12 cities have the conditions required for a regional innovation pole.

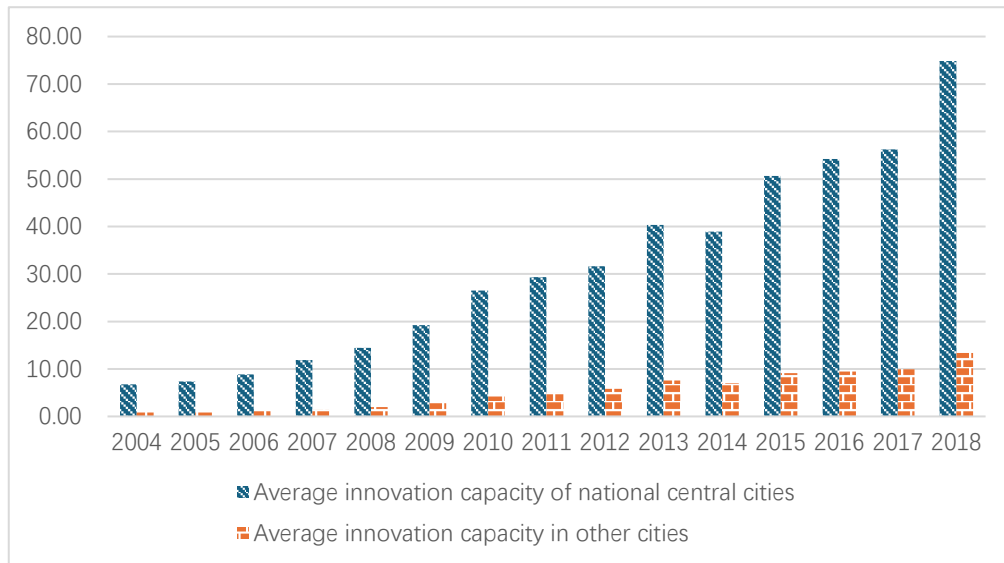


FIGURE 7 Average innovation capacity of national central cities (patents granted per 10,000 people)

Source: composed and calculated by authors based on China City Statistical Yearbook (2005-2019)

The 12 innovation pole cities include Beijing, Shanghai, Guangzhou, Shenzhen, Wuhan, Chengdu, Xi'an, Chongqing, Hangzhou, Nanjing, Tianjin, and Zhengzhou. The most important innovation pole cities are Beijing, Shanghai, Guangzhou, and Shenzhen, which have the most powerful innovation ability and have been regarded as China's first-tier cities economically. These cities have a higher level of technological innovation, a higher concentration of high-quality elements, and a relatively stronger innovation-driven capacity than other cities do. Wuhan, Chengdu, Xi'an, Chongqing, Hangzhou, Nanjing, Tianjin, and Zhengzhou lag behind the other four cities both technologically and economically but are still far more advanced than their respective surrounding cities and the rest of the country. The location distribution of innovation pole cities and prefecture level cities are shown in Figure 8.

