External Knowledge Linkages and the Evolution of Comparative Advantage

An Examination of Territorial Knowledge Dynamics in China

Wang, Tengfei; Halkier, Henrik; James, Laura; Gu, Renxu; Chi, Cheng

Published in:
Sustainability

DOI (link to publication from Publisher):
10.3390/su14084685

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

sustainability

Article

External Knowledge Linkages and the Evolution of Comparative Advantage: An Examination of Territorial Knowledge Dynamics in China

Tengfei Wang [1,2,*], Henrik Halkier [3], Laura James [3], Renxu Gu [1,2,*] and Cheng Chi [4]

[1] The Institute of Urban Development, East China Normal University, Shanghai 200062, China
[2] School of Urban and Regional Science, East China Normal University, Shanghai 200241, China
[3] Department of Culture and Learning, Aalborg University, 9220 Aalborg, Denmark; halkier@ikl.aau.dk (H.H.); leja@ikl.aau.dk (L.J.)
[4] Department of Materials and Production, Aalborg University, 9220 Aalborg, Denmark; cchi@mp.aau.dk
* Correspondence: 52183902003@stu.ecnu.edu.cn (T.W.); rxgu@re.ecnu.edu.cn (R.G.)

Abstract: In the era of the knowledge economy with the superfluidity of information, labor, and goods, the ability to establish external knowledge linkages has become an indispensable asset for the development of regional industries. Based on the assumption that knowledge spillovers decay with distance, several existing studies have explored the role of neighboring regions in local industrial upgrading. Meanwhile, a small but growing literature has explored the evolution of regional comparative advantage from the perspective of multi-location territorial knowledge dynamics (TKDs), exploring multi-locational knowledge interactions (including proximity interactions and distance interactions) and their regional economic effects in the process of knowledge flows. Inspired by the literature on multi-location TKDs, this paper examines two hypotheses: (1) In addition to local capabilities, external knowledge linkages also have a positive effect on local industrial upgrading; (2) the stronger the knowledge linkages, the more similar the regional comparative advantage. Through an analysis of data on authorized patent citation and the two-digit manufacturing industry from Chinese cities in 2011 and 2016, we find that the knowledge flow networks among Chinese cities are characterized by strong external knowledge linkages to both adjacent and distant regions. Further analysis reveals that a particular Chinese city has a higher probability of developing comparative advantages if it maintains strong knowledge linkages with a city specialized in the same industry. In addition, the comparative advantages of regions with strong knowledge linkages are more similar than regions with weak knowledge linkages.

Keywords: regional development; external knowledge linkages; territorial knowledge dynamics; China

Citation: Wang, T.; Halkier, H.; James, L.; Gu, R.; Chi, C. External Knowledge Linkages and the Evolution of Comparative Advantage: An Examination of Territorial Knowledge Dynamics in China. *Sustainability* **2022**, *14*, 4685. https://doi.org/10.3390/su14084685

Academic Editors: Luigi Mastronardi and Luca Romagnoli

Received: 15 March 2022
Accepted: 12 April 2022
Published: 14 April 2022

1. Introduction

In recent years, two streams of research, which are from evolutionary economics and economic geography, have rekindled interest in the evolution of regional industry. Many contributions to the evolutionary economic geography literature emphasize the role of local capabilities based on path dependence theory [1]. In short, the school of evolutionary economic geography believes that regional economic development is a primarily endogenous process. The evolution of regional industries is embedded in the local context and technical capability, and regions tend to develop new industries with strong technical linkages to existing local industries.

Following earlier work [2], recent studies have focused on the impact of neighboring regions on the evolution of local industries [3–5]. Some empirical studies found that when knowledge is disseminated to adjacent regions, it can trigger the evolution of the comparative advantage there [6]. According to Bahar, Hausmann and Hidalgo [3] and

Boschma, Martín and Minondo [4], new knowledge of neighboring countries has an important impact on the development of local industries.

However, with the pervasive development of information technologies and the improvement of transport infrastructure, knowledge flow characterized by multi-location interaction not only occurs between neighboring regions, but also between distant regions [7–12]. Studies of multi-local knowledge flows show that the proximity mechanism based on innovation trajectories and knowledge accumulation has limitations in the era of globalization. Instead, it is argued that the multi-local knowledge interaction mechanism (proximity interaction and distance interaction) is crucial to the evolution of regions and industries. While there are studies of territorial knowledge dynamics in developed European countries, such as Sweden and Germany [7,11], there is, as yet, no literature that explores the evolution of comparative advantage in China specifically from the perspective of territorial knowledge dynamics. China is an interesting case study for a number of reasons. Firstly, it is a developing country with a low technical level, which potentially makes regional economic development more dependent on learning from external knowledge. Secondly, as a country with a large land area and economy, China's interregional economic and knowledge interactions are likely to be extensive. Thirdly, with the market-oriented transformation of the Chinese economy, local governments actively attempt to attract investments to develop new industries that can support the evolution of regional comparative advantage.

The purpose of this paper is to examine whether territorial knowledge dynamics are suitable for application to the evolution of comparative advantage in China. The paper addresses two questions: firstly, whether, in addition to local capabilities, external knowledge linkages play an important role in local industrial upgrading; secondly, whether regions with strong knowledge linkages tend to have a more similar comparative advantage. The article contributes to the literature on TKDs by showing that multi-locational knowledge dynamics have developed in China and that these have a positive impact on regional comparative advantage. This paper also provides a guide to China's regional industrial upgrading policies from a perspective of territorial knowledge dynamics.

This paper measures inter-regional knowledge networks using authorized patent citation data and comparative advantage using the location quotient of two-digit manufacturing industries to explore the above questions. The data presented in this paper show that external knowledge linkages have a positive impact on the evolution of China's regional comparative advantage, and regions with strong knowledge linkages tend to have more similar comparative advantages than regions with weak knowledge linkages. The study's results imply that it is important for policymakers to support the development of links to potentially advantageous industries in distant regions.

The article is structured as follows. Section 2 puts forward two hypotheses based on a literature review on the evolution of comparative advantage. Section 3 introduces the data sources and methods. Section 4 is divided into two parts. In the first part, we describe the characteristics of knowledge linkages between cities in China by using authorized patent citation data in order to test whether external knowledge linkages have an impact on the evolution of regional comparative advantage. The second part investigates whether a particular Chinese city has a greater opportunity for industrial upgrading if it maintains strong knowledge linkages with a city specialized in the same industry. Section 5 presents the conclusions and policy implications of the analysis.

