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## Article

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## Research Article

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# A Study of Knowledge Spillovers within Chinese Mega-Economic Zones

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**Abstract:** Using a prefectural level data, we shed the light on the knowledge spillovers within three mega-economic zones (MEZs) in China by adopting spatial econometric methods. We first examine the spillovers within all regions, and then the spillovers within the MEZs, and finally the spillovers from core cities. The results show that there are pronounced spillovers between cities in China, which is stronger between cities with high techno-proximity. Moreover, spillovers within the MEZs are found to be stronger but unequal. Spillovers between cities in the Pearl River Delta are the greatest among the MEZs, while the spillovers within Jing-jin-ji are the lowest. Eventually, Shenzhen outperforms Shanghai and Beijing in knowledge spillovers, whereas Beijing may even adversely affect the innovation of neighbors.

**Keywords:** knowledge spillovers, mega-economic zones, innovation, China

## 1 Introduction

After the reform and opening-up, China has achieved great economic success with a nearly two-digit annual growth. It became the second largest economy in 2015 over the world. China's outstanding performance in economic growth experienced in the past four decades has been mainly contributed by international trade. Export-led growth model enables China to take advantage of the abundant and cheap labor force and participate in the global value chain. However, export-led growth seems to be unsustainable due to the increasing labor cost

and deteriorated environmental pollution. Being aware of the weakness of the existing model, China started to reorient its economy from export-driven model towards innovation-led model. Therefore, the past several years have witnessed more efforts put on promoting technical innovation nationwide. This new orientation is strengthened by the report of the 19th National Congress of the Communist Party of China, which places unprecedented significance on innovation in the economic development.

A well-established fact is that technological innovation is an important approach to enhance the competitiveness of a country. Two important factors determining regional innovation capability are innovation investment and knowledge spillover (Abramovitz, 1986). However, the distribution of innovation resources between regions is extremely unbalanced. Innovation activities are much more likely to happen in economically developed areas thanks to their abundant endowment of innovation resources (Audretsch & Feldman, 1996). Under this circumstance, it is an effective way for less developed regions to promote local innovation by exploiting the spillover of innovation.

For decades, the knowledge spillover has been investigated intensively in a variety of directions. A strand of studies keeping a close eye on measuring the effects of knowledge spillovers was led by Jaffe (1986), who used a “knowledge production function” first introduced by Griliches (1979). Other studies by Acs, Anselin, and Varga (2002), Anselin, Acs, and Varga (1997), and Moreno, Paci, and Usai (2005) join this research category. Other related studies investigated various channels of knowledge spillover including foreign trade (Coe & Helpman, 1995; Coe, Helpman, & Hoffmaister, 1997; Keller, 2002; Parrado & Cian, 2014), Foreign direct investment (Damijan, Rojec, Majcen, & Knell, 2013; Girma, Gong, & Holger, 2008; Hu & Jefferson, 2002), and human mobility (Audretsch & Feldman, 1996). Another group of studies examined the key factors in explaining the determinants of spillover effect. They found that technology spillover effect is not unconditional (Autant-Bernard & LeSage, 2019). Firms from host country must have certain absorptive capacity in order to successfully imitate, absorb, and digest

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foreign advanced technology (Bond-Smith, McCann, & Oxley, 2018; Cohen & Levinthal, 1990; Griffith, Harrison, & Van Reenen, 2006; Narula & Dunning, 2000). And the absorptive capacity is closely related to multi-dimensional proximities including geographical proximity, organizational proximity, and institutional proximity (Boschma, 2005; Jaffe, Trajtenberg, & Henderson, 1993; Kazakis, 2019; Torre & Gilly, 2000).

China's science and technology (S&T) have evolved in line with its stages of economic development (Li, 2009; Wang, Sutherland, Ning, & Pan, 2015). In China's catch-up phase started in the 1980s, S&T policies were focused on facilitating this transition and putting into place instruments to strengthen industry-research linkages and incentivize innovation in firms. Currently, China's S&T policy is aimed at supporting innovation-led growth by strengthening the innovation system and building capabilities in frontier technologies (Liu, Simon, Sun, & Cao, 2011; World Bank/Development Research Center of the State Council, the People's Republic of China, 2019). The innovative capacity and contribution of S&T to the economic development keeps increasing after the implementation of S&T policies in China. Statistics from Ministry of Science and Technology shows that the proportion of R&D expenditure in GDP is 2.19%. The contribution rate of scientific and technological progress reached 59.5% in 2019.