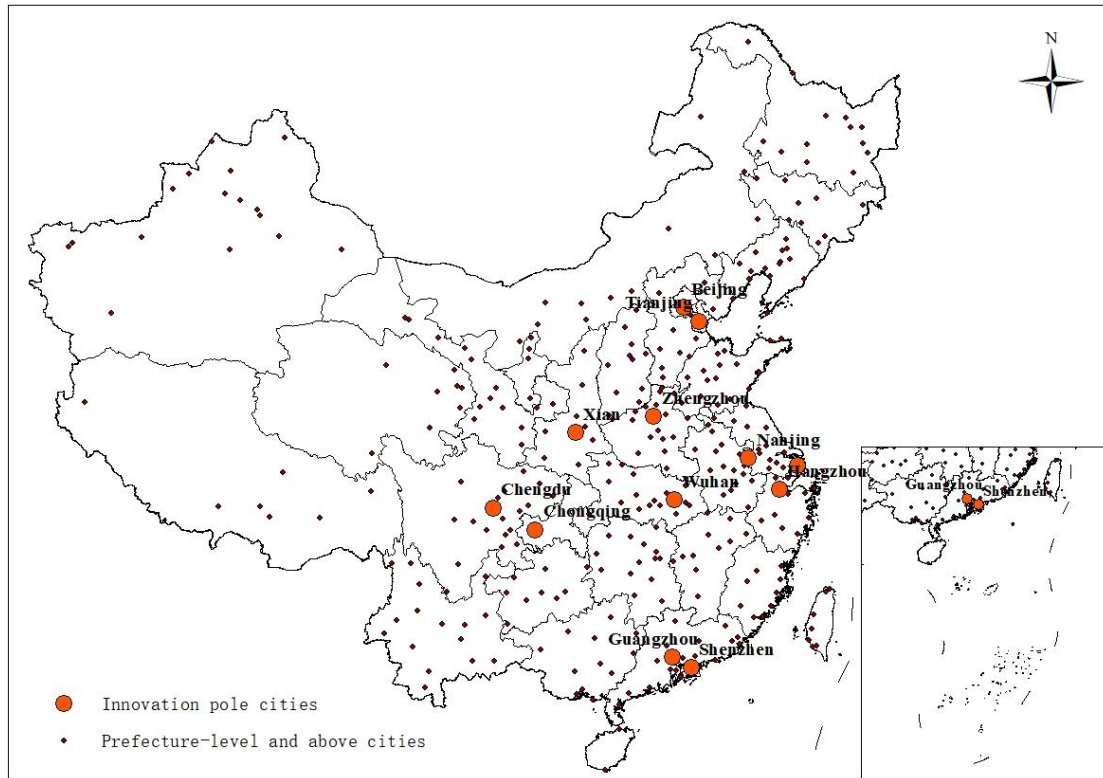


FIGURE 8 Distribution of regional innovation poles in China

Source: Drawn by authors based on the map from the National Geomatics Center of China

Given this distribution of regional innovation poles, this study identifies spillover effects by including a dummy variable which is specified by a physical distance from any city under concern and its nearest innovation pole city. For example, if the distance of a city is less than 150 km from the nearest innovation pole city, the dummy variable takes the value of 1, and 0 otherwise. Based on the regression equation (28), four range dummy variables are defined, reflecting the various distances between the city under concern and its closest innovation pole city, i.e., 150 km, 250 km, 350 km, and 400 km, respectively as shown in equation (29). The results with random effect estimation are presented in Table 5. The results suggest that the overall estimate of the model is good, and the Wald test still indicates that the SDM is appropriate. The spatial effect coefficient is 0.630 and significant, and the pole150 variable direct effect and total effect are positive and

significant. The innovation pole effect range dummy variable indicates that the existence of the innovation pole within the 150 km range has a direct effect on the city within the range, which also means that the city receives more significant spillover effects from the innovation pole. The pole250 and pole350 variables are insignificant, and the pole400 variable is significant but negative, indicating that innovation pole cities have a weak impact on urban economic development of nearby cities if the distance goes beyond 150 km. In the extreme case, if the distance is farther than 400 km, the innovation pole effect is even negative, reflecting a net “siphoning effect” in the geo-economics literature.

TABLE 5 Panel data regression (Spatial Durbin Model) results showing direct, indirect and total effects of innovation pole effect among China's 284 prefecture-level and above cities (2005-2018)

DV= g_{it}	Direct effect	Indirect effect	Total effect
$lnpat_{it}$	0.001(2.02)**	0.001(1.16)	0.003(2.12)**
lnh_{it}	0.004(2.13)**	0.013(3.48)***	0.018(4.70)***
lny_{it-1}	-0.009(-6.07)***	-0.014(-5.12)***	-0.023(-7.83)***
lnk_{it}	-0.002(-4.15)***	-0.003(-2.34)**	-0.004(-3.59)***
$ln(n+\gamma+\delta)_{it}$	0.005(0.47)	-0.061(-3.22)***	-0.057(-2.97)***
g_{it-1}	0.426(24.72)***	0.197(8.13)***	0.623(24.10)***
se_{it}	0.013(2.43)**	0.027(2.74)***	0.040(3.43)***
fdi_{it}	0.101(4.70)***	0.082(1.65)*	0.184(3.49)***
pf_{it}	-0.014(-2.55)**	-0.026(-2.07)**	-0.040(-2.93)***
$pole150$	0.003(2.01)**	0.004(0.99)	0.007(2.07)**
$pole250$	-0.000(-0.14)	-0.003(-0.64)	-0.003(-0.65)
$pole350$	0.003(1.51)	0.007(1.22)	0.011(1.54)
$pole400$	-0.005(-2.06)**	-0.018(-3.09)***	-0.022(-3.52)***
ρ		0.409(26.84)***	
σ^2_e		0.000(40.82)***	
R^2		0.6353	
Log-lik		9507.69	
Wald spatial lag test		30.99***	
Wald Spatial error test		233.39***	

Note: ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively; the t-values are in parentheses.