2. Literature Review on the Evolution of Comparative Advantage

Comparative advantage means being able to produce a good or service at a lower opportunity cost than in another region/country. Classical economic theory holds that the labor force is the only factor leading to comparative advantage. In fact, there are structural differences in the endowments of production factors, such as labor, capital, and land, in various countries, and these factors are essential elements consisting of comparative advantages. Rooted in this logic, Ohlin, a scholar representative of the Neoclassical

Trade School, put forward the famous Heckscher–Ohlin theory: A country exports those commodities that can be produced on the basis of factors that are relatively abundant in the country [13]. It should be mentioned that both of the above comparative advantage theories were based on the static assumption that the technical level, returns to scale, and economic structure remained unchanged. With the continuous refinement of the industrial division of labor and the increasing frequency of trade and cooperation between countries and regions, the regional technology level and economic structures have also changed in most places, and, therefore, the above static comparative advantage theory cannot explain the evolving pattern of interregional trade. In order to reveal the increasingly complex regional trade relations, many scholars have tried to analyze the evolution mechanism of regional comparative advantage since the 1960s [9,14–17], and several schools of thought have been identified. Previous research in this area can be divided into four schools of thought, as illustrated by Table 1.

Table 1. Comparison of schools in the evolution of regional comparative advantage.

Schools	Core View	Scales	Scholars
Endogenous Growth School	Technological progress is the core factor affecting comparative advantage.	Local scale	Arrow, K.
Evolutionary Economic Geography School	The local capability formed by the interaction between the institution and local knowledge base determines the evolution of comparative advantage.	Local scale and Neighbor regions	Boschma, R.
Relational Economics Geography School	The level and function of local participation in global production and innovation networks have become the core elements of the evolution of comparative advantage.	Local and global scale (buzz/pipeline model)	Bathelt, H.
Territorial Knowledge Dynamics School	Local capability and external knowledge networks jointly affect the evolution of regional comparative advantage, and they pay attention to multi-scale knowledge networks and knowledge combinations.	Multi-scalar (including local, adjacent, and distant regional networks)	Crevoisier, O. Jeannerat, H. Asheim, B. James, L.

In the early 1960s, the endogenous growth school explained the evolution mechanism of regional comparative advantage from a dynamic perspective around local knowledge spillovers. Arrow first put forward the learning-by-doing concept and insisted that technological progress and productivity improvement can be achieved by accumulating experience in the production process [14]. According to Zhu, et al. [15], the knowledge accumulation generated by learning by doing is the key factor in the evolution of industrial structure.

In contrast to this, evolutionary economic geography scholars have used path dependence as the core concept when attempting to explain the evolution of regional comparative advantage. They believe that the product space is heterogeneous and discrete, and once new products exceed the cognitive scope of entrepreneurs, product upgrading is difficult to achieve. In other words, the evolution of regional comparative advantage does not occur randomly, but depends on the existing local capabilities [1,17]. According to Rodríguez-Pose [18], local capabilities are the result of long-term interactions between the local knowledge base and local institutions. These 'localized capabilities' enable regions to get tacit knowledge, providing unimitated comparative advantage. In fact, as an important source of technological and industrial diversification, local capabilities also have a positive impact on industrial specialization. Evolutionary economic geographers have produced a rich discussion of regional diversification around the concept of 'related variety'. For example, Neffke first systematically studied the diversity evolution path of regional 'industrial space' by analyzing the characteristics of the Swedish economic evolution from 1969 to 2002, where he found that the evolution process of this industry was significantly affected by path dependence, i.e., that new technologies or industries came from the reorganization of local related technology and industries [19]. Similar evidence can also be found in different countries or regions, such as the United States [20], Europe [21], and China [22–24].

Most of the evolutionary economic geography literature explores innovation mechanisms based on the hypothesis that agents search for the knowledge source of their innovation from local networks. However, to some extent, this perspective limits our understanding of the spatial flow of knowledge. To avoid economic lock-in, regional agents need to establish external linkages and learn non-local knowledge. In order to reveal the process of knowledge creation and regional development more thoroughly, the relational economic geography school emphasizes both local and global knowledge flows to and from industrial clusters. Some authors argue that enterprises in regional clusters need to learn knowledge from other places and consciously establish a pipeline connecting to global knowledge sources in order to maintain regional vitality, often referred to as the "local buzz and global pipelines" model [16].

However, the buzz and pipeline model has been questioned and criticized by a growing number of scholars. Asheim argued that local buzz does not fully show the meaning of face-to-face communication and acknowledged the differences among synthetic, analytical, and symbolic knowledge [25]. Moodysson applied the buzz and pipelines to life science communities in Sweden and found that the most mobile knowledge creation occurred in the global professional knowledge networks [26]. Crevoisier and Jeannerat [9], like Moodysson [26], argued that the local buzz and global pipeline model is oversimplified, and an alternative model, dubbed territorial knowledge dynamics, was put forward by the authors. The term is defined as the changes in the patterns of knowledge flows that include both intraregional and interregional linkages. TKDs study the effect of social and technological development on knowledge interaction and regional innovation, emphasizing the combined dynamics of multi-location milieus of new knowledge creation. Crevoisier and Jeannerat distinguished four regional development models based on the strength of proximity and distance interactions of knowledge [9]. Among them, traditional innovative milieus are rich in local interactions, but poor in distance interactions, while multi-location TKDs are rich in both. Networks of distant TKDs are rich in distance interactions but poor in local interactions, while constellations of independent entities are rich in both.

The existing literature has mainly used models of TKDs to explain the new path creation mechanisms in European countries, including in the Swedish automobile industry, innovation processes in Germany, and electronics [7,11]. For example, by analyzing the innovation and development process of the Swedish automobile industry, James, et al. found that non-local knowledge relationships are very important for anchoring new knowledge [11]. Moreover, they also asserted that enterprises' advanced-stage innovation generally needs multi-location interactions of knowledge. Dahlström, Olsen and Halkier argued that regardless of which type of region a firm is located in, firms depend on knowledge interactions crossing the regional boundaries [27]. Olsen, like Dahlström, et al. [27], suggested that the knowledge combination, the external linkages, and the producer and consumer networks are the three core elements of models of TKDs and emphasized the important role of establishing external relations in regional innovation [28]. Other schools within regional innovation have made a similar argument to that of Crevoisier and others. For example, Isaksen and Trippl found that the new synthetic and analytical knowledge of external regions played a key role in the industrial upgrading of Norway and Austria [29]. Inspired by the above studies, some authors acknowledged the importance of non-local knowledge for new path creation and argued that complex technology innovation depends more on external knowledge linkages [30]. Bahar and Rapoport suggested that migration promotes the development of national comparative advantage by increasing the flow of knowledge [31]. In a similar line, Fan, Li and Pan [32] argued that the international knowledge diffusion generated by FDI plays a positive role in the evolution of comparative advantage.