However, like other developed countries, not only industrial but also innovative activity shows different degrees of geographic clustering in China. Several studies have studied the spatial distribution of innovation in China (Huang & Zhang, 2019). Most of them found that innovative activities were unevenly distributed across Chinese provinces, with a much higher concentration in the economically more developed regions (Liu, 2014; Ma & Liu, 2019). However, few or no studies go a step further

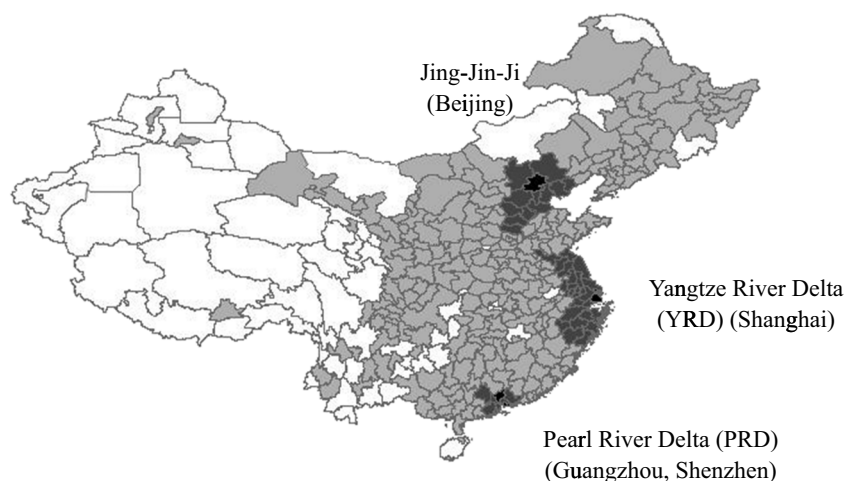
to link spatial unequal distribution of innovative activity with spillover effect.

In this article, we try to fill the research gap by investigating center-periphery knowledge spillovers within Chinese metropolitan areas including Beijing–Tianjin–Hebei (JJJ), Pearl River Delta (PRD), and Yangtze River Delta (YRD). Specifically speaking, we attempt to examine whether spillovers within the three mega-economic zones (MEZs) are larger than spillovers between other Chinese cities and their hinterlands. The results show that there are pronounced spillovers between cities in China, which is stronger between cities with high techno-proximity. Moreover, spillovers within three MEZs are found to be stronger but unequal. Spillovers between cities in the PRD are the greatest among the three economic zones, while the spillovers within JJJ are the lowest. Eventually, Shenzhen outperforms Shanghai and Beijing in knowledge spillovers, whereas Beijing may even adversely affect the innovation of neighbors.

The remainder of the article is organized as follows. Section 2 briefly introduces the three MEZs. Section 3 introduces the specification, data and empirical method. Section 4 presents and discusses the empirical findings. Section 5 provides the conclusion.

## 2 Background Information

The economic development in China is quite unequal, the most advanced region is eastern coastal China and the western regions are still underdeveloped. In particular, the three MEZs have been formed including JJJ, YRD, and PRD as shown in Figure 1. The main economic indices of the three economic zones are reported in Table 1.



**Figure 1:** Distribution of three mega-economic zones.

**Table 1:** Main economic indices of three MEZs

	Cities	Land area (km <sup>2</sup> )	Population		GDP (RMB)		GDP per capita	
			2016	2020	2016	2020	2016	2020
JJJ	13	218,000	112 million	113 million	7.5 trillion	8.6 trillion	67,699	77,254
YRD	26	358,000	222 million	227 million	17.7 trillion	24.5 trillion	80,022	107,833
PRD	9	55,368	60 million	92 million	6.8 trillion	8.9 trillion	89,738	148,542

Source: China Statistical Book.

## 2.1 JJJ

The JJJ region, known as Beijing–Tianjin–Hebei, is China's capital economic area, in which Beijing, Tianjin, and Shijiazhuang are the core areas. The JJJ region is located in the heart of Bohai Sea in northeast China. It is the largest and most dynamic area in northern China. In 2019, the GDP of JJJ region in China reached 8458.008 billion-yuan, accounting for 8.5% of the nation.

- ◆ Beijing, the capital of China, is the national political, cultural, and innovation center.
- ◆ Over the past years, JJJ did poor in realizing coordinated development, and the gap between Beijing and its neighboring cities within JJJ has been obviously widening. Some reasons are:
  - 1) Serious administrative barriers between Beijing and other cities, and the development of Beijing is always at the cost of the others.
  - 2) A great amount of resources (financial resources, human resources, energy, etc.) actively or passively flow into Beijing;
  - 3) Poor industry connection and huge regional gap allows little cooperation between Beijing and other cities.

Based on this, the coordinated development of Beijing–Tianjin–Hebei has become the national strategy nowadays. Some political measures<sup>1</sup> (in terms of innovation) include:

- 1) Build JJJ innovation system where Beijing acts as the origin of innovation, Tianjin conducts innovation transformation, and Hebei applies and popularizes it;
- 2) Share the innovation resources and technological achievements, strengthen the training and exchange of R&D personnel, and encourage innovation communication and cooperation. For example, set up the JJJ Alliance

of Higher Education that encourages Beijing and other cities to cooperatively run universities and construct disciplines; encourages Beijing and other cities to cooperatively build innovation zones.