4.4: Mechanism test

Through the above spatial model analysis, it can be seen that when there is no regional innovation pole within a certain range around the city, the driving force of urban economic growth comes from exploring and improving local innovation capabilities. Yet when a regional innovation pole city exists within 150 kilometers of a given city, the spillover effect of the innovation pole can further promote local economic growth. In order to verify the mechanism of action between innovation poles and urban innovation, that is, whether there is a compensatory or complementary effect, the interaction term between innovation poles and urban innovation is introduced, which is "innovation pole150km*local innovation, innovation pole150km*innovation from other regions". The testing of interaction effects can be analyzed using non-spatial panel models, which can provide a certain supplementary insight to the key role of innovation poles. Among them, equation (1) is a regression that does not include the innovation pole effect, estimated based on the time and individual dual fixed effects model. Equations (2) and (3) are the regression incorporating the innovation pole effect. To avoid the collinearity problem between the innovation pole variable and individual fixed effects, the random effect model is used for estimation. Equation (2) presents the regression without interaction terms, and (3) presents the regression after including interaction terms. The results are shown in Table 6.

The estimation results of the non-spatial model (1) in Table 6 show that after fixing individual differences in cities, local independent innovation ($lnpat_{it}$) and absorption of external innovation (lnh_{it}) significantly promotes economic growth, with coefficients of 0.005 and 0.013, respectively, and a total impact of 0.018. After adding innovation pole variables and interaction terms to equations

(2) and (3), there was a difference in the local innovation ($lnpat_{it}$) results. The reason for this difference emerges from the estimation method of the random effects model, which does not affect the interpretation of innovation poles and interaction terms in equations (2) and (3). From the results of (2) and (3), it can be seen that the innovation pole effect ($pole150$) has a significantly positive effect on economic growth, and the "innovation pole * local innovation, innovation pole * local external innovation absorption" is also significantly positive. Meanwhile, we found that there is a certain complementary relationship between the variable coefficients. Although the local innovation ($lnpat_{it}$) in equation (2) is not significant, the innovation pole ($pole150$) effect is 0.004. The sum of the local innovation ($lnpat_{it}$), external innovation absorption (lnh_{it}), and innovation pole ($pole150$) coefficients is exactly 0.018. The equation (3) innovation pole*local innovation ($lnpat_{it} \times pole150$) the coefficient is 0.002, which is a complement for local innovation ($lnpat_{it}$) -0.002. This result provides further insights into the mechanism of effect between local innovation and innovation poles, by explaining the complementary effect between innovation pole cities and local innovation within a certain range.

TABLE 6 Test of the mechanism of innovation pole effect among China's 284 prefecture-level and above cities (2005-2018)

DV= g_{it}	Regression of non-spatial model	Regression of non-spatial model with adding innovation pole variables	Regression of non-spatial model with adding interaction terms
$lnpat_{it}$	0.005(3.80)***	-0.000(-0.17)	-0.002(-3.08)***
lnh_{it}	0.013(2.68)***	0.014(8.81)***	0.022(8.46)***
lny_{it-1}	-0.094(-7.84)***	-0.016(-13.58)***	-0.016(-13.08)***
lnk_{it}	-0.002(-2.64)***	-0.003(-6.46)***	-0.003(-6.27)***
$ln(n+\gamma+\delta)_{it}$	0.040(3.60)***	-0.035(-3.89)***	-0.040(-4.45)***
g_{it-1}	0.373(13.70)***	0.579(48.21)***	0.567(46.65)***
se_{it}	0.117(7.95)***	0.027(6.25)***	0.030(6.86)***

fdi_{it}	0.117(2.99)***	0.153(7.06)***	0.154(7.10)***
pf_{it}	-0.005(-0.53)	-0.037(-7.70)***	-0.037(-7.56)***
$pole150$	-	0.004(3.41)***	0.034(2.81)***
$lnpat_{it} \times pole150$	-	-	0.002(1.73)*
$lnh_{it} \times pole150$	-	-	0.015(2.54)**
Time-fixed	YES	NO	NO
City-fixed	YES	NO	NO
Cons	1.055(8.78)***	0.145(6.66)***	0.146(6.69)***
N	3976	3976	3976
R ²	0.7198	0.6078	0.6122

Note: ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively; the t-values are in parentheses.

