sustainability

MDPI

Article

A Multi-Regional Input–Output Model to Measure the Spatial Spillover of R&D Capital

Chunyun Wang [1], Senyu Xing [1] and Lixiao Xu [2,*]

[1] School of Mathematics and Statistics, Beijing Technology and Business University, Beijing 100048, China; wangchunyun@btbu.edu.cn (C.W.)
[2] School of Data Sciences, Zhejiang University of Finance and Economics, Hangzhou 310018, China
* Correspondence: lixiao.xu@zufe.edu.cn

Abstract: Reallocating innovative capital elements can improve the growth of total factor productivity and promote high-quality economic development. The multi-regional multiplier model measures the spatial spillover effects of R&D capital to trace the interregional R&D flows and explore the engines of the longer-term economic growth in China. Results show that the direct R&D intensity in different regions is all concentrated in basic research sectors supported by government funds, and decreased from coastal areas to inland areas. Second, R&D gradually flowed from China's coastal regions to inland regions, from upstream basic research sectors to downstream infrastructure construction sectors. Third, Guangdong, Jiangsu and Beijing are the main contributors, with R&D spillover intensities reaching 1.69%, 1.40%, and 1.37%, respectively. Xinjiang, Tibet, and Hainan are the main beneficiaries, with R&D inflow intensities reaching 0.49%, 0.53%, and 0.50%, respectively. Finally, the channel of R&D spatial spillover manifests a circular distribution and contact-type and jump-type modes.

Keywords: research and development investment intensity; inter-regional spillover; multi-regional input–output model; China

check for updates

Citation: Wang, C.; Xing, S.; Xu, L. A Multi-Regional Input–Output Model to Measure the Spatial Spillover of R&D Capital. *Sustainability* **2023**, *15*, 11208. https://doi.org/10.3390/su151411208

Academic Editor: Wen-Hsien Tsai

Received: 9 June 2023
Revised: 10 July 2023
Accepted: 17 July 2023
Published: 18 July 2023

1. Introduction

Technological innovation is a source of long-term economic growth for a country (or region) [1]. Research and Development (R&D) expenditures, also called R&D capital investment, promote fundamental creative activities to increase the stock of knowledge (including knowledge, culture, and society) utilized to explore and develop new products, such as improving the quality of existing products or exploring and developing newer and more efficient production processes [2,3]. Serving as a measure of innovation, R&D expenditure is an important input to ensure the implementation of China's innovation strategy and economic growth. In 2021, the total R&D expenditure in China reached CNY 2795.63 billion, 171.46% higher than that in 2012; the intensity of R&D input increased from 1.91% to 2.43% [4]. China exceeded 28 EU countries as the world's second-largest R&D expenditure after the United States, and become a leading country among the set of developing economies [5].

With the expansion of R&D capital investment, the spatial allocation and utilization efficiency of R&D attracted great research attention [6–9]. Given the imbalances in regional economies, there are disparities in R&D investment intensity and industrial distribution [8,9]. The former steps down from coastal regions to inland regions and presents spatial agglomeration and geographical links. Beijing, Shanghai, and Shenzhen are the core of the "center-periphery" pattern, which is continuously strengthening [10]. On the one hand, the spatial agglomeration pattern of innovation may cause spatial mismatch and aggravate the polarization of regional development. On the other hand, with the rapid development of information and communication technology and transport, the flows of interregional innovation facilitate the spatial spillover of knowledge in agglomeration areas. Therefore, optimizing the allocation of innovative resources to clarify the spatial distribution and industrial structure layout of R&D capital elements, and tracing and measuring the spatial network relations [11] are of great theoretical and policy value.

The input–output multiplier theory is used to estimate the direct and indirect effects of the change in final demand of an industrial sector on the whole economic system. Applying input–output multiplier theory, Dietzenbacher and Los (2002) [12] create regional R&D backward and forward multipliers to describe the output changes caused by the increase in R&D expenditure driven by the change in per unit final demand (FD) and the increase in per unit R&D cost, respectively. With the development of multi-regional input–output models, the interregional multiplier can not only describe the multiplier effects among industrial sectors in one region, but also fully reflect the complete effect of the output changes in the region on all industrial sectors in other regions [13].

To identify the impact of innovation resource spillover on the scale and structure of innovation in different regions and industrial sectors, and quantify the spatial spillover effect of R&D capital, we construct an R&D spatial spillover effect model based on multi-regional input–output (MRIO) multiplier theory. This model matches the MRIO table with the R&D expenditure of 31 regions and 15 industrial sectors in 2012. We calculate the complete R&D spillover intensity among the regions of China. We also analyze the scale and structure of China's R&D spatial spillover effect by exploring the spillover and agglomeration effects of R&D capital from the industry level to the spatial level. This study offers several contributions to the literature. First, based on multiplier theory and input–output analysis, we establish a multi-regional R&D spatial spillover effect model to unpack the "black box" system of R&D spillovers among different industrial sectors and regions, thus providing a method to support the optimization of the spatial allocation of R&D capital. Second, we trace the flows of R&D capital among industrial sectors and regions of China, thereby comprehensively quantifying the interregional R&D spillover effect and providing data to further explore the contribution of R&D spatial spillover to productivity growth.

The remainder of this paper is organized as follows. Section 2 provides a brief review of some of the pertinent literature on measurement of R&D spillover effects. Section 3 develops the basic accounting framework and model, and describes the R&D expenditure data and the 2017 MRIO table. Here, we also outline the data processing and calculations for the complete spillover effect of interregional R&D capital. Section 4 presents the results on the spillover effects of R&D. Section 5 is discussion and policy recommendations.

2. Review of Literature

According to the endogenous growth model, pioneered by Romer (1986) [1], technological innovation and R&D are used in the production of final goods and leads to permanent increases in the growth rate of output [14–16]. The empirical studies of endogenous growth models generally involve testing the effect of R&D variables on GDP growth. For example, Griliches and Lichtenberg (1984) [17] and Philippe and Peter (1997) [18] provide strong evidence that in the U.S. economy R&D investment and economic growth are positively related. Beñat and Andrés (2004) [19] first identify the impact of R&D investment of the private, public, and higher education sectors on economic growth in the EU, and their results show that R&D investment can promote innovation and bring economic growth, but it will be influenced by region-specific socioeconomic. Yan and Gong (2013) [20] explore the effect of R&D investment and R&D structure on China's economic growth, and they find that the basic research and the high school R&D investment have positive effects on economic growth. The positive relationship between countries' own R&D and economic growth has been also confirmed by studies using other countries [21,22] and international panel data [23,24]. However, Minsung (2020) [25] investigates the relationship between the cross-industry distribution of R&D investments and economic growth across 14 countries for the period from 1996 to 2013, and their results indicate an inverted U-shaped relationship between the concentration of R&D investment and economic growth.

With non-exclusivity and non-competition, R&D will benefit sectors besides the economic owners, a phenomenon called R&D capital spillover. Based on endogenous growth theory, Romer (1986) [1] incorporated innovation spillover as an independent parameter into the production function, which theoretically proved the existence of innovation spillover. The effects are crucial to reallocate resources and promote economic growth [26]. Wolff (1997) [27] shows that R&D spillover occurs through product transactions in the market, Blanco et al. (2016) [28] find that the positive effect of R&D spillovers across the U.S. states is larger when they consider R&D spillovers across states based on economic similarity of R&D across sectors. Aysun and Yom (2021) [29] confirm that the spillover of innovation across industries has the largest impact on output. The R&D spillover effects of an industrial sector are calculated by weighting R&D intensity of other sectors with the direct consumption coefficients of the input–output table. The theoretical logic is that as the technology of products in upstream enterprises improves, the technology of downstream enterprises that apply those products will also improve. However, Jaffe (1986) [30] argues that most interindustry innovation spillover emerges among industries with similar production technologies and input structures. Inspired by this idea, Los (2000) [31] constructed a technological similarity matrix with the direct consumption coefficients from input–output tables to measure the innovation spillover effects among R&D sectors. To create a complete measurement, Zhu et al. (2016) [32] combined the upstream and downstream vertical R&D effects with the horizontal R&D spillover effects of similar industries and built a two-dimensional R&D spillover effect model of industrial sectors in China.

Since the 1990s, with the rise of new economic geography [26], Grossman and Helpman (1991) [15] investigate the theoretical mechanism of innovation spillover from the spatial perspective. Based on endogenous growth theory and new economic geography, Fujita and Thisse (2003) [33] establish a theoretical model of the relationship between R&D flows, spatial knowledge spillover, and economic growth, demonstrating that the spatial spillover effects of innovation could be achieved through the free flows of various knowledge among regions. Spatial spillovers are crucial in explaining long-run economic growth [34]. Meanwhile, there is strong evidence that R&D spillovers from industrialized countries to developing countries have positive effects on the economic growth of the latter [35,36]. Pio et al. (2021) [37] use the dynamic panel method to capture the spillover effects of China's exports on the global and indicate both negative and positive spillovers. Jiao et al. (2018) [38] focus on sub-regions of China to establish an inter-provincial R&D spillover network. However, limited by geographical distance, R&D spillover has an effective radiation range, resulting in the spatial agglomeration of technology and industry [6]. Keller (2002) [39] found that technological knowledge was to a substantial degree local, not global, as the benefits from foreign spillover were declining with distance: on average, a 10% higher distance to a major technology-producing country was associated with a 0.15% lower level of productivity. In a more recent study, Bai et al. (2017) [40] exploit gravity models to quantify the intensity of interregional innovation correlation, but these models provide the R&D spatial correlation intensity in a region and do not show the R&D spillover of an industry. Using social network analysis [41], researchers can analyze the innovation correlation among cities in China under gravity models with patent transaction applications [42] and paper cooperation data [43]. In addition, some scholars explore the spatial innovation correlation by complex network theory [44] and social network assessment indicator systems [45].