It is obvious that models of TKDs are not as widespread as the literature related to local capacity. Moreover, the existing literature mainly focuses on case studies of European countries and it lacks empirical research evidence from other continents. However, its great strength is that it allows for different combinations of proximity and distance relations. Based on prior evidence that regional and extra-regional networks have a positive impact on industrial development and that the interactions of local and non-local knowledge promote regional innovation, we predict two effects of external knowledge linkages on the evolution of regional comparative advantage:

Hypothesis 1. *In addition to local networks, external knowledge linkages also have an important effect on local industrial upgrading, and the stronger the knowledge linkages, the greater the effect.*

Hypothesis 2. *Regions with strong knowledge linkages also tend to have more similar comparative advantages.*

3. Methods and Data Sources

3.1. Research Methods

This paper investigates TKDs in China, a country that has witnessed a number of economic reforms since the 1980s. In the process of economic transformation, economic liberalization has promoted interregional labor mobility, industrial linkages, and R&D cooperation to a great extent [33,34]. More specifically, plenty of cities, especially in the central and coastal regions, have upgraded and diversified local industries as part of the economic transformation [35,36]. Recent research shows that a significant characteristic of China's industrial diversity is path dependence [23]. In addition, some of the literature shows that external regional linkages combined with internal innovation may be conducive to the creation of new paths for China's industrial upgrading [22]. In the same vein, some authors argue that the rapid development of the Chinese economy is the result of collective learning between industries and regions (neighboring regions) [37]. In addition to geographical distance, cultural differences and institutional distance have a significant impact on the evolution of China's regional comparative advantage by affecting the location of knowledge flow [6]. However, less attention has been paid to the impact of multi-locational knowledge learning (including proximity and distance learning) on the evolution of China's regional comparative advantage.

The essence of the evolution of regional comparative advantage is industrial development. According to the product space theory, a product is the carrier of the knowledge and ability of a country or region, which comprehensively reflects the factor endowment information of the economy and all of the production conditions, including the organization mode and social system required for product production [17]. Therefore, we believe that comparative industrial advantage can effectively represent a regional comparative advantage. Following Bahar, Hausmann and Hidalgo [3] and Hidalgo, et al. [17], regional comparative advantage is obtained through the following expression:

$$LQ_{c,i}^{t} = \frac{V_{c,i}^{t} / \sum_i V_{c,i}^{t}}{N_i^{t} / \sum_i N_i^{t}} \tag{1}$$

where $LQ_{c,i}^{t}$ is the location quotient of city c in industry i at time t. $V_{c,i}^{t}$ is the gross industrial output value of city c in industry i at time t. N_i^{t} is the national gross industrial output value in industry i at time t.

According to relevant studies on the development of new industries [3,4], we use the change in the industrial location quotient to measure the evolution of regional comparative advantage. Some scholars have used the spatial economics approach to analyze the effect of geographical distance on interregional and inter-industry knowledge spillovers [2]. Spatial econometric models are suitable for exploring issues in which the dependent variable is continuous. However, the dependent variable (regional industrial upgrading or no upgrading) is a binary variable in this paper. Therefore, we use a discrete-choice model to explore the role of external knowledge linkages in the evolution of comparative advantage. We frame the following regression:

$$\begin{gathered} U_{c,i,t+5} = \alpha + \beta_1 \ln LLQ_{nc,i,t} + \beta_2 \ln density_{c,i,t} + \beta_3 \ln import_{c,i,t} + \beta_4 \ln fdi_{c,i,t} + \\ \beta_5 \ln output_{c,i,t} + \beta_6 \ln share_{c,i,t} + \beta_7 \ln profit_{c,i,t} + \beta_8 policy_{c,i,t} + \\ \varepsilon_{c,i,t} \end{gathered} \tag{2}$$

$U_{c,i,t+5}$ is a binary variable indicating whether a Chinese city c develops the industry i from time t to time t+5. The value of $U_{c,i,t+5}$ is set to 1 if the city c develops the industry i, and it is set to 0 otherwise. Following Boschma, Martín and Minondo [4], if the *LQ* (location quotient) of an industry is greater than 1, this means that the city has developed a comparative advantage in that industry. We set a strict condition for upgrading and evolution of comparative advantage: This paper assumes that the new industry i is upgraded if the value of *LQ* of industry i at time t is below 0.1, and the value of the *LQ* of that industry at time t+5 is greater than 1. In fact, the development of new industries and the further upgrading of local existing specialized industries represent the evolution of comparative advantage. Therefore, to avoid condition settings for the development of local industries that are too strict, we also set a loose condition for industrial comparative advantage upgrading: This paper holds that a new industry i is upgraded if the value of the *LQ* of industry i at time t is below 0.5, and the value of the *LQ* of that industry at time t+5 is greater than 1, or, alternatively, if the *LQ* of an industry in the city is greater than one at time t, and the added value of the *LQ* is greater than one at time t+5.

Hypothesis 1 makes predictions about the effects of external knowledge linkages on local industry upgrading. Following Boschma, Martín and Minondo [4], we consider that the higher the comparative advantage of a city in a particular industry is, the higher the probability will be that the city where it has a strong knowledge linkage with the former city will develop a comparative advantage in that industry in the future. To test Hypothesis 1, the variable that we focus on is $\ln LLQ_{nc,i,t}$, the natural logarithm of $LLQ_{nc,i,t}$. $LLQ_{nc,i,t}$ denotes the revealed comparative advantage of industry i in city nc with a strong knowledge linkage with city c at time t (note: According to the natural classification results of the number of patent citations in Chinese cities, the cities in the lowest level are weak knowledge-linked cities, and the other levels are strong knowledge-linked cities). $LLQ_{nc,i,t}$ can be measured as the value of the largest *LQ* in industry i among all cities with a strong knowledge linkage with city c. This paper replaces the variable $\ln LLQ_{nc,i,t}$ with a binary variable $BLLQ_{nc,i,t}$ to analyze the robustness of the estimation results. The value of $BLLQ_{nc,i,t}$ is set to 1 if the largest *LQ* of city nc with strong knowledge linkages with city c is higher than 1, and zero otherwise.