4.5: Robustness tests

Innovation pole cities are the most economically developed in the country. Many of these cities are large provincial capital cities (except Shenzhen) or the metropolitan cities (Beijing, Shanghai, Tianjin and Chongqing), which greatly impact regional economic growth, so they may potentially become extreme values in the sample. There are large differences in the impact of coastal and inland locations on cities in economic development. There are clear differences between the inland and coastal cities in terms of economic and technological development, with the latter having a much fewer number and being economically as well as technologically more advanced than the former. The robustness of the regression results can be tested in a number of ways. We can observe the impact of eliminating the extreme values in the samples. Further, we can consider reverse causality and simultaneity and replace the explanatory variables and lagged explanatory variables.

First, the robustness of innovation capability is tested, and the SDM with fixed time and fixed city is used for estimation. Table 7 lists the robustness test results after removing the sample extreme values: (1) removing the innovation pole cities, (2) removing the coastal cities, and (3) removing both the innovation pole and coastal cities.

TABLE 7 Robustness tests: Results of direct, indirect and total effects after removing extreme values of innovation ability among China's 284 prefecture-level and above cities (2005-2018)

DV= g_{it}	IV	Removing the innovation pole cities	Removing the coastal cities	Removing both types of cities
Direct effect	$lnpat_{it}$	0.002(2.16)**	0.003(2.74)***	0.003(2.81)***
	lnh_{it}	0.008(2.47)**	0.012(3.25)***	0.012(3.01)***
Indirect effect	$lnpat_{it}$	0.004(2.27)**	0.005(2.49)**	0.005(2.18)**
	lnh_{it}	0.009(1.30)	0.013(1.71)*	0.013(1.62)
Total effect	$lnpat_{it}$	0.006(3.40)***	0.008(3.94)***	0.008(3.68)***
	lnh_{it}	0.018(2.29)**	0.025(3.01)***	0.024(2.87)***
ρ		0.342(20.52)***	0.327(18.19)***	0.332(18.39)***
sigma2_e		0.000(43.15)***	0.000(39.78)***	0.000(39.15)***
R^2		0.6277	0.6257	0.6228
Log-lik		9511.40	7989.58	7715.98
Time-fixed		YES	YES	YES
City-fixed		YES	YES	YES
Hausman test		253.07***	235.44***	254.38***
Wald spatial lag test		17.64**	23.02***	27.12***
LR spatial lag test		28.44***	30.61***	32.66***
Wald Spatial error test		207.14***	205.33***	200.38***
LR spatial error test		86.62***	81.57***	75.65***

Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively; the t-values are in parentheses.

Table 8 lists the robustness test results of replacing the dependent variable and lagged explanatory variable: (1) The explained variable is replaced, and the logarithm of GDP ($lngdp_{it}$) is chosen as the new variable. (2) Local independent innovation ($lnpat_{it}$) and absorption of external innovation (lnh_{it}) are lagged by one period. It should be noticed that the robustness test in column (2) uses the lag variable. Thus, there is no significance in the Wald spatial lag test. It suggests that at this point, the SDM will degenerate into the spatial lag model (SAR). To get the results of column (3), we further tested column (2) using a spatial lag model.

TABLE 8 Robustness tests: Results of direct, indirect and total effects after replacing variable of the innovation ability among China's 284 prefecture-level and above cities (2005-2018)

DV= g_{it}	IV	Replacing the dependent variable with $lngdp_{it}$	Lagging explanatory variable with $lnpat_{it-1}$ and lnh_{it-1}	Lagging explanatory variable with spatial lag model (SAR)
Direct effect	$lnpat_{it}$ lnh_{it}	0.003(1.17) 0.006(0.70)	0.003(3.05)*** 0.021(6.05)***	0.004(3.79)*** 0.017(5.23)***
Indirect effect	$lnpat_{it}$ lnh_{it}	0.019(3.64)*** 0.016(0.81)	0.004(1.98)** -0.011(-1.41)	0.002(3.82)*** 0.008(5.02)***
Total effect	$lnpat_{it}$ lnh_{it}	0.022(4.01)*** 0.021(0.99)	0.007(3.57)*** 0.010(1.25)	0.005(3.83)*** 0.025(5.22)***
ρ		0.410(25.84)***	0.336(19.82)***	0.336(21.82)***
σ^2_e		0.002(43.96)***	0.000(42.52)***	0.000(42.60)***
R^2		0.987	0.317	0.328
Log-lik		6338.10	9317.84	9302.13
Time-fixed		YES	YES	YES
City-fixed		YES	YES	YES
Hausman test		1295.12***	200.21***	240.19***
Wald spatial lag test		1681.93***	11.17	-
LR spatial lag test		286.88***	31.41***	-
Wald Spatial error test		140.81***	200.52***	-
LR spatial error test		106.12***	89.14***	-

Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively; the t-values are in parentheses.