The common point of R&D spillover effect measurements above is that they provide the R&D spillover effect of a region (or industry) by the weighted R&D investment of other regions (or industries). These studies lay the foundation for the measurement of R&D spatial spillover effect in this study. With the rapid development of China's digital economy, information technology breaks the original geographical boundary and reduces transport costs. Simply applying the gravity model of geographical proximity and neural networks may underestimate the intensity of R&D spillover. Deep research should combine the R&D horizontal spillover effects, which reflect geographical elements, with the vertical industrial correlation spillover effects to trace the flow of China's interregional R&D capital.

3. Accounting Framework and Model

3.1. Decomposition Framework of R&D Spatial Spillover Effect

Trade breaks the geographical boundary and realizes the cross-regional flow of R&D capital. In addition to the direct R&D investment of the local sector, the R&D capital investment of specific sectors in other specific regions includes the indirect R&D investment that enters into the local sector with trading. Taking three regions as an example, this paper constructs the basic form of the multi-regional input–output table including R&D satellite account. Figure 1 intuitively shows the four sources of R&D capital of various sectors in different regions.

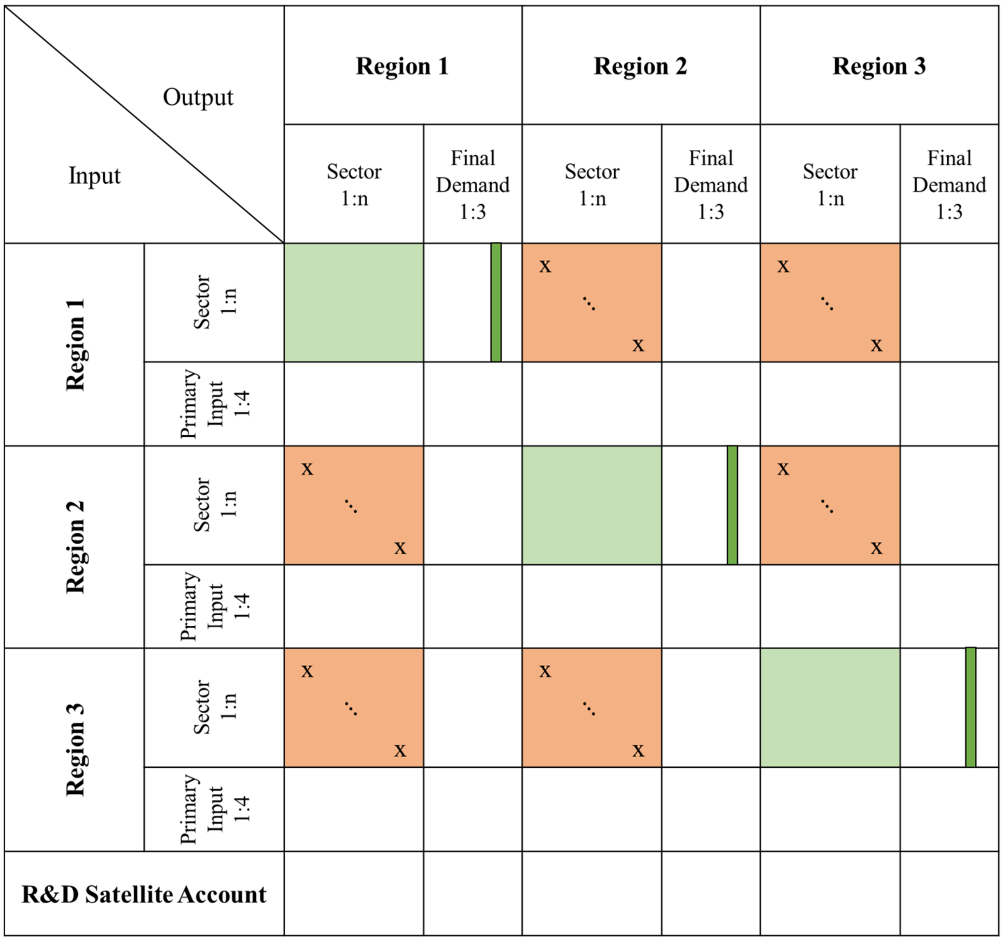

Figure 1. Decomposition Framework of R&D Capital Spatial Spillover Effect. Note: Compiled by the author, Figure 1 shows the multi-regional input–output table of China's three regions. Different color has different meanings. The light green indicates the intra-regional connections. The orange means the inter-regional connections. The dark green means the sectoral direct R&D capital in final demand.

(1) Direct R&D capital investment. The amount of direct R&D capital investment depends on the number of R&D expenditure of a sector of a region, which is counted in the gross fixed capital formation of the final demand of each region in the multi-region input–output table. In Figure 1, the dark green parts of Region 1, Region 2, and Region 3 in the final demand column represent the sectoral direct R&D capital input in three regions. (2) R&D capital flow of upstream and downstream sectors in a region. This part of R&D capital investment improves the R&D capital scale of sectors indirectly through the market transaction in both upstream and downstream sectors within regions. In Figure 1, the

light green parts mean the intersection of sectors within each region, which indicates the R&D capital spillover among sectors within the three regions. (3) R&D capital flows across regions in the same sectors or similar technique sectors. When it comes to the same sectors across regions, they have similar input–output structures, so they will improve their innovative ability through active or passive learning. Searching Figure 1 in a horizontal way, the diagonal line of the light green area formed by the intersection of Region 1, Region 2 and Region 3 indicates the R&D capital spillover of the same sectors or similar technique sectors across the region. (4) R&D capital flows across regions and industrial sectors. The R&D capital flow across regions and sectors makes the sharing of R&D activities come true. Thanks to the development of information technology and transport, sectoral correlation breaks regional barriers, interregional trade is free and promotes the cross-regional flow of R&D capital. Depicting Figure 1 in a vertical way, besides the elements on the main diagonal, the other light green area formed by the intersection of Region 1, Region 2 and Region 3 signifies the R&D capital flow across regions and sectors.

In summary, combining with the multi-regional input–output model, the R&D spatial spillover effect framework comprehensively composites the direct R&D expenditure of each region and the R&D spillover effect caused by intraregional and interregional sectoral transactions, revealing the operating mechanism of regional innovation system, which can be regarded as the total R&D spillover effect.

3.2. Basic Input–Output Model

Interregional trade breaks geographical boundaries and leads to R&D capital flow across boundaries. In addition to direct R&D, one sector will employ indirect R&D investment from other regions, which is embodied in interregional trade, thus the certain spatial spillover effect is likely to exist. For exploring the spatial spillover effect of R&D capital, the input–output model, which is an excellent tool for linkages among inter- and intra- regions and sectors, is chosen. The basic input–output model is developed by the famous work of Leontief (1936) [46]. It could be written as follows:

$$\boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{y} = \boldsymbol{L}\boldsymbol{y} \tag{1}$$

Here, $\boldsymbol{x}$ indicates the vector of output, $\boldsymbol{I}$ represents an identity matrix, $\boldsymbol{y}$ denotes the vector of final demands. $\boldsymbol{A}$ is the direct requirement matrix, and $\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1}$ yielding direct requirements and indirect requirements means the total requirement matrix. The basic model is also called the demand-driven input–output model.

The counterpart of the demand-driven input–output model is the supply-driven input–output model that is proposed by Ghosh (1958) [47]. The model is

$$\boldsymbol{x} = \boldsymbol{v}(\boldsymbol{I} - \boldsymbol{B})^{-1} = \boldsymbol{v}\boldsymbol{G} \tag{2}$$

where $\boldsymbol{v}$ denotes the vector of primary inputs, also called value added. $\boldsymbol{B}$ indicates the direct output matrix. $\boldsymbol{G} = (\boldsymbol{I} - \boldsymbol{B})^{-1}$ represents Ghosh inverse matrix.

We take R&D capital as a satellite account in this study and introduce this index into Equations (1) and (2) by R&D intensity r. $r = R_i/x_i$ denotes R&D inputs in sector i for producing per unit output of sector i. Thus, Equations (1) and (2) could be rewritten as

$$\boldsymbol{R} = \boldsymbol{r}\boldsymbol{L}\boldsymbol{y} \tag{3}$$

$$\boldsymbol{R} = \boldsymbol{v}\boldsymbol{G}\boldsymbol{r} \tag{4}$$

3.3. Model of Spatial Spillover of R&D Capital

Combining the multiplier theory of input–output analysis and multiregional input–output (MRIO) tables, we could construct the comprehensive framework of R&D spatial allocation effects including direct effects and indirect effects on inter- and intra-regions and among sectors throughout the economic system. Following the method proposed by

Dietzenbacher and Los (2002) [12], we extend the single region model to the multi-region model and portray the impact of changes in final demand by backward multipliers and changes in primary inputs by forward multipliers. The output multiplier of MRIO analysis indicates the direct and indirect output effects per unit of final demand in a sector of the entire economic system [13]. We derive the R&D capital input multiplier by multiplying the output multiplier by the R&D capital input intensity. The multiplier refers to the direct and indirect R&D capital input of the whole economy driven by final demand.

(1) **Multi-regional backward multiplier**

We calculate the multi-regional R&D backward multiplier using the demand-driven input–output model, which reflects the effect of final demand on R&D investment. Hence, we obtain the multi-regional backward output multiplier, namely the Leontief inverse matrix,

$$\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1} \tag{5}$$

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{A}^{11} & \boldsymbol{A}^{12} & \cdots & \boldsymbol{A}^{1p} \\ \boldsymbol{A}^{21} & \boldsymbol{A}^{22} & \cdots & \boldsymbol{A}^{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{A}^{p1} & \boldsymbol{A}^{p2} & \cdots & \boldsymbol{A}^{pp} \end{bmatrix} \tag{6}$$

where $\boldsymbol{A}^{st} = \left[a_{ij}^{st}\right]$ $(i = 1,2,\cdots,N;\ j = 1,2,\cdots,N)$ represents the direct input coefficient matrix. $\boldsymbol{L} = \left[l_{ij}^{st}\right]$, l_{ij}^{st} indicates that region s sector i satisfies the total demand of region t sector j, $h_{ij}^{st} = \frac{R_i^s}{x_i^s} l_{ij}^{st}$.