The $density_{c,i,t}$ indicates the product density of industry i in city c at time t. Product density denotes the local knowledge networks of a particular industry and can reflect the capabilities of a city developing this industry. According to Hidalgo, et al. [17], the density indicator is measured through the following expression:

$$density_{c,i,t} = \frac{\sum_j \varnothing_{i,j,t} x_{c,j,t}}{\sum_j \varnothing_{i,j,t}} \tag{3}$$

where $x_{c,j,t}$ is given 1 if city c has a comparative advantage in industry j and 0 otherwise, and $\varnothing_{i,j,t}$ is the industrial closeness value between i and j measured as:

$$\varnothing_{i,j,t} = \min\{P(LQ_{i,t}|LQ_{j,t}), P(LQ_{j,t}|LQ_{i,t})\} \tag{4}$$

where $P(LQ_{i,t}|LQ_{j,t})$ is a variable that measures the probability of comparative advantage in industry i once the city is specialized in industry j. $P(LQ_{j,t}|LQ_{i,t})$ is similar to $P(LQ_{i,t}|LQ_{j,t})$. If a Chinese city has a specialized industry (comparative advantage) in all industries relevant to industry i, the value of *density* will be given 1. In contrast, if a Chinese city does not specialize in any industries linked to industry i, the value of *density* will be given 0.

Because the regional industry development is affected by many factors, it is necessary to control other variables. According to Bahar, Hausmann and Hidalgo [3] and Boschma, Martín and Minondo [4], as well as Miguelez and Moreno [5], we consider the following control variables: the natural logarithm of the *import*, *fdi* (foreign direct investment), industry *share*, industry *output*, and industry *profit*. The *policy* variable takes the value of 1 if a city supports the development of industry i in the 'Outline of the 12th Five Year Plan for National Economic and Social Development' or zero otherwise.

Expression (2) is estimated with a linear probability model. The reason behind this is that it can report the odds ratio, which provides a better explanation of the economic implications of the regression results. In order to get rid of this heteroscedasticity inherent to this model, we report clustered standard errors at the city level.

More knowledge can be shared among regions under the condition of strong knowledge linkages. Therefore, we expect that the regions with strong knowledge linkages have a more similar comparative advantage (Hypothesis 2). To test Hypothesis 2, based on Boschma, Martín and Minondo [4], we measured the comparative advantage similarity index, as shown in the following:

$$similarity^t_{c,c'} = \frac{\sum_i \left(h^t_{c,i} - \overline{h^t_c}\right) \sum_i \left(h^t_{c',i} - \overline{h^t_{c'}}\right)}{\sqrt{\sum_i \left(h^t_{c,i} - \overline{h^t_c}\right)^2 \sum_i \left(h^t_{c',i} - \overline{h^t_{c'}}\right)^2}} \quad (5)$$

where $h^t_{c,i}$ is the natural logarithm of the LQ of city c in an industry i at time t and $\overline{h^t_c}$ is the mean of $h^t_{c,i}$ overall industries in city c at time t. It should be mentioned that $h^t_{c,i}$ is the natural logarithm of LQ + 0.1. The LQ is accounted for in a natural logarithm to avoid the covariance bias that is brought by a very large LQ. The 0.1 fraction is given when it comes to industries whose LQ is 0. If the similarity index is more than 0, it means that the city c and another city c' have comparative advantages in similar industries. On the contrary, once the value is less than 0, it represents that neither of the cities have comparative advantages in different industries.

3.2. Sources of Data and Descriptive Statistics

Following Lee and Kim [38], we use the citation data of Chinese authorized patents to measure the knowledge flow between cities and represent the knowledge flow intensity with the total number of patent citations between cities. Since the Chinese patent examination process (from application to authorization) takes four years, the latest and complete Chinese authorized patent data have been updated to 2017. Meanwhile, considering that the Chinese government formulates a national socioeconomic development plan every five years, we determine the research period of this study as 2011 and 2016. Chinese authorized patent data in 2011 and 2016 were obtained from the global patent database (https://www.incopat.com/ (accessed on 5 March 2020)). Because knowledge-intensive industries depend on advanced and complex scientific and technological knowledge, the patent data of such industries are a suitable measure of knowledge flow. According to the statistical classification of intellectual property (patent) intensive industries, this study examines the authorized patent data of four knowledge-intensive industries: the pharmaceutical manufacturing industry, new equipment manufacturing industry, information technology manufacturing industry, and information and communication technology service industry. In 2011 and 2016, the numbers of authorized patents in those four knowledge-intensive industries were 35,757 and 59,118, respectively.

As the regional comparative advantage is usually measured with the industrial location quotient, considering the industrial types of patent data and the differences in the technical complexity of manufacturing industries, we selected 15 two-digit high-tech manufacturing industries (including the medicine manufacturing industry, the automobile, railway, ship, aerospace, and other transport equipment manufacturing industry, the communication equipment, computer, and other electronic equipment manufacturing industry, and 12 other high-tech manufacturing industries, including the industry for the smelting and pressing of ferrous metals, the industry for the smelting and pressing of nonferrous metals, the general-purpose machinery manufacturing industry, etc.). The data on the gross industrial output value, share, profit in corresponding industries and imports, and foreign direct investment are from the Chinese City Statistical Yearbook for the years 2012 (2011 data) and 2017 (2016 data). Data on the industry policy are from the Five-Year Planning Outline.

Table 2 provides a statistical description of the data used in the empirical part of this study. Column (5) (Mean) shows that the average value of *U_loose* is almost twice that of *U_strict*, which shows that the number of existing industries upgraded is almost equal to the number of new industries developed in the region during the study period (from 2011 to 2016). The average value of the independent variable (ln*LLQ*) that we are interested in is positive, indicating that the average value of the *LLQ* of a strong knowledge-linked city is greater than 1. That is, on the whole, strong knowledge-linked cities can provide specialized knowledge for local industrial upgrading.

Table 2. Descriptive statistics for data used in the comparative advantage evolution analysis.