From the results in Tables 7 and 8, it can be seen that the main explanatory variable test agrees with the previous model estimates, significant spatial effect (ρ), better fitting R^2 , and consistent comparative significance. These findings support Hypothesis 1's inference that both the capacity for local innovation and the capability to absorb external innovation can promote overall economic growth.

The spatial Durbin random effect model is then employed for an estimate as the robustness of the innovation pole effect is examined. Table 9 lists the results of each robustness test: (1) removing the

innovation pole cities; (2) removing the coastal cities; (3) removing both the innovation pole and coastal cities; (4) replacing the explained variable with the logarithm of GDP ($lngdp_{it}$); (5) local independent innovation ($lnpat_{it}$) and absorption of external innovation (lnh_{it}) are lagged by one period. We mainly observe the robustness of the innovation pole effect. The robustness result is acceptable. These results support Hypothesis 2's inference that the existence of a regional innovation pole within a specific range (150 km) can promote urban economic growth in the region.

TABLE 9 Robustness tests: Results of direct, indirect and total effects of the innovation pole effect among China's 284 prefecture-level and above cities (2005-2018)

DV= g_{it}	IV	Removing the innovation pole cities	Removing the coastal cities	Removing both types of cities	Replacing the dependent variable with $lngdp_{it}$	Lagging explanatory variable with $lnpat_{it-1}$ and lnh_{it-1}
Direct effect	$lnpat_{it}$	0.002(2.16)**	0.002(2.44)**	0.002(2.79)***	0.001(1.30)	0.007(3.76)***
	lnh_{it}	0.004(1.68)*	0.005(2.04)**	0.004(1.45)	0.005(2.55)**	0.018(3.16)***
	$pole150$	0.003(1.84)*	0.003(1.43)	0.003(1.46)	0.003(1.91)*	0.003(0.66)
Indirect effect	$lnpat_{it}$	0.002(1.21)	0.002(1.25)	0.001(0.95)	0.001(0.70)	0.002(0.38)
	lnh_{it}	0.012(2.96)***	0.014(2.92)***	0.014(3.00)***	0.009(2.30)**	0.019(1.37)
	$pole150$	0.003(0.80)	0.006(1.24)	0.005(1.17)	0.005(1.28)	0.040(2.85)***
Total effect	$lnpat_{it}$	0.003(2.28)**	0.004(2.42)**	0.004(2.36)**	0.002(1.32)	0.009(1.88)*
	lnh_{it}	0.016(3.91)***	0.019(3.85)***	0.018(3.69)***	0.014(3.74)***	0.037(2.61)***
	$pole150$	0.006(1.58)	0.008(1.96)**	0.008(1.85)*	0.008(2.14)**	0.044(3.09)***
ρ		0.411(26.66)***	0.395(23.53)***	0.395(23.34)***	0.416(26.73)***	0.528(38.52)***
sigma2_e		0.000(39.83)***	0.000(36.75)***	0.001(36.09)***	0.000(39.09)***	0.003(41.51)***
R ²		0.6329	0.6210	0.6197	0.634	0.995
Log-lik		9057.70	7608.20	7345.79	8864.9867	5478.4557
Wald spatial lag		27.68***	25.74***	28.96***	18.97*	1691.27***
Wald Spatial error		219.40***	208.31***	203.84***	209.41***	153.41***

Note: ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively; the t-values are in parentheses.

In summary, there are three sources of urban economic growth paths identified in this study: local

innovation ability, innovation learning ability, and the regional innovation pole. Overall, the latter has a significant and positive contribution to local economic growth and neighboring regions, as well as contributing to overall economic growth through spillovers. Simultaneously, the central role of the regional innovation pole has emerged as a distinct feature. There are innovation pole cities within 150 km of the city that positively affect the urban economic growth of the region. However, it is undeniable that the spillover level of innovation is still low, the regional characteristics of innovation poles do not seem to have become fully evident, and the imbalance of innovation and development within a region is still problematic. Combined with the previous exploration of the urban economic growth path, China's current innovation-driven growth mechanism is not fully mature, and there remain large gaps. Nonetheless, the research findings seem supportive of the view that innovation does offer genuine opportunities for achieving growth potential as a driving force for overall economic growth, although they also imply that much more effort needs to be made by both the central and regional authorities to encourage scientific and innovation activities, especially in the large provincial capitals and the metropolitan cities.