Based on the multi-regional backward output multiplier, one unit final demand of region t sector j needs the direct and indirect R&D of region s sector i, $h_{ij}^{st} = \frac{R_i^s}{x_i^s} l_{ij}^{st}$, which we define as the total R&D multiplier:

$$\boldsymbol{H} = \hat{\boldsymbol{R}}\hat{\boldsymbol{x}}^{-1}\boldsymbol{L} \tag{7}$$

where $\boldsymbol{H} = \left[h_{ij}^{st}\right]$ $(i = 1,2,\cdots,N;\ j = 1,2,\cdots,N)$. $\hat{\boldsymbol{x}}^{-1} = \begin{bmatrix} \frac{1}{x^1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{1}{x^p} \end{bmatrix}$ and $\boldsymbol{x}^s = \left[x_j^s\right]$ $(i = 1,2,\cdots,N)$, where x_j^s denotes the total output of region s sector j. $\hat{\boldsymbol{R}} = \begin{bmatrix} \boldsymbol{R}^1 & \cdots & \boldsymbol{0} \\ \vdots & \ddots & \vdots \\ \boldsymbol{0} & \cdots & \boldsymbol{R}^p \end{bmatrix}$ indicates the diagonal matrix of R&D. $\boldsymbol{R}^s = \left[R_i^s\right]$ $(i = 1,2,\cdots,N)$ indicates the R&D of region s sector i.

The sum of each column of $\boldsymbol{H}$ represents the R&D backward multiplier of region t sector j, indicating the total R&D driven by per unit final demand of region t sector j. Then, the R&D backward multiplier could be written as

$$m(h)_j^t = \sum_{s=1}^{p} \sum_{i=1}^{N} h_{ij}^{st} \tag{8}$$

(2) **Multi-regional R&D forward multiplier**

The multi-regional R&D forward multiplier from the supply-side input–output model is constructed by Ghosh (1958) [47], and it reflects the influence of primary input on regional and sectoral R&D. We obtain the multi-regional forward output multiplier, also called the output inverse,

$$\boldsymbol{G} = (\boldsymbol{I} - \boldsymbol{B})^{-1} \tag{9}$$

$$\boldsymbol{B} = \begin{bmatrix} \boldsymbol{B}^{11} & \boldsymbol{B}^{12} & \cdots & \boldsymbol{B}^{1p} \\ \boldsymbol{B}^{21} & \boldsymbol{B}^{22} & \cdots & \boldsymbol{B}^{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{B}^{p1} & \boldsymbol{B}^{p2} & \cdots & \boldsymbol{B}^{pp} \end{bmatrix} \tag{10}$$

where $\boldsymbol{B}^{st} = \left[b_{ij}^{st}\right]$ $(i = 1, 2, \cdots, N;\ j = 1, 2, \cdots, N)$ represents the distribution of region s' outputs, that are sold to region t as interindustry inputs of region t. Thus, it is frequently called the allocation coefficient. For $\boldsymbol{G} = \left[g_{ij}^{st}\right]$, the element g_{ij}^{st} indicates the direct and indirect total output of region t sector j induced by per unit primary inputs of region s sector i.

Based on the multi-regional forward output multiplier, the total R&D intensity of per unit primary input of region s sector i spill over to region t sector j is $\widetilde{h}_{ij}^{st} = \frac{R_i^s}{x_i^s} g_{ij}^{st}$. Then, the total R&D intensity is

$$\widetilde{\boldsymbol{H}} = \hat{\boldsymbol{R}} \boldsymbol{G} \hat{\boldsymbol{x}}^{-1} \tag{11}$$

where $\widetilde{\boldsymbol{H}} = \left[\widetilde{h}_{ij}^{st}\right]$ is the multi-regional R&D forward multiplier. $\hat{\boldsymbol{x}}^{-1} = \begin{bmatrix} 1/\boldsymbol{x}^1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1/\boldsymbol{x}^p \end{bmatrix}$ indicates the diagonal matrix of reciprocal total outputs. $\hat{\boldsymbol{R}} = \begin{bmatrix} \boldsymbol{R}^1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \boldsymbol{R}^p \end{bmatrix}$ indicates the diagonal matrix of regional and sectoral R&D.

The row sum of $\widetilde{\boldsymbol{H}}$ indicates the R&D forward multiplier of region s sector i. It denotes the full spillover effect of the R&D of region s sector i on other regions and sectors. That is,

$$m(h)_i^s = \sum_{t=1}^{p} \sum_{j=1}^{N} \widetilde{h}_{ij}^{st} \tag{12}$$

(3) **Linkages between Multi-regional backward multiplier and Multi-regional R&D forward multiplier**

The backward and forward multipliers have different economic assumptions. The former is demand-oriented, and its background is economic depression, and it is necessary to increase demand in order to stimulate economic growth. The latter is production-oriented, and its background is economic prosperity, where insufficient inputs will limit a sector's capacity to expand its production. Although their economic backgrounds differ, the multi-regional R&D backward multiplier $\boldsymbol{H}$ and forward multiplier $\widetilde{\boldsymbol{H}}$ in this study could be connected.

As $\boldsymbol{B} = \hat{\boldsymbol{x}}^{-1} \boldsymbol{A} \hat{\boldsymbol{x}}$ and $\boldsymbol{G} = \hat{\boldsymbol{x}}^{-1} \boldsymbol{L} \hat{\boldsymbol{x}}$,

$$\begin{aligned} \widetilde{\boldsymbol{H}} &= \hat{\boldsymbol{R}} \boldsymbol{G} \hat{\boldsymbol{x}}^{-1} \\ &= \hat{\boldsymbol{R}} \left(\hat{\boldsymbol{x}}^{-1} \boldsymbol{L} \hat{\boldsymbol{x}}\right) \hat{\boldsymbol{x}}^{-1} \\ &= \left(\hat{\boldsymbol{R}} \hat{\boldsymbol{x}}^{-1}\right) \boldsymbol{L} \left(\hat{\boldsymbol{x}} \hat{\boldsymbol{x}}^{-1}\right) \\ &= \hat{\boldsymbol{R}} \hat{\boldsymbol{x}}^{-1} \boldsymbol{L} \\ &= \boldsymbol{H}. \end{aligned} \tag{13}$$

Then, row i of $\boldsymbol{H}$ indicates the R&D spillover effect of region s sector i to other regions and sectors. In this measurement, region s sector i is a technical contributor that promotes the development of other regions and sectors. Column j indicates the R&D spillover effect obtained by region t sector j from other regions and sectors. Region t sector j is a technical winner benefiting from R&D of other regions and sectors. Based on the backward and forward effect models of R&D, we explore the full path of the R&D spillover effect of a specific region and sector. However, the linkage between the backward multiplier $\boldsymbol{H}$ and the forward multiplier $\widetilde{\boldsymbol{H}}$ has proven that they have the same form, and the sum of different directions could yield different information. The horizontal sum signifies the regions and regions contributing to the R&D spillover effect, while the vertical sum indicates the regions and sectors gaining the R&D spillover effect.

3.4. Data

To measure the spatial spillover effect of R&D capital among all sectors within and between regions based on forward and backward multipliers of multi-regional R&D spillover, we require two kinds of data: (1) regional and sectoral R&D data, and (2) the MRIO table.

(1) Regional and sectoral R&D data. R&D fixed capital formation is a better indicator to represent R&D inputs, as the SNA2008 transferred R&D from intermediate inputs to fixed capital formation. Based on this adjustment of R&D from the international standard, China's National Bureau of Statistics (NBS) adjusted the accounting method of R&D expenditure and revised its Gross Domestic Product (GDP) since 1952. In this study, we still choose internal R&D expenditure to measure sectoral R&D inputs, for several reasons: (a) Internal R&D expenditure could wholly reflect sectoral primary R&D inputs. Part of the internal R&D expenditure is regarded as intermediate consumption to produce, while the other part is capitalized and formed as sectoral R&D fixed capital formation [2,48]. (b) The ratio of internal R&D expenditure to GDP is an important indicator of the R&D inputs of a given region. The OECD database reports this indicator for the main regions during 1981–2021. Additionally, the *China Statistical Yearbook on Science and Technology* gives provincial data during 2011–2021. (c) As of yet, we have no unified method of quantifying capitalized R&D, which can lead to mismeasurements of R&D fixed capital formation. Since 1952, the NBS releases only adjusted GDP to indicate the change in R&D; however, the measures of R&D differ at the regional [49,50] and sectoral levels [51], so they cannot be compared.

(2) Data source and data processing. The regional and sectoral internal R&D expenditure are the main data. We obtain these data from *The Second National R&D Resources Inventory Data Compilation* (2009) [52], which provides internal R&D expenditure for 31 provinces and 14 sectors. The MRIO table is another key dataset. The NBS does not release a Chinese MRIO table, so we obtain the table in 2017 from Zheng et al. (2022) [53]. We assume that the structure of regional and sectoral internal R&D expenditure is the same for 2009–2021, and obtain the data for provincial internal R&D expenditure during 2012–2021 from the *China Statistical Yearbook on Science and Technology* to construct 15 sectors (details in Table S2) of provincial internal R&D expenditure during 2012–2021. Thus, we match the provincial and sectoral internal R&D expenditure with the 2017 MRIO. To unify the sectoral classifications of R&D and MRIO, we merge 42 sectors in the MRIO into 15 sectors to match the R&D classification.

4. Results

4.1. Direct R&D Intensity

The spatial distribution of direct R&D intensity is uneven and moves from coastal areas to inland areas. The spatial distribution of direct R&D intensity conforms to China's urbanization pattern and generally shows a downward trend from coastal to inland regions. The direct R&D intensities of coastal regions are largely higher than those of inland regions and the whole country. In 2017, the direct R&D intensities of the northern, eastern, and southern coastal regions were 3.12%, 2.76%, and 2.24%, respectively. Beijing had the highest direct R&D intensity in China (5.64%), and Shanghai has the second highest direct R&D intensity in China, at 4.00%. However, the direct R&D intensity of Hebei and Hainan, located in the coastal area, was only 1.26% and 0.52%, respectively, and below the national average. Hainan was only higher than Tibet, whose intensity was 0.22%. The average direct R&D intensities of the Yellow River, Central Yangtze River, and Southwest regions were between 1.3% and 1.7%. The direct R&D intensity of the Northwest was only 0.80%, the lowest in China.