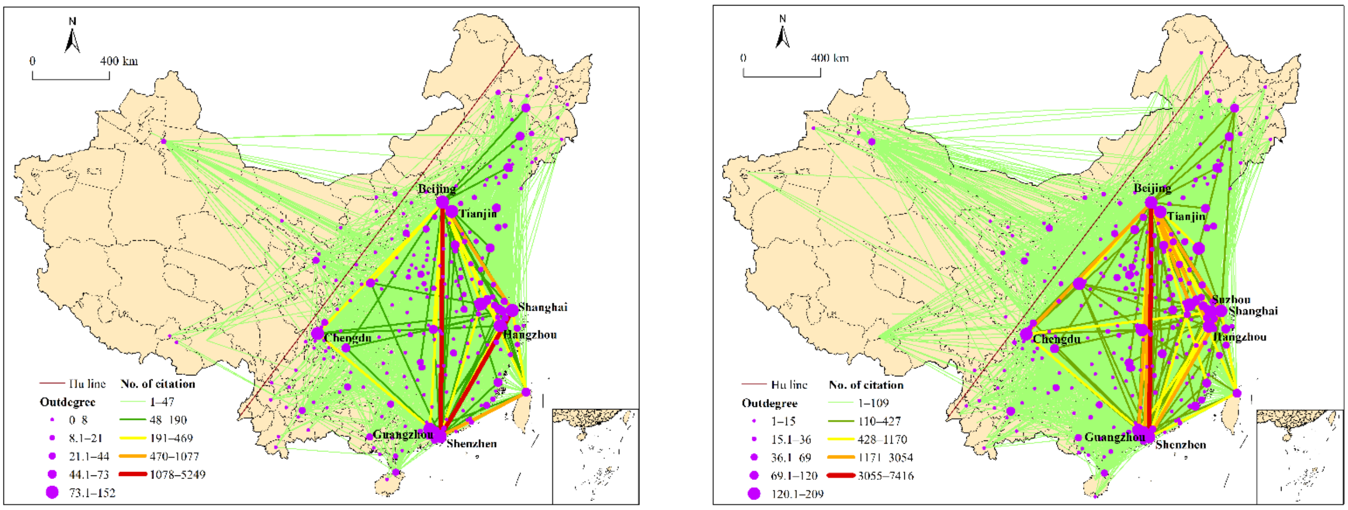
Variable	Max	Min	Median	Mean	Std. Dev.
U_strict	1	0	0	0.0171	0.1296
U_loose	1	0	0	0.0341	0.1816
lnLLQ	2.1793	−3.9606	0.4509	0.3906	0.8735
BLLQ	1	0	1	0.7519	0.4322
lndensity	−0.1655	−2.9178	−0.7857	−0.8667	0.4306
lnimport	9.7892	2.9164	6.1679	6.3341	1.5996
lnfdi	6.6324	−0.4018	4.8655	4.7056	1.2820
lnoutput	9.2745	−14.5087	5.1901	4.8027	2.4302
lnshare	−0.4039	−22.7512	−3.6072	−3.9933	2.2097
lnprofit	6.5274	−5.2983	2.4587	2.0755	2.0201
policy	1	0	0	0.2760	0.4473

Note: All independent variables are measured at time *t*.

4. Analysis of the Results

4.1. Multi-Location Characteristics of Knowledge Flow Networks of Cities in China

In order to analyze the characteristics of the knowledge flow networks of cities in China, we used the ArcGIS 10.2 software to map the geographical location of knowledge flow with authorized patent citations. Figure 1 shows the knowledge flow networks of cities in China in 2011 and 2016. From 2011 to 2016, the number of cities with a patent citation relationship and the number of patent citations between cities increased. In terms of knowledge linkages among central Chinese cities, the knowledge citations between Beijing and Chengdu, Beijing and Shenzhen, Beijing and Guangzhou, Beijing and Suzhou, and Beijing and Hangzhou increased significantly, while the citations between Shanghai and Shenzhen and between Shenzhen and Taiwan decreased. The reason for the decline of knowledge citations among some cities may be that China's reform and opening-up policy led some Taiwan-funded and foreign-funded enterprises to set up factories and carry out industrial cooperation in China's southeast coastal cities (Shenzhen, Guangzhou, Dongguan, etc.) from the 1990s to the early 21st century. After 2006, with the further liberalization of the Chinese economy, the investment focus of Taiwan-funded and foreign-funded enterprises began to shift to the central cities in northern and western China (Beijing, Chengdu, Xi'an, etc.), and industrial and innovation cooperation were carried out. At the spatial level, there were obvious differences in knowledge flow networks on both sides of China's "Hu line" (note: The Hu line, also known as the Aihui Tengchong line, is a geographical dividing line of China's population proposed by Hu Huanyong in 1935; the population on the east side of this line is significantly bigger than that on the west side). The regional knowledge networks on the east side of the line were significantly denser than those in the west, and the eastern regional knowledge networks roughly formed a diamond structure with Beijing, Shanghai, Shenzhen, and Chengdu as the apexes. More importantly, strong knowledge linkages existed not only between neighbor cities (such as Beijing–Tianjin, Guangzhou–Shenzhen, and Shanghai–Suzhou), but also between distant cities (such as Beijing–Shenzhen, Beijing–Shanghai, Shanghai–Shenzhen, and Shenzhen–Hangzhou). Chinese knowledge flow networks resemble multi-location interactions. In other words, the evolution mechanism of China's regional comparative advantage is driven by the knowledge flow networks to a certain extent. To test Hypothesis 1, we investigate whether a city tends to develop industries (including new industries and existing specialized industries) in which its strong knowledge-linked cities are also specialized in the next section.



(**a**) (**b**)

Figure 1. The knowledge flow networks of cities in China ((**a**) the knowledge flow networks in 2011; (**b**) the knowledge flow networks in 2016).

4.2. *External Knowledge Linkages and the Evolution of the Comparative Advantage of Chinese Cities*

To test Hypothesis 1, we used regression 2 to analyze the role of external knowledge linkages in the evolution of regional comparative advantage in China. Column (2) in Table 3 provides the baseline regression results under strict promotion conditions. In order to explain the regression results, we report the odds ratio rather than the coefficient. Column (2) shows that the odds ratio for ln*LLQ* is 1.7168 and statistically significant, which shows that the probability of industry development in strong knowledge-related cities is 5.5667([EXP(1.7168)]) times higher than that in weak knowledge-related cities. In addition, the odds ratio of *policy* is 3.5829, indicating that the development probability of new industries with industrial policy support is 3.5829 times that without industrial policy. However, the results of ln*density* and other control variables are not statistically significant. In order to determine the robustness of the regression results under strict upgrading conditions, we set ln*LLQ* as a binary variable (*BLLQ*) and then estimated the model. The column (3) shows that the results of ln*density* and other control variables are still not statistically significant. One possible explanation is that it is difficult for new industries with industrial bases in cities that are too weak to achieve specialization quickly.