5. CONCLUSIONS

In spite of the fact that some cities in China have successfully crossed the middle-income trap, the number of those cities remains small relative to the large number of cities in the country. As a consequence, the national economy of China still faces the challenge of crossing the middle-income trap. One of the main reasons for this is that China's overall level of innovation is still commensurate with that of a relatively low stage of development. Economically developed cities have reached relatively high economic development and innovation capacity levels. However, this does not

represent the average degree of all cities. Based on a theoretical framework of endogenous economic growth, this study focuses on an economic growth path based on innovation dynamics and regional innovation pole spillovers from an urban spatial linkage perspective. The work offers some broad and fundamental conclusions.

The level of urban innovation in China is uneven, and most cities' innovation capacity is still low. However, innovation seems to be important (potentially even vital) in promoting economic growth for overall development. China's regional innovation poles have emerged gradually. At present, innovation pole cities significantly impact urban economic development within a given region, making it easier for cities to converge to developed cities and promote local economic growth. When there is no regional innovation pole within a certain range around the city, the impetus of urban economic growth mainly comes from exploring and improving local innovation capacity. When a regional innovation pole exists within 150 km of the city, local economic growth can be further boosted by the spillover effect of the regional innovation pole.

From the perspective of China's current economic development, regional innovation poles with spillover effects have been formed during rapid growth, and most cities that crossed the middle-income trap come from these regions. Therefore, several policy implications arise if the country as a whole is to successfully cross the middle-income trap and sustain long-term high-quality economic development: (1) The leading role of cities or city clusters that have become regional innovation poles should be fully utilized to strengthen regional synergy and cooperation. This might help build high-level platforms, to explore multi-channel communication, and to actively promote efficient spillover of innovation achievements and experiences from regional innovation poles to other regions. (2) The government could seek to identify and consciously cultivate some potential cities

or city clusters to become new regional innovation poles. For example, the central government announced its plan to make Wuhan, a large city with a population of over 12 million people in central China, the fifth national science and innovation pole of the country on June 25, 2022. The other four national science and innovation pole cities (city clusters) are the Beijing-Tianjin-Hebei Area, the Changjiang River Delta, the Guangdong-Hong Kong-Macau Greater Bay Area, and the Chengdu-Chongqing Twin-Cities Economic Circle. The northeast region in China arguably also needs to build an innovative city cluster with an advanced international level as a new driving force to revitalize this important old industrial base. (3) The government ought to continue cultivating innovation capacity, especially local independent innovation ability. The econometric evidence presented herein indicates that innovation has noticeable regional differences. There is thus a need to strengthen and expand the existing regional innovation poles and cultivate more new regional innovation poles to better foster innovation in the service of promoting sustainable and high-quality development for the national economy. Ultimately, this distills to giving greater policy attention to supporting basic research and intellectual property protection.

The study results are potentially helpful in explaining regional economic growth, especially the role of innovation and its spatial effects in regional development. Although it is difficult to execute, exploring the specific spatial mechanisms of innovation between cities still requires setting appropriate models for verification in future research. Due to data limitations, future research can define innovative pole cities through multidimensional indicators to identify them. In addition, case studies focusing on specific cities may help identify specific growth mechanisms within cities. This provides some supplementary insights in helping to explain urban economic growth and imbalance in regions.

FOOTNOTES

¹ Source: China Statistical Yearbook 2020.

² Source: The World Bank. <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519>

³ Source: Based on the Per adult GDP index of the WDI database. <https://wid.world/data/>

⁴ Source: Report to the 19th CPC National Congress.

http://www.xinhuanet.com/politics/19cpcnc/2017-10/27/c_1121867529.htm

⁵ We use per capita GDP as the measure of the total output of the national economy. And GDP per capita converted to US\$ according to the World Bank Atlas algorithm. <https://wid.world/data/>

⁶ By cognition we mean a cluster exhibiting some capacity for understanding, learning and comprehending the external environment. It also implies that such clusters have some awareness of their limitations and actively engage in discovering and learning about new technologies.

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