The direct R&D intensities of most provinces in China increased continuously, with a small number of provinces showing a phased downward trend (see Table 1). The national average direct R&D intensity increased from 1.91% in 2012 to 2.43% in 2021. The scientific and technological strength was further enhanced, and major innovative achievements emerged. Benefiting from the support of local policies, the growth rates of direct R&D intensity of the East coast, South coast, Central Yangtze River, and Southwest regions exceeded the national average, especially Shanghai, with its intensity increasing from 3.37% in 2012 to 4.21% in 2021. Compared with the above four regions, the direct R&D intensity of the North coast and Central Yellow River regions increased slowly. Shandong and Inner Mongolia were steady. Tianjin and Shanxi had negative growth before 2017, with the former decreasing from 2.80% to 2.47% and the latter reducing from 1.09% to 0.99%. In addition to Liaoning and Ningxia, the direct R&D intensity of the Northeast and Northwest regions showed a downward trend. Heilongjiang decreased from 1.14% in 2012 to 0.83% in 2018, the largest decline, indicating an acute shortage of R&D.

Table 1. Direct R&D Investment Intensity in China: 2012–2021.

Region	2017	Province	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Northeast	1.57	Liaoning	1.57	1.64	1.52	1.27	1.69	1.8	1.82	2.04	2.19	2.18
		Jilin	0.92	0.92	0.95	1.01	0.94	0.84	0.76	1.27	1.30	1.39
		Heilongjiang	1.07	1.14	1.07	1.05	0.99	0.90	0.83	1.08	1.26	1.31
North coast	3.12	Beijing	5.95	5.98	5.95	6.01	5.96	5.64	6.17	6.31	6.44	6.53
		Tianjin	2.80	2.96	2.96	3.08	3.00	2.47	2.62	3.28	3.44	3.66
		Hebei	0.92	0.99	1.06	1.18	1.20	1.26	1.39	1.61	1.75	1.85
		Shandong	2.04	2.13	2.19	2.27	2.34	2.41	2.15	2.10	2.30	2.34
East coast	2.76	Shanghai	3.37	3.56	3.66	3.73	3.82	4.00	4.16	4.00	4.17	4.21
		Jiangsu	2.38	2.49	2.54	2.57	2.66	2.63	2.7	2.79	2.93	2.95
		Zhejiang	2.08	2.16	2.26	2.36	2.43	2.45	2.57	2.68	2.88	2.94
South coast	2.24	Fujian	1.38	1.44	1.48	1.51	1.59	1.68	1.80	1.78	1.92	1.98
		Guangdong	2.17	2.31	2.37	2.47	2.56	2.61	2.78	2.88	3.14	3.22
		Hainan	0.48	0.47	0.48	0.46	0.54	0.52	0.56	0.56	0.66	0.73
Central Yellow River	1.38	Shaanxi	1.99	2.12	2.07	2.18	2.19	2.10	2.18	2.27	2.42	2.35
		Shanxi	1.09	1.22	1.19	1.04	1.03	0.99	1.05	1.12	1.20	1.12
		Henan	1.05	1.10	1.14	1.18	1.23	1.29	1.40	1.46	1.64	1.73
		Inner Mongolia	0.64	0.69	0.69	0.76	0.79	0.82	0.75	0.86	0.93	0.93
Central Yangtze River	1.73	Hubei	1.73	1.80	1.87	1.90	1.86	1.92	2.09	2.09	2.31	2.32
		Hunan	1.30	1.33	1.36	1.43	1.50	1.64	1.81	1.98	2.15	2.23
		Jiangxi	0.88	0.94	0.97	1.04	1.13	1.23	1.41	1.55	1.68	1.70
		Anhui	1.64	1.83	1.89	1.96	1.97	2.05	2.16	2.03	2.28	2.34
Southwest	1.30	Yunnan	0.67	0.67	0.67	0.80	0.89	0.95	1.05	0.95	1.00	1.04
		Chongqing	1.40	1.38	1.42	1.57	1.72	1.87	2.01	1.99	2.11	2.16
		Sichuan	1.47	1.52	1.57	1.67	1.72	1.72	1.81	1.87	2.17	2.26
		Guizhou	0.61	0.58	0.60	0.59	0.63	0.71	0.82	0.86	0.91	0.92
		Guangxi	0.75	0.75	0.71	0.63	0.65	0.70	0.71	0.79	0.78	0.81
Northwest	0.08	Gansu	1.07	1.06	1.12	1.22	1.22	1.15	1.18	1.26	1.22	1.26
		Qinghai	0.69	0.65	0.62	0.48	0.54	0.68	0.60	0.69	0.71	0.80
		Ningxia	0.78	0.81	0.87	0.88	0.95	1.13	1.23	1.45	1.52	1.56
		Tibet	0.25	0.28	0.26	0.30	0.19	0.22	0.25	0.25	0.23	0.29
		Xinjiang	0.53	0.54	0.53	0.56	0.59	0.52	0.53	0.47	0.45	0.49
Total	2.11	Total	1.91	1.99	2.02	2.07	2.11	2.13	2.14	2.23	2.40	2.43

We calculated the regional and sectoral direct R&D intensity for 31 provinces, the sector-wise internal R&D expenditure of 2017, and value-added from China's interregional input–output table of 2017 (see Figure 2). The industrial distribution of direct R&D intensity is imbalanced. The industrial distribution of direct R&D investment intensity is imbalanced. As Figure 2 shows, *Scientific Research, Technical Services, and Geological Prospecting* (S10), *Education* (S12), and *Manufacturing* (S3) are the main sectors in each province and R&D-intensive sectors. *Scientific Research, Technical Services, and Geological Prospecting* (S10) ranges from 3.38% to 47.64%. *Education* (S12) is in the range of 0.52–16.03%. The R&D intensities of other tertiary sectors are rather small. The *Financial Sector* (S8), *Transport, Storage, and Postal Services* (S6), and *Culture, Sports, and Entertainment* (S14) are less than 0.6%. Compared with the tertiary sectors, the R&D intensities of secondary sectors and the primary sector are relatively low. *Manufacturing* (S3) is on the scale of 0.83–9.57%. *Mining* (S2), and *Production and Supply of Electricity, Gas, and Water* (S4) are within 0.04–5.86%. *Agricultural, Forestry, Animal Husbandry, and Fishery* (S1) were less than 1.0%.

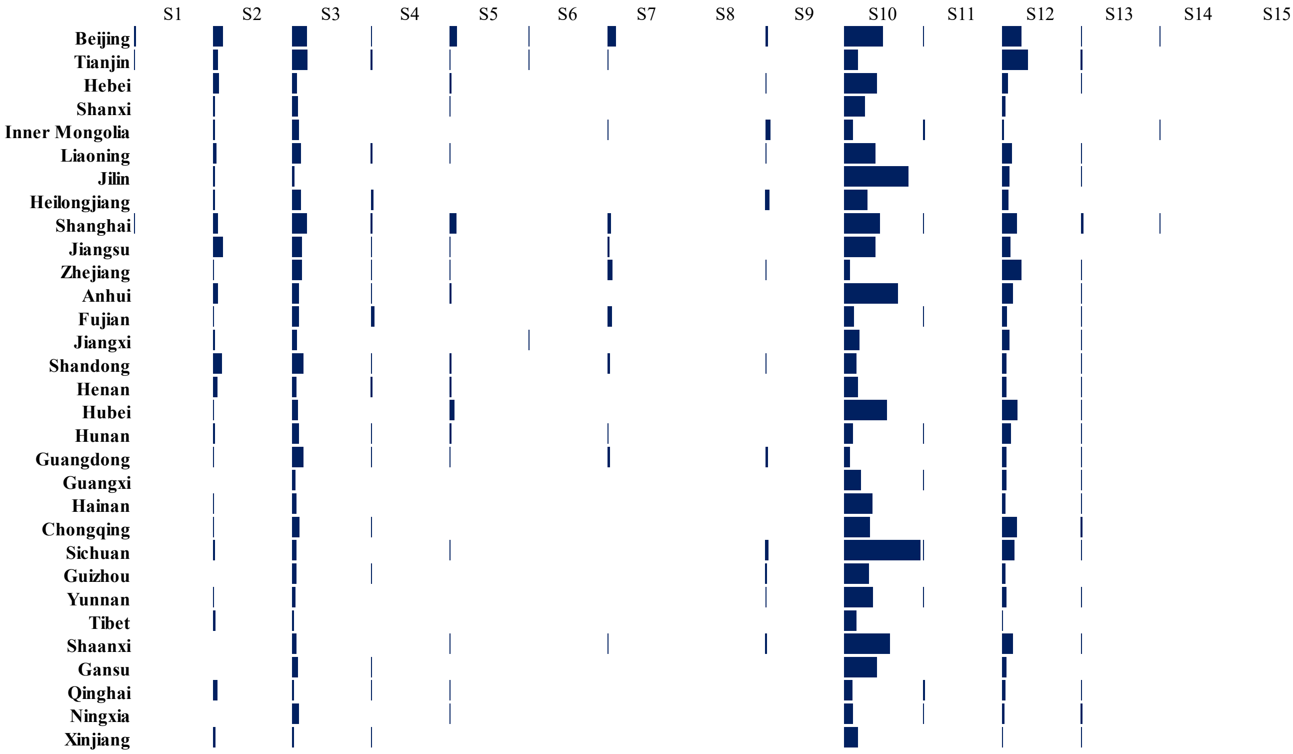

Figure 2. Direct R&D intensity of 31 provinces and 15 sectors in China, 2017.