In other words, after five years of development (from 2011 to 2016), only a small proportion of industries in a city with an initial *LQ* less than 0.1 achieved an *LQ* greater than 1.

Table 3. Results of the dynamic analysis of comparative advantage of Chinese cities.

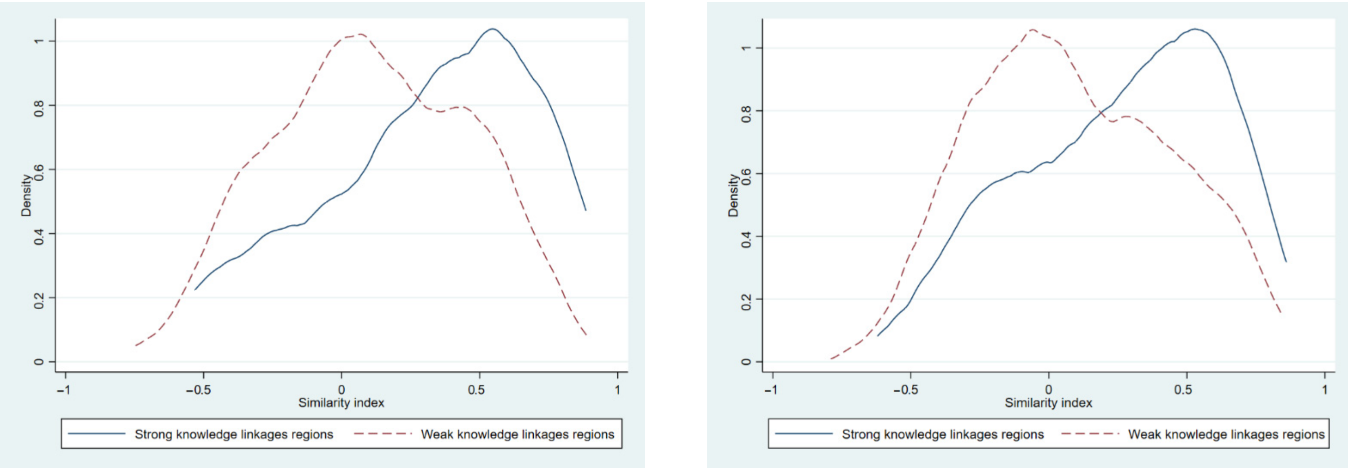
Variable	Strict Upgrading Condition		Loose Upgrading Condition	
	Baseline Model	**Robustness**	**Baseline Model**	**Robustness**
lnLLQ	1.7168 ** (0.4676)		1.9820 *** (0.4468)	
BLLQ		3.3106 * (2.3540)		2.2542 ** (1.0103)
lndensity	0.4936 (0.2233)	0.5013 (0.2329)	0.1948 *** (0.1070)	0.2096 *** (0.1130)
lnimport	0.2770 (0.0925)	0.2999 *** (0.0950)	0.2804 *** (0.0988)	0.3094 *** (0.1033)
lnfdi	1.2512 (0.5600)	1.2652 (0.5574)	1.3883 (0.3418)	1.4249 (0.3372)
lnoutput	1.3640 (1.1841)	1.2495 (1.0455)	2.1260 (1.0669)	1.8407 (0.8686)
lnshare	0.5558 (0.4927)	0.6028 (0.5247)	0.3776 * (0.1901)	0.4387 * (0.2147)
lnprofit	1.3166 (0.3357)	1.3775 (0.3247)	1.2110 (0.3189)	1.2731 (0.3042)
policy	3.5829 * (2.5198)	3.7373 * (2.5786)	3.5706 ** (2.0069)	3.8771 ** (2.1271)
Constant	0.0179 (0.0944)	0.0107 (0.0590)	0.0003 *** (0.0009)	0.0004 ** (0.0013)
Pseudo R^2	0.2857	0.2763	0.3136	0.2887
Observations	645	645	645	645

Note: (1) The dependent variable (*U*) of the baseline model is continuous value; (2) the dependent variable (*U*) of the robustness analysis is a 0—1 binary variable; (3) all models are fitted with clustered standard errors at the city level shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To solve the problem that the upgrading conditions of new industries are too strict, we estimated the model under loose upgrading conditions. Column (4) shows that the odds ratio for ln*LLQ* is 1.982 and statistically significant, which shows that the probability of industrial development (including the development of new industries and existing specialized industries) in strong knowledge-related cities is 7.2572([EXP(1.982)]) times higher than that in weak knowledge-related cities. In addition, the results of ln*density* and other control variables (ln*import*, *policy*) are also statistically significant and positive, which shows that local capacities, import level, and industrial policy have a positive impact on the evolution of regional comparative advantage. In short, the baseline regression results under the condition of loose upgrading verify the main conclusions of this study. The evolution of a regional comparative advantage depends not only on the support of local capacities, but also on the comparative advantage of cities with strong knowledge linkages. In other words, a city develops industries in which its strong knowledge-linked cities are specialized. Column (5) verifies the robustness of the above conclusions. This finding that external knowledge linkages play an important role in local industrial upgrading leads us to conclude that Hypothesis 1 is supported by our data. In addition, the empirical results show that the industrial policy has a strong and positive impact on the development of industries of cities in China. The reason is that with regional decentralization, local governments play a key role in resource allocation in the processes of the development of cities in China.

4.3. Comparison of the Similarity of the Comparative Advantage of Cities in China

To compare the similarity of the comparative advantage among cities with different knowledge linkage strengths, we take the lowest of the five levels of patent citation in the legend in Figure 1 as the weak knowledge-linked cities, and the other citation levels are strong knowledge-linked cities. Then, the similarity of the comparative advantage between strong knowledge-related cities and weak knowledge-related cities in 2011 and 2016 is compared with the density function. Clearly, Figure 2 shows that the density function curve (solid blue line) of strong knowledge-linked cities is to the right of the curve (dotted red line) of weak knowledge-linked cities in 2011 and 2016. The result of the regional comparative advantage similarity comparison shows that the regions with strong knowledge linkages have a more similar comparative advantage than the regions with weak knowledge linkages. This result shows that Hypothesis 2 is also supported by our data.