Disparities of capital sources are the main reason explaining this imbalance of R&D among provinces and sectors. Governments provide most of the internal R&D expenditure in the *Scientific Research, Technical Services, and Geological Prospecting* (S10), *Education* (S12), and other tertiary sectors, while the fund sources for the primary and secondary sectors, including *Agriculture, Forestry, Animal Husbandry, and Fishery* (S1), *Mining* (S2), and *Manufacturing* (S3) are mainly from enterprises. Figure 3 depicts intramural expenditure on R&D by region and sources in 2017. It is obvious that the higher the percentage of government capital, the higher the direct R&D intensity of the *Scientific Research, Technical Services, and Geological Prospecting* (S10) and *Education* (S12). For example, Beijing's government funding accounts for 52.06%, and hence the direct R&D intensity of *Scientific Research, Technical Services, and Geological Prospecting* (S10) reached 23.90% and ranked first in the North coast region, with 5.29% of its total direct R&D intensity. Shaanxi also reflects the same situation. Its government funding is 50.46% in total. Its direct R&D intensity in the *Scientific Research, Technical Services, and Geological Prospecting* (S10) sector is 28.80%, and its total intensity is 2.15%, higher than the other provinces in the Central Yellow River region. The government plays a significant role in improving local R&D.

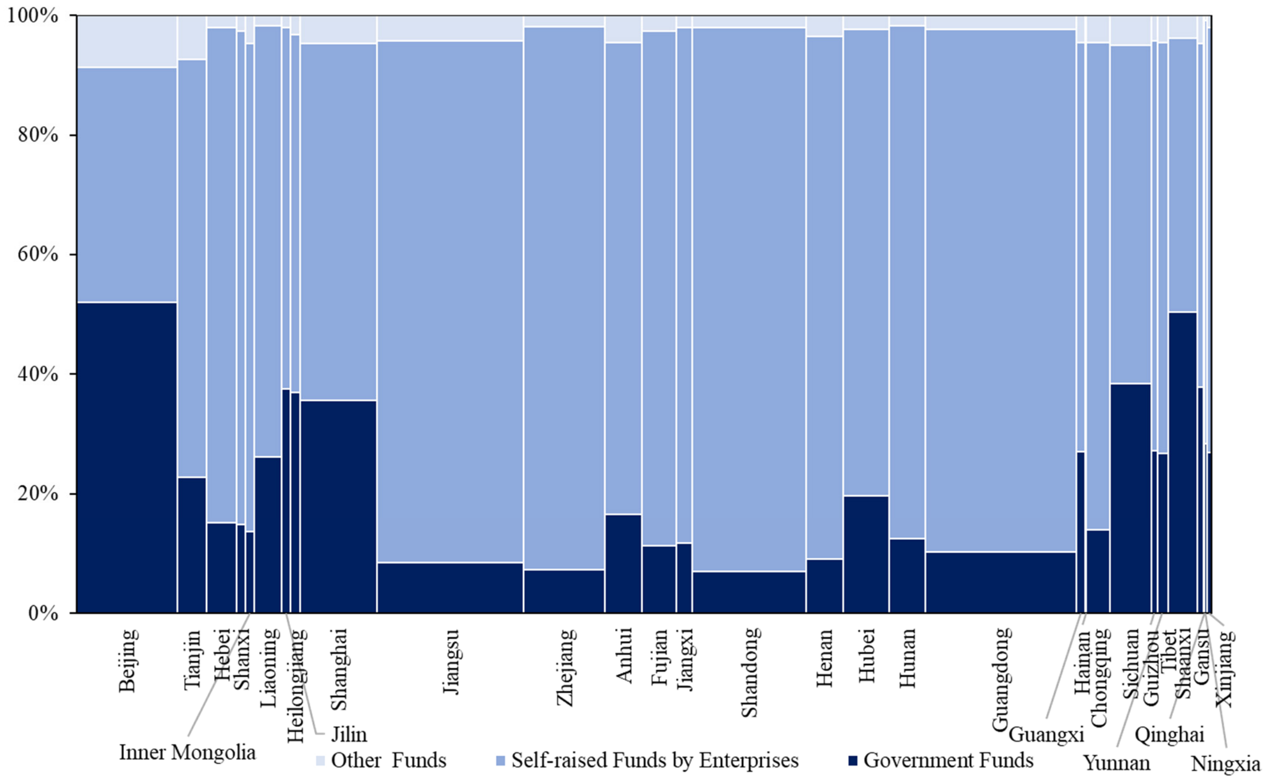

Figure 3. Intramural expenditure on R&D by region and sources in China, 2017.

4.2. China's R&D Spatial Spillover Effect

4.2.1. Regional R&D Spatial Spillover Effect

We illustrate the results in Figure 4. Compared with direct R&D intensity, R&D gradually spills out from coastal provinces to inland provinces. It has an increasing trend from the East to the West. The total R&D intensity of the North, East, and South coasts were 2.11%, 1.84%, and 1.17%, respectively, corresponding to a 35.85% decline on average. Beijing has the largest drop, from 5.29% to 2.69%, with a 49.06% decrease. Shanghai follows, with a decline from 3.66% to 2.14%. Guangdong has a drop from 2.56% to 1.11%. Beijing, Shanghai, and Guangzhou have fully exerted their radiation effects as the leading areas of innovation.

The total R&D intensity of the Central Yangtze River and Central Yellow River regions is 1.76% and 1.41%, only with an average rise of 1.86% and 2.16%. The R&D intensity of Anhui and Hubei increased to 2.41% and 2.12%, respectively, with their geographical advantages. Their total R&D intensities exceeded those of the surrounding areas and became typical winners of innovation spillover. Anhui is close to Jiangsu, Zhejiang, and Shanghai, so its sectors, especially manufacturing, are greatly affected by the innovation spillover effect of these areas. As a traditional inland transportation hub, Hubei has become a logistics transfer station connecting all directions and promotes cross-regional R&D with transport.

The total R&D spillover intensity in the Northeast, Southwest and Northwest regions respectively increased to 1.76%, 1.63% and 1.14%, with an average increase of 13.71%. Under the implementation of the innovation-driven strategy, Jilin continuously improves its *Scientific Research, Technical Services, and Geological Prospecting* (S10) sector, and its total R&D intensity increased from 1.17% to 1.70%, obtaining the biggest proceeds with a 44.93% increase in intensity among the three Eastern Provinces. As an important intersection and transport corridor connecting the South and central areas of China, the Southwest, and Northwest, as well as Central Asia, South Asia, and Southeast Asia, Sichuan is a crucial distribution center of goods and services in western China. It is committed to building a high-tech industrial base with military-civilian integration, increasing innovation inputs, enhancing the introduction of scientific research and technical services, and striving to improve corporate R&D intensity. Sichuan increased its R&D intensity from 1.68% to 2.66%, placing it second following Beijing. Tibet, located in the Northwest, is the biggest winner in China. Its complete R&D intensity increased from 0.21% (the lowest intensity) to 1.04%. *Mining* (S2), *Manufacturing* (S3), and *Construction* (S5) benefit the most.

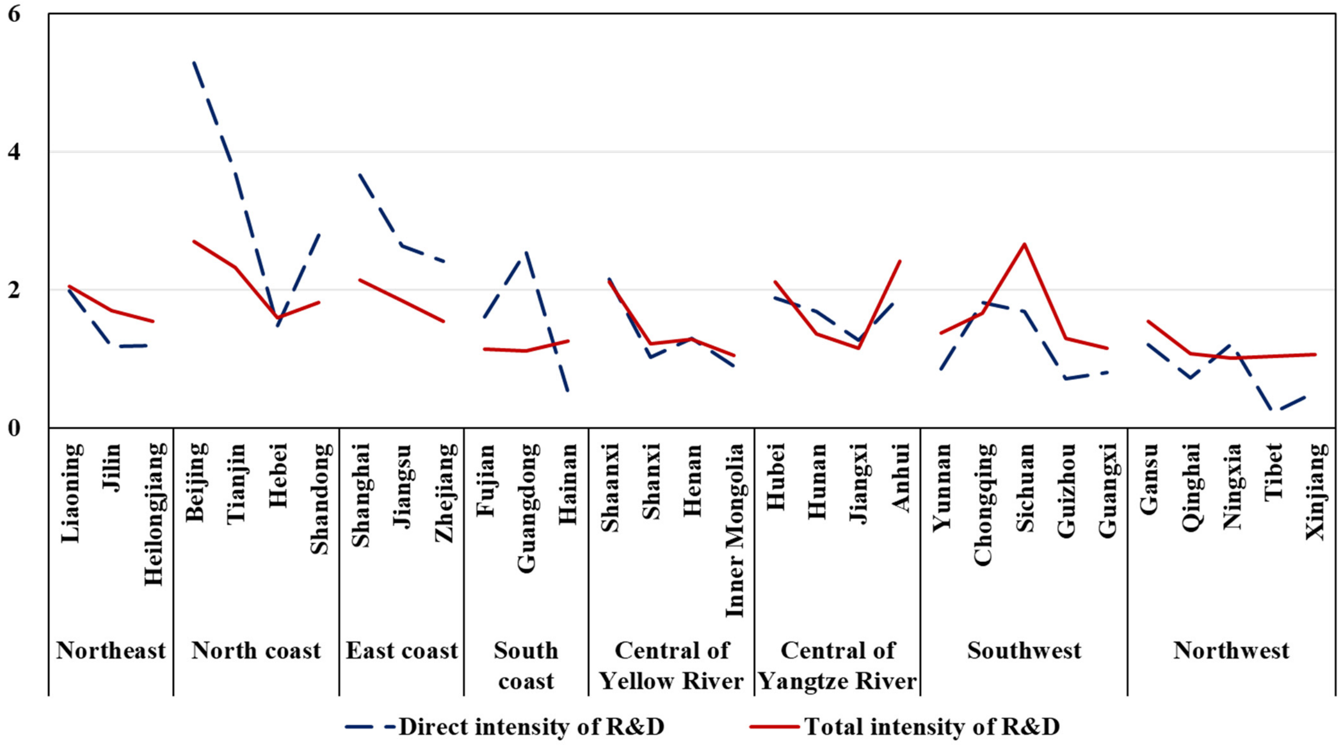

Figure 4. The provincial direct intensity and complete intensity of R&D in China, 2017.

4.2.2. Sectoral R&D Spatial Spillover Effect

In terms of the sectoral R&D spatial spillover effect, the disparities among sectors are significant. *Scientific Research, Technical Services, and Geological Prospecting* (S10) and *Education* (S12) are the main contributors of R&D spillovers in many regions, while the other sectors are gainers. Figure 5 indicates the direct and total R&D intensity of 31 provinces and 15 sectors in 2017. The total R&D spillover effects of tertiary sectors such as *Finance* (S8), *Culture, Sports, and Entertainment* (S14), *Transport, Storage, and Postal Services* (S6), *Agriculture, Forestry, Animal Husbandry, and Fishery* (S1) and *Construction* (S5) are higher. The growth rates are 28.5–94.4-fold, compared with their direct R&D intensity. *Management of Water Conservancy, Environment and Public Facilities* (S11), *Information Transmission, Computer Services, and Software* (S7), *Production and Supply of Electricity, Gas, and Water* (S4) have 6.7–9.8-fold growth rates, while the other sectors are under 5-fold.

4.3. Main Sources and Destinations of R&D Spillover Effects

Using the link between multi-regional R&D forward and backward multipliers, we can identify sources of R&D spillover effects from the rows and destinations of R&D spillover effects from the columns (details in Figure 6). We trace regional R&D intensity, estimate the flows streaming in and out, and obtain the net R&D intensity, which indicates the balance of total R&D intensity and direct R&D intensity.

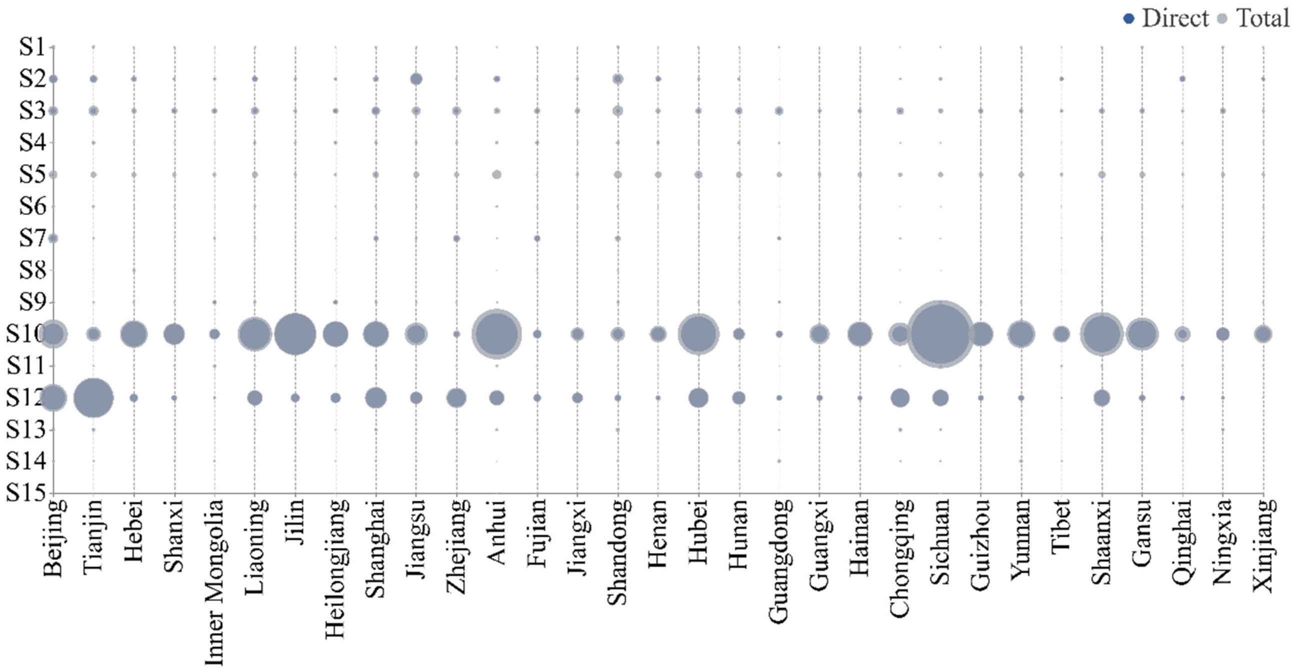

Figure 5. The direct and total R&D spillover effect of 31 provinces and 15 sectors, 2017.

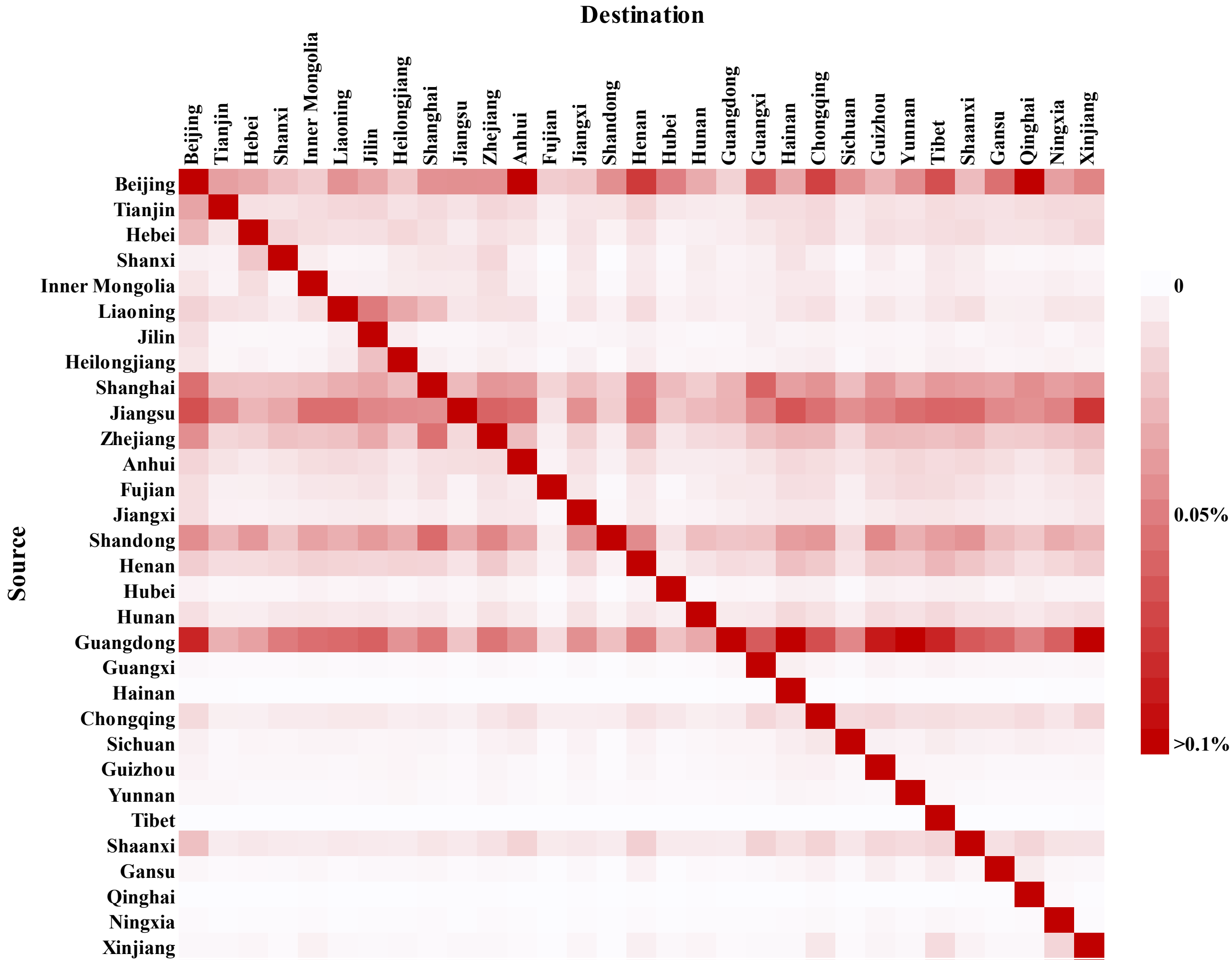

Figure 6. Sources and destinations of R&D spillover effects for 31 provinces, 2017.

Guangdong, Jiangsu and Beijing are the main sources of R&D spillover effects, with 1.69%, 1.40%, and 1.37% of R&D spillover intensities, respectively. Tibet, Xinjiang, and Hainan are the main destinations of R&D spillover effects. The gains of R&D spillover effects in their total R&D are 104.25%, 85.91%, and 65.98%, respectively. In addition, the R&D spillover effects obtained by Ningxia and Qinghai account for more than 60% of the total R&D spillover effects.

Although Guangdong is not the province with the highest direct R&D intensity, it has the highest R&D spillover effect in China. Its spillover intensity achieves 1.69%, accounting for 65.49% of its total R&D spillover intensity. Its R&D radiates to the surrounding areas. Yunnan, Hainan and Guizhou, which are adjacent to Guangdong, are the direct beneficiaries, gaining 0.10%, 0.11% and 0.09% of R&D spillover effect. In addition to that, developed provinces, like Beijing, Shanghai, and developing provinces, like Xinjiang, Tibet, Gansu, and Ningxia are the main destinations of Guangdong's R&D spillover effects. Xinjiang, which follows Yunnan, gains 0.103% of Guangdong's R&D spillover effect, accounting for 11.55% of its direct R&D intensity. *Manufacturing* (S3) of Guangdong is the main sector of R&D spillover effect, spilling their R&D intensity to *Information Transmission, Computer Services, and Software* (S7) and *Leasing and Commercial Services* (S9) of Xinjiang.