(**a**) (**b**)

Figure 2. Comparison of the similarity of comparative advantages of Chinese cities: strong knowledge linkages vs. weak knowledge linkages ((**a**) the similarity index in 2011; (**b**) the similarity index in 2016).

5. Conclusions and Discussion

5.1. Conclusions and Policy Implications

Based on the data of Chinese authorized patent citations and two-digit manufacturing industries in 2011 and 2016, we found that strong knowledge linkages exist not only between neighboring cities, but also between distant cities in China, a finding that is in line with the multi-location knowledge flows entailed in multi-location TKDs. In relation to Hypothesis 1, the results showed that both local capabilities and external knowledge linkages play a positive role in local industrial upgrading, and the stronger the external knowledge linkages, the greater their role in industrial upgrading. In addition, by comparing the comparative advantage similarity index of regions with strong/weak knowledge linkages, we found that those regions with strong knowledge linkages also tend to have more similar comparative advantages than those with weak knowledge linkages, which provides evidence for Hypothesis 2. Thus, we can conclude that multi-locational knowledge dynamics have developed in China and that these have a positive impact on regional comparative advantage. The perspective of TKDs is, therefore, a useful way to theorize knowledge dynamics in this context and also has important policy implications.

Firstly, policymakers should be skeptical about only focusing on proximity learning and should also support distant knowledge linkages in order to achieve more efficient knowledge interaction and learning. More specifically, policymakers should try to encourage industrial and innovation cooperation between a particular region and other regions (including adjacent and distant regions) with which it has strong knowledge linkages. Secondly, the positive effect of external knowledge linkages on the development of comparative advantage implies that policymakers should strengthen collective learning among regions and promote industrial upgrading through regional integration strategies. Thirdly, as the empirical results show that the local capability variable also has a positive impact on the evolution of regional comparative advantage, policymakers should develop comparative advantages based on existing local industries and technology bases, rather than developing industries that are not related to local knowledge bases. In sum, policymakers should consider broadening their geographical horizons with regard to regional development because of the increasing mobility of information, labor, capital, and technology, as well as the importance of combining local and non-local knowledge.

5.2. Limitations and Future Research

In line with previous studies, this study also has some limitations. Firstly, our study attempts to use authorized patent citation data to measure Chinese knowledge flow networks, which may have some limitations. For example, the knowledge networks in China that we describe mainly reflect the flow characteristics of synthetic and analytical knowledge, ignoring the flow of symbolic knowledge. Future research should also include other knowledge flow data (such as academic paper citations, labor flows, or trade data) to measure the characteristics of China's regional knowledge flow networks. Secondly, our research paid less attention to the knowledge linkages between China and other countries. In fact, some Chinese cities are actively learning technologies from foreign cities in order to develop industries. Therefore, future research should expand the geographic scope of the research. Thirdly, the contextual factors should also be further explored. For instance, it should be determined whether different industries, especially low-tech and high-tech industries, have the same degree of dependence on external knowledge linkages. From this perspective, it will be of great significance to continue to refine the industry classification and investigate what kind of industry has a stronger interaction between regions with strong knowledge linkages. Finally, as a result of the outbreak of the COVID-19 pandemic, China's import and export trade volumes have decreased significantly since January 2020, particularly in the processing and manufacturing industries and the transportation industry. The COVID-19 pandemic has also caused dramatic changes in trade relations between China and its major foreign trading partners. China's foreign trade growth is mainly in export trade with ASEAN and other countries along the "Belt and Road", while import and export trade with countries and regions such as the United States, the European Union, and Japan has declined significantly. Future research should explore the impact of comparative advantage on the commodity structure and trade geography of China's foreign trade in the post-pandemic situation.

Author Contributions: Conceptualization, T.W., H.H. and L.J.; methodology, T.W.; software, T.W.; validation, T.W.; investigation, T.W.; resources, T.W.; data curation, T.W.; writing—original draft preparation, T.W.; writing—review and editing, H.H., L.J. and C.C.; visualization, T.W.; supervision, R.G., H.H. and L.J.; project administration, R.G. and T.W.; funding acquisition, R.G. and T.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by "The Program of Future Scientists and Outstanding Scholars of East China Normal University" (WLKXJ202009).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used to support the findings of this study are available from the corresponding author upon request.