Jiangsu and Beijing are in the coastal region and have higher spillover intensity than other provinces after Guangdong. Their spillover intensities are 1.40% and 1.37%, accounting for 46.78% and 39.03% of their total R&D spillover intensity, respectively. Benefiting from its location advantage in the eastern coast of China, Jiangsu spills its R&D throughout all regions, including Liaoning, Beijing, Zhejiang, Hainan, Inner Mongolia, Anhui, Chongqing and Xinjiang. *Manufacturing* (S3) is the main sector, with higher spillover effects for Jiangsu. Anhui is the biggest gainer of the R&D spillover effect of Beijing (0.14%). Qinghai following Anhui wins 0.11 percent of Beijing's R&D spillover effect. accounting for 15% of its direct R&D intensity. By sector, *Scientific Research, Technical Services, and Geological Prospecting* (S10) in Beijing spill their R&D to the *Construction* (S5) and *Scientific Research, Technical Services, and Geological Prospecting* (S10) of Anhui and Qinghai.

Tibet, Xinjiang, and Hainan obtain R&D spillover effects from coastal provinces like Jiangsu, Guangdong, Shandong, Beijing, Shanghai, and Zhejiang, with 0.03–0.11% of R&D intensity. *Manufacturing* (S3) is the main sector of R&D spillover effects. When coastal provinces sales products from the *Manufacturing* (S3) to other provinces, the corresponding technology flow into the *Manufacturing* (S3) of Xinjiang, Tibet, and Hainan and enhance the technologies of critical local sectors.

In general, the North, East, and South coast regions, led by Beijing, Shanghai, and Guangzhou, drive other regions. We should increase the R&D inputs of *Scientific Research, Technical Services, and Geological Prospecting* (S10) and *Information Transmission, Computer Services, and Software* (S7) in all three of these coastal regions. Anhui, Hubei, and Shaanxi link East and West, and the North and South of China should input greater R&D into transportation and manufacturing to spur high-quality development in manufacturing. While the Southwest and Northwest regions, including Xinjiang, Tibet, Qinghai, and Yunnan, should focus on *Construction* (S5), *Leasing and Commercial Services* (S9), and *Transport, Storage, and Postal Services* (S6), they should also extend the R&D inputs of the infrastructure sectors to improve the mobility of R&D spillover effects by connecting the eastern and central regions.

5. Discussion and Policy Recommendations

5.1. Conclusions

This study constructs a framework of multi-regional R&D spatial spillover effects by combining input–output multiplier theory and the SNA 2008, opens the "black box" of flows of R&D inputs among regions and sectors, and quantifies the inter-provincial R&D spillover effects of China. The main findings are as follows:

(1) We find significant disparities of provincial direct R&D intensities. In general, the direct intensities dropped from the coastal regions to inland regions. The direct R&D

intensities of coastal regions and the Central Yangtze River regions were increasing, while the Northeast and the Northwest regions were declining. Similarities exist in the industrial structure of R&D inputs among provinces. *Scientific Research, Technical Services, and Geological Prospecting* (S10), *Education* (S12), and *Manufacturing* (S3) are key sectors of R&D inputs. They are R&D-intensive sectors supported largely by local government funds.

(2) We find remarkable spatial R&D spillover effects among provinces. We analyze the sources and destinations of R&D spillover effects and find that R&D spillover effects flow from coastal regions to inland regions, with a growing trend from the East to the West. The tertiary sectors, like *Scientific Research, Technical Services, and Geological Prospecting* (S10) and *Information Transmission, Computer Services, and Software* (S7), are the critical sources of R&D spillover effects, while the downstream basic infrastructure sectors like *Construction* (S5), *Leasing and Commercial Services* (S9), and *Transport, Storage, and Postal Services* (S6) are the key beneficiaries of R&D spillover effects from the source sectors. The balance between R&D direct intensity and R&D total intensity shows that Guangdong (1.69%), Jiangsu (1.40%), and Beijing (1.37%) are the main contributors of R&D spillover effects. Xinjiang (0.49%), Tibet (0.53%), and Hainan (0.50%) are the major winners.

5.2. Comparing the Results with the Existing Studies

Most studies do not provide the level and direction of R&D spillover, but we combine the R&D horizontal spillover effects which reflect geographical elements with the vertical industrial correlation spillover effects, and quantify the spatial spillover effect of R&D capital. For example, Zhu et al. (2016) [32] regard 33 industrial sectors of China between 1998–2011 panel data as the object, and analyze the features of vertical and horizontal R&D spillover. It is found that the asymmetry of vertical spillover effects and the forward spillover is not significant, with the significance of backward spillover and horizontal spillover for R&D capital. Bai (2017) [40] only shows that the growth effect of spatial knowledge spillovers accounts for more than half of the gross growth effect, and the growth effect of R&D capital flow accounts for more than 10%.

Furthermore, it is significant to study the impact of the R&D spillover upon economic growth, especially investigating the intrinsic mechanism of how the dynamic flow of inter-regional R&D elements influences economic growth through spatial knowledge spillovers. The exercise upon a panel of regions with R&D spillover data from this paper and TFP growth data could be of great significance from both theoretical and empirical perspectives. Moreover, the results only show R&D intensity among provinces of China, but many regions have the bitter experience of creating innovative clusters and encouraging innovative activity. Many attempts failed in spite of seemingly favorable conditions and factors for successful innovations in these areas [54]. It is important to identify those areas (provinces or cities) that possess high innovation susceptibility in terms of new developments and creation of innovative clusters. These issues are therefore preserved as the future research agenda.

5.3. Policy Recommendations

Based on the above issues, this paper attempts to propose policy recommendations that are more instructive and targeted.

(1) Encourage the coastal regions to reach new heights of innovation and improve the channels of R&D spillover effects. Beijing, located in the North coast region, has the highest R&D direct intensity in China and the strongest R&D spillover effects. Except for provinces surrounding Beijing, developing provinces like Qinghai, Tibet, Inner Mongolia, Hainan, Guangxi, and Xinjiang are the main beneficiaries of Beijing's R&D inputs. In the North coast region, other provinces such as Tianjin, Hebei, and Shandong have a lower growth of R&D direct intensity than the national average. Nevertheless, R&D direct intensities in the East coast and South coast regions, like Shanghai and Guangdong, show rapid growth. Increasing the R&D inputs of the *Scientific Research, Technical Services, and Geological Prospecting* (S10) among provinces belonging to the source of R&D spillover

effects could encourage greater innovation in the North, East, and South coast regions. Most provinces in the Central Yellow River, Northeast, and Northwest regions do not gain larger benefits from provincial R&D spillover effects and show lower growth in direct R&D intensity than the national average. Notably, Heilong and Jilin have negative growth. Thus, the government should enhance R&D direct inputs in infrastructure sectors like *Construction* (S5) and *Transport, Storage, and Postal Services* (S6). Moreover, interregional trade should be noticed as well. Governments should facilitate cross-regional sectoral chains, forge an innovation path through upstream basic research, midstream technologies, and downstream technology promotion and industrialization, and boost the international level of the local sci-tech innovation overall [55].

(2) Create a regional innovation system with various characteristics to promote industrial agglomeration. Our results show that the regional sectoral structures of R&D inputs are similar. The tertiary sectors, such as *Scientific Research, Technical Services, and Geological Prospecting* (S10), *Education* (S12), and *Information Transmission, Computer Services, and Software* (S7) are focused. Homogenization of regional sectoral structures ignores regional comparable sectoral advantages, leads to the misallocation of R&D resources, and aggravates the unbalance of regional innovation outputs. To improve this situation, the government should encourage growth in all R&D inputs, especially comparative advantage sectors identified through their stage of development and industrial structure. For example, coastal regions, like Beijing, Shanghai, and Guangdong, should increase their R&D inputs to *Scientific Research, Technical Services, and Geological Prospecting* (S10). The Central Yellow River and Central Yangtze River regions, including Anhui, Shaanxi, and Hubei, should focus on *Manufacturing* (S3) and *Transport, Storage, and Postal Services* (S6). The Northwest, such as Qinghai, Xinjiang, and Tibet, should highlight infrastructure and public services to share resources with the East region. Thus, a complementary network between regions could be established [56]. They also should facilitate natural resources and geographical advantages, support the development of new energy and the aerospace industry, and form an industrial layout with complementary advantages among the eastern, central, and western regions of China.

(3) *Information Transmission, Computer Services, and Software* (S7) should take the priority in development to push the digital industrialization process. Our results show that R&D spillover effects flow among regions and sectors through the *Transport, Storage, and Postal Services* (S6), *Manufacturing* (S3), and *Information Transmission, Computer Services, and Software* (S7). Significantly, the digital capital elements built by Information and Communications Technology (ICT) capital and R&D inputs play a role in improving capital utilization efficiency, sharing regional information, and promoting high-quality economic development [57]. Besides developing the infrastructure of information technology, such as Internet service, cloud computing, the Internet of things, and artificial intelligence, the government should focus on industrial policies, talent policies, and land policies in the development of new technologies and infrastructure; encourage creative R&D activities in enterprises to increase their knowledge stock, such as by reducing taxes on innovation-oriented enterprises and providing staff welfare; and provide the impetus and intellectual support for the digital economy.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su151411208/s1, Table S1. The correspondence of 8 regions to 31 provinces in China. Table S2. The list of sectors.

Author Contributions: Conceptualization, C.W.; methodology, L.X.; formal analysis, C.W., S.X. and L.X.; data curation, C.W.; writing—original draft preparation, C.W. and L.X.; writing—review and editing, C.W., S.X. and L.X.; visualization, L.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by [the National Social Science Foundation for Youth Program] grant number [20CTJ006].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

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

References

1. Romer, P.M. Increasing Returns and Long-Run Growth. *J. Political Econ.* **1986**, *94*, 1002–1037. [CrossRef]
2. European Commission; International Monetary Fund; Organisation for Economic Co-Operation and Development; United Nations; World Bank. *2008 System of National Accounts*; United Nations: New York, NY, USA, 2009.
3. Myers, K.R.; Lanahan, L. Estimating Spillovers from Publicly Funded R&D: Evidence from the US Department of Energy. *Am. Econ. Rev.* **2022**, *112*, 2393–2423.
4. National Bureau of Statistics and Ministry of Science and Technology. *China Statistical Yearbook on Science and Technology-2022*; China Statistics Press: Beijing, China, 2022. (In Chinese)
5. European Commission. China's R&D Strategy. 2022. Available online: https://knowledge4policy.ec.europa.eu/foresight/topic/expanding-influence-east-south/industry-science-innovation_en (accessed on 15 August 2022).
6. Audretsch, D.; Feldman, M. R&D Spillovers and the Geography of Innovation and Production. *Am. Econ. Rev.* **1996**, *86*, 630–640.
7. Bai, J. On Regional Innovation Efficiency: Evidence from Panel Data of China's Different Provinces. *Reg. Stud.* **2013**, *47*, 773–788. [CrossRef]
8. Meng, F.J. Comparative Study of R&D Spillover Effect for High Technology Industry and Traditional Industry. *Adv. Mater. Res.* **2014**, *989–994*, 5278–5281.
9. Sakurai, N.; Papaconstantinou, G.; Ioannidis, E. Impact of R&D and Technology Diffusion on Productivity Growth: Empirical Evidence for 10 OECD Countries. *Econ. Syst. Res.* **1997**, *9*, 81–109.
10. Qin, X.; Du, D.; Kwan, M. Spatial spillovers and value chain spillovers: Evaluating regional R&D efficiency and its spillover effects in China. *Scientometrics* **2019**, *119*, 721–747.
11. Nishioka, S.; Ripoll, M. Productivity, trade and the R&D content of intermediate inputs. *Eur. Econ. Rev.* **2012**, *56*, 1573–1592.
12. Dietzenbacher, E.; Los, B. Externalities of R&D Expenditures. *Econ. Syst. Res.* **2002**, *14*, 407–425.
13. Miller, R.E.; Blair, P.D. *Input-Output Analysis: Foundations and Extensions*, 3rd ed.; Cambridge University Press: New York, NY, USA, 2022.
14. Aghion, P.; Howitt, P. A Model of Growth through Creative Destruction. *Econometrica* **1992**, *60*, 323–351.
15. Grossman, G.M.; Helpman, E. Quality Ladders in the Theory of Growth. *Rev. Econ. Stud.* **1991**, *58*, 43–61. [CrossRef]
16. Romer, P.M. Endogenous Technological Change. *J. Political Econ.* **1990**, *98*, S71–S102. [CrossRef]
17. Griliches, Z.; Lichtenberg, F. Interindustry Technology Flows and Productivity Growth: A Reexamination. *Rev. Econ. Stat.* **1984**, *66*, 324–329. [CrossRef]
18. Philippe, A.; Peter, H. *Endogenous Growth Theory*; The MIT Press: Cambridge, MA, USA, 1997.
19. Beñat, B.O.; Andrés, R.P. From R&D to Innovation and Economic Growth in the EU. *Growth Change* **2004**, *35*, 434–455.
20. Yan, C.; Gong, L. R&D Ratio, R&D Structure and Economic Growth. *Nankai Econ. Stud.* **2013**, *2*, 3–19. (In Chinese)
21. Nair, M.; Pradhan, R.P.; Arvin, M.B. Endogenous dynamics between R&D, ICT and economic growth: Empirical evidence from the OECD countries. *Technol. Soc.* **2020**, *62*, 101315.
22. Shahateet, M.I. The role of R&D in economic growth in Arab countries. *Int. J. Comput. Econ. Econom.* **2020**, *10*, 345–365.
23. Das, R.C. Interplays among R&D spending, patent and income growth: New empirical evidence from the panel of countries and groups. *J. Innov. Entrep.* **2020**, *9*, 18.
24. Das, R.C.; Mukherjee, S. Do Spending on R&D Influence Income? An Enquiry on the World's Leading Economies and Groups. *J. Knowl. Econ.* **2020**, *11*, 1295–1315.
25. Minsung, K. Cross-industry distribution of R&D investments and economic growth. *Appl. Econ. Lett.* **2020**, *27*, 679–684.
26. Krugman, P. Increasing Returns and Economic Geography. *J. Political Econ.* **1991**, *99*, 483–499. [CrossRef]
27. Wolff, E.N. Spillovers, Linkages and Technical Change. *Econ. Syst. Res.* **1997**, *9*, 9–23. [CrossRef]
28. Blanco, L.R.; Gu, J.; Prieger, J.E. The impact of research and development on economic growth and productivity in the US States. *South. Econ. J.* **2016**, *82*, 914–934. [CrossRef]
29. Aysun, U.; Yom, Z. R&D Characteristics, Innovation Spillover, and Technology-Driven Business Cycles. *J. Ind. Compet. Trade* **2021**, *21*, 339–365.
30. Jaffe, A.B. Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. *Am. Econ. Rev.* **1986**, *76*, 984–1001.
31. Los, B. The empirical performance of a new inter-industry technology spillover measure. In *Technology and Knowledge; from the Firm to Innovation Systems*; Saviotti, P.P., Nooteboom, B., Eds.; Edward Elgar Publishing: London, UK, 2000; pp. 118–151.
32. Zhu, P.; Xiang, G.; Wang, Y. R&D Spill-over Effects: Evidence from Chinese Industrial Sectors. *Econ. Res. J.* **2016**, *51*, 44–55. (In Chinese)
33. Fujita, M.; Thisse, J. Does Geographical Agglomeration Foster Economic Growth? And Who Gains and Loses from It? *Jpn. Econ. Rev.* **2003**, *54*, 121–145. [CrossRef]
34. Bengoa, M.; Román, V.M.; Pérez, P. Do R&D activities matter for productivity? A regional spatial approach assessing the role of human and social capital. *Econ. Model.* **2017**, *60*, 448–461.

35. Coe, D.T.; Helpman, E.; Hoffmaister, A. *North-South R&D Spillovers*; C.E.P.R. Discussion Papers: London, UK, 1995.
36. Jiang, R.; Cai, H.; Li, Y.; Li, H. China's Sustained Economic Growth: Do Direct R&D Spillovers Matter? *China World Econ.* **2010**, *18*, 37–53.
37. Pio, J.G.; Gonçalves, E.; Vasconcelos, C.R.F. Technology Spillovers through Exports: Empirical Evidence for the Chinese Case. *J. Ind. Compet. Trade* **2021**, *21*, 423–443. [CrossRef]
38. Jiao, J.; Jiang, G.; Yang, R. Impact of R&D technology spillovers on carbon emissions between China's regions. *Struct. Change Econ. Dyn.* **2018**, *47*, 35–45.
39. Keller, W. Geographic Localization of International Technology Diffusion. *Am. Econ. Rev.* **2002**, *92*, 120–142. [CrossRef]
40. Bai, J.; Wang, Y.; Jiang, F.; Li, J. R&D Element Flow, Spatial Knowledge Spillovers and Economic Growth. *Econ. Res. J.* **2017**, *52*, 109–123. (In Chinese)
41. Jaffe, A.B.; Trajtenberg, M. *Patents, Citations, and Innovations: A Window on the Knowledge Economy*; The MIT Press: Cambridge, MA, USA, 2002.
42. Liu, C.; Guan, M.; Duan, D. Spatial pattern and influential mechanism of interurban technology transfer network in China. *Acta Geogr. Sin.* **2018**, *73*, 1462–1477. (In Chinese)
43. Lyu, L.; Liang, Z.; Huang, R. The Innovation Linkage among Chinese Major Cities. *Sci. Geogr. Sin.* **2015**, *35*, 30–37. (In Chinese)
44. Song, X.; Zhao, Y. Study on Regional Innovation Spatial Correlation and Influence Factors in China. *J. Quant. Tech. Econ.* **2018**, *35*, 22–40. (In Chinese)
45. Li, W.; Li, Q.; Qiu, Z. Research on Evolution of Cooperative Technological Innovation about Guangdong-Hong Kong-Macao Greater Bay Area Based on Patent Measurement. *Stat. Res.* **2019**, *36*, 74–86. (In Chinese)
46. Leontief, W. Quantitative Input and Output Relations in the Economic Systems of the United States. *Rev. Econ. Stat.* **1936**, *18*, 105. [CrossRef]
47. Ghosh, A. Input-Output Approach in an Allocation System. *Economica* **1958**, *25*, 58–64. [CrossRef]
48. Gao, M. Understanding and Proposal of R&D Capitalization and GDP Adjustment. *Stat. Res.* **2017**, *34*, 3–14. (In Chinese)
49. Hou, R.; Chen, Y. The Estimation of Capital Stock of China's Provincial R&D in the Framework of SNA. *Stat. Res.* **2018**, *35*, 19–28. (In Chinese)
50. Sun, F.; Jiang, Y. The Measurement of China's Regional R&D Capital Stock: 1978–2015. *Stat. Res.* **2018**, *35*, 99–108. (In Chinese)
51. Wang, Y.; Wang, C. Capital Stock Accounting of Research and Development at Chinese Industrial Level. *J. Quant. Tech. Econ.* **2018**, *35*, 94–110. (In Chinese)
52. National Bureau of Statistics. *The Second National R&D Resources Inventory Data Compilation*; China Statistics Press: Beijing, China, 2011. (In Chinese)
53. Zheng, H.; Többen, J.; Dietzenbacher, E.; Moran, D.; Meng, J.; Wang, D.; Guan, D. Entropy-based Chinese city-level MRIO table framework. *Econ. Syst. Res.* **2022**, *34*, 519–544. [CrossRef]
54. Mingaleva, Z.; Mingaleva, A. Assessing Innovation Susceptibility of Regions and Municipal Districts. *Procedia-Soc. Behav. Sci.* **2013**, *81*, 595–599. [CrossRef]
55. Song, H.; Zhang, M. Spatial Spillovers of Regional Innovation: Evidence from Chinese Provinces. *Emerg. Mark. Financ. Trade* **2017**, *53*, 2104–2122. [CrossRef]
56. Audretsch, D.B.; Belitski, M. The role of R&D and knowledge spillovers in innovation and productivity. *Eur. Econ. Rev.* **2020**, *123*, 103391.
57. Zhang, W.; Zhang, T.; Li, H.; Zhang, H. Dynamic spillover capacity of R&D and digital investments in China's manufacturing industry under long-term technological progress based on the industry chain perspective. *Technol. Soc.* **2022**, *71*, 102129.