Acknowledgments: Thanks to everyone who contributed to this paper. We would also like to thank the reviewers for their valuable comments.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Boschma, R.; Frenken, K. Evolutionary economic geography. In *The New Oxford Handbook of Economic Geography*, 2nd ed.; Clark, G.L., Feldman, M.P., Gertler, M.S., Wójcik, D., Eds.; Oxford University Press: Oxford, UK, 2018; pp. 213–229.
2. Autant-Bernard, C.; LeSage, J.P. Quantifying knowledge spillovers using spatial econometric models. *J. Reg. Sci.* **2011**, *51*, 471–496. [CrossRef]
3. Bahar, D.; Hausmann, R.; Hidalgo, C.A. Neighbors and the evolution of the comparative advantage of nations: Evidence of international knowledge diffusion? *J. Int. Econ.* **2014**, *92*, 111–123. [CrossRef]
4. Boschma, R.; Martín, V.; Minondo, A. Neighbour regions as the source of new industries. *Pap. Reg. Sci.* **2017**, *96*, 227–245. [CrossRef]
5. Miguelez, E.; Moreno, R. Relatedness, external linkages and regional innovation in Europe. *Reg. Stud.* **2018**, *52*, 688–701. [CrossRef]
6. Mao, Q.; Mao, X. Cultural barriers, institutional distance, and spatial spillovers: Evidence from regional industrial evolution in China. *Growth Chang.* **2021**, *52*, 1440–1481. [CrossRef]
7. Butzin, A.; Widmaier, B. Exploring territorial knowledge dynamics through innovation biographies. *Reg. Stud.* **2016**, *50*, 220–232. [CrossRef]
8. Crespo, J.; Vicente, J. Proximity and distance in knowledge relationships: From micro to structural considerations based on territorial knowledge dynamics (TKDs). *Reg. Stud.* **2016**, *50*, 202–219. [CrossRef]
9. Crevoisier, O.; Jeannerat, H. Territorial knowledge dynamics: From the proximity paradigm to multi-location milieus. *Eur. Plan. Stud.* **2009**, *17*, 1223–1241. [CrossRef]
10. Halkier, H.; James, L.; Dahlström, M.; Manniche, J. Knowledge dynamics, regions and public policy. *Eur. Plan. Stud.* **2012**, *20*, 1759–1766. [CrossRef]
11. James, L.; Vissers, G.; Larsson, A.; Dahlström, M. Territorial knowledge dynamics and knowledge anchoring through localized networks: The automotive sector in Västra Götaland. *Reg. Stud.* **2016**, *50*, 233–244. [CrossRef]
12. Jeannerat, H.; Crevoisier, O. From 'territorial innovation models' to 'territorial knowledge dynamics': On the learning value of a new concept in regional studies. *Reg. Stud.* **2016**, *50*, 185–188. [CrossRef]
13. Ohlin, B.G. *Interregional and International Trade*; Harvard University Press: Cambridge, MA, USA, 1933.
14. Arrow, K.J. The economic implications of learning by doing. *Rev. Econ. Stud.* **1962**, *29*, 155–173. [CrossRef]
15. Zhu, W.; Zhu, Y.; Lin, H.; Yu, Y. Technology progress bias, industrial structure adjustment, and regional industrial economic growth motivation—Research on regional industrial transformation and upgrading based on the effect of learning by doing. *Technol. Forecast. Soc. Chang.* **2021**, *170*, 120928. [CrossRef]
16. Bathelt, H.; Malmberg, A.; Maskell, P. Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Prog. Hum. Geogr.* **2004**, *28*, 31–56. [CrossRef]
17. Hidalgo, C.A.; Klinger, B.; Barabási, A.-L.; Hausmann, R. The product space conditions the development of nations. *Science* **2007**, *317*, 482–487. [CrossRef]
18. Rodríguez-Pose, A. Institutions and the fortunes of territories. *Reg. Sci. Policy Pract.* **2020**, *12*, 371–386. [CrossRef]
19. Neffke, F.; Henning, M.; Boschma, R. How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Econ. Geogr.* **2011**, *87*, 237–265. [CrossRef]
20. Essletzbichler, J. Relatedness, industrial branching and technological cohesion in US metropolitan areas. *Reg. Stud.* **2015**, *49*, 752–766. [CrossRef]
21. Kogler, D.F.; Essletzbichler, J.; Rigby, D.L. The evolution of specialization in the EU15 knowledge space. *J. Econ. Geogr.* **2017**, *17*, 345–373. [CrossRef]
22. Zhu, S.; He, C.; Zhou, Y. How to jump further and catch up? Path-breaking in an uneven industry space. *J. Econ. Geogr.* **2017**, *17*, 521–545. [CrossRef]
23. He, C.; Zhu, S. Evolution of export product space in China: Technological relatedness, national/local governance and regional industrial diversification. *Tijdschr. Voor Econ. En Soc. Geogr.* **2018**, *109*, 575–593. [CrossRef]
24. Mi, Z.; Shang, Y.; Zeng, G. The impact of knowledge base on technological innovation of emerging industries from the perspective of related variety: A case study of China's fuel cell industry. *Growth Chang.* **2021**, *53*, 57–75. [CrossRef]
25. Asheim, B. Differentiated knowledge bases and varieties of regional innovation systems. *Innov. Eur. J. Soc. Sci. Res.* **2007**, *20*, 223–241. [CrossRef]
26. Moodysson, J. Principles and practices of knowledge creation: On the organization of "buzz" and "pipelines" in life science communities. *Econ. Geogr.* **2008**, *84*, 449–469. [CrossRef]
27. Dahlström, M.; Olsen, L.S.; Halkier, H. Multi-actor and multi-scalar regional development policies in the knowledge economy. In *Regional Development Agencies: The Next Generation*; Bellini, N., Danson, M., Halkier, H., Eds.; Routledge: Abingdon, UK, 2012; Volume 59, pp. 7–24.
28. Olsen, L.S. Territorial knowledge dynamics: Making a difference to territorial innovation models and public policy? *Eur. Plan. Stud.* **2012**, *20*, 1785–1801. [CrossRef]
29. Isaksen, A.; Trippl, M. Exogenously led and policy-supported new path development in peripheral regions: Analytical and synthetic routes. *Econ. Geogr.* **2017**, *93*, 436–457. [CrossRef]

30. Trippl, M.; Grillitsch, M.; Isaksen, A. Exogenous sources of regional industrial change: Attraction and absorption of non-local knowledge for new path development. *Prog. Hum. Geogr.* **2018**, *42*, 687–705. [CrossRef]
31. Bahar, D.; Rapoport, H. Migration, knowledge diffusion and the comparative advantage of nations. *Econ. J.* **2018**, *128*, F273–F305. [CrossRef]
32. Fan, Z.; Li, H.; Pan, L. FDI and international knowledge diffusion: An examination of the evolution of comparative advantage. *Sustainability* **2019**, *11*, 581. [CrossRef]
33. Liu, Z.; Zhu, S. Changing institutional context and regional industrial dynamics: New evidence from the establishment of administrative approval centers in China. *Growth Chang.* **2021**, *52*, 1271–1294. [CrossRef]
34. Zhao, Y.; He, F.; Feng, Y. Research on the industrial structure upgrading effect of the employment mobility of graduates from China's "double first-class" colleges and universities. *Sustainability* **2022**, *14*, 2353. [CrossRef]
35. He, C.; Yan, Y.; Rigby, D. Regional industrial evolution in China. *Pap. Reg. Sci.* **2018**, *97*, 173–198. [CrossRef]
36. Wang, F.; Wang, R.; He, Z. Exploring the impact of "double cycle" and industrial upgrading on sustainable high-quality economic development: Application of spatial and mediation models. *Sustainability* **2022**, *14*, 2432. [CrossRef]
37. Gao, J.; Zhou, T. Quantifying China's regional economic complexity. *Phys. A Stat. Mech. Its Appl.* **2018**, *492*, 1591–1603. [CrossRef]
38. Lee, S.; Kim, W. The knowledge network dynamics in a mobile ecosystem: A patent citation analysis. *Scientometrics* **2017**, *111*, 717–742. [CrossRef]