## 2.2 YRD

The YRD is a triangle-shaped metropolitan region generally comprising of Shanghai, southern Jiangsu province, and northern Zhejiang province. With less than 4% of its territory, the YRD has created nearly one-fourth of China's GDP and one-third of its trade volume. The YRD region is one of the most active, open, and innovative regions in China.

- ◆ Shanghai: an international center for economic, finance, trade, and shipping, and striving for global innovation center nowadays.
- ◆ Over the past years, YRD did well in realizing coordinated development and Shanghai well pushes the development of its neighboring cities.

YRD has always been the important business and trade centers since olden days. The cities here, as well as Shanghai and its neighbors, are willing to and capable of keeping close contact with each other in various aspects (technology, human capital, finance, etc.), due to their historical links, open and equal atmosphere, good industry connection, and more importantly, the impetus of market economy. In other word, Shanghai pulls the development of its neighboring cities, and in return, the cities within YRD support improvement of Shanghai.

- ◆ Some political measures towards a regional convergence are:

- 1) Speed up the development of modern service industry with Shanghai as the international shipping center and international financial center, and strive for an industry structure with service industry as core (*The Guidance of State Council on Further Promoting the Reform and Opening up and Economic and Social*

<sup>1</sup> Sources: *The Plan for the Coordinated Development of Beijing–Tianjin–Hebei* (approved in 2015); *The Pilot Scheme for Systematically Promoting the Reform of Comprehensive Innovation* (approved in 2016).

*Development in the Yangtze River Delta*, approved in 2008).

- 2) Give full play to the core role of Shanghai as the international center for economic, finance, trade, and shipping, and speed up its development of modern service industry and high-end manufacturing industry, and other cities should well take advantage of this in order to coordinately promote the industrial upgrading, technological innovation, and further development (*Regional Plan for Yangtze River Delta*, approved in 2010).

## 2.3 PRD

The PRD metropolitan region is in the south-central part of Guangdong province, consisting of nine cities. The total area of PRD accounts for less than one-third of Guangdong province, while it has 53.35% of the population and 79.67% of the GDP of Guangdong province. It is one of the biggest urban agglomerations with the strongest innovation ability in China. Today, as a national strategy, Guangdong–Hong Kong–Macao Greater Bay Area is formed in this area.

- ◆ There are two core cities in PRD: Guangzhou and Shenzhen. Guangzhou, the capital of Guangdong, works for the concentration of high-end elements, technological innovation, cultural leading, and providing comprehensive service. Shenzhen is the national economic center and the national innovation city.<sup>2</sup>
- ◆ Like YRD, PRD did well in realizing coordinated development in the past. The close links between cities, and core cities to its neighbors is also mainly driven by the market economy (without so much political issues). There are many specific cases demonstrating this positive cooperation between core cities and its neighbors. For example, Shenzhen benefits its cities nearby by the transfer of industries, technology, talents, and so on.
- ◆ During 2016–2020, a regional innovation system (“1 + 1 + 7”) has been set up where the leading roles of Guangzhou and Shenzhen were more prominent, the mechanism of regional innovation cooperation has been greatly improved and an efficient division-

cooperation system has been established (*The Plan for the Construction of National Independent Innovation Demonstration Zone of Pearl River Delta (2016–2020)*, approved in 2016)

## 3 Specification, Data and Method

### 3.1 Specification

In order to investigate the spillover effect within three MEZs, we develop a knowledge production function rooted in models of endogenous economic growth in open economies (e.g., Grossman & Helpman, 1990):

$$P_{it} = A_{it-1} E_{it-1}^{\alpha} (K^*)_{it-1}^{\beta}.$$

Patents in city  $i$  ( $P_{it}$ ) depends on recent own research effort ( $E_{it-1}^{\alpha}$ ) (R&D expenditures), available knowledge stock ( $(K^*)_{it-1}^{\beta}$ ), and controls ( $A_{it-1}$ ) including total factor productivity in R&D, local specificities, and other confounding effects. The available knowledge stock ( $K^*$ ) is given by:

$$(K^*)_{it-1}^{\beta} = K_{it-1}^{\beta_0} \left( \prod_{j=1}^N \prod_{j \neq i} K_{jt-1}^{\beta_{ij}} \right) FDI_{it-1}^{\beta_f} TR_{it-1}^{\beta_t}.$$

The available knowledge stock consists of own knowledge developed in the past ( $K_{it-1}^{\beta_0}$ ), knowledge that spilled over from other cities ( $K_{jt-1}^{\beta_{ij}}$ ), knowledge that spilled over from foreign investors ( $FDI_{it-1}^{\beta_f}$ ), and knowledge that spilled over from international trade partners ( $TR_{it-1}^{\beta_t}$ ). Inter-city weights are measured with geographical distance adopting the inverse exponential distances between city pairs ( $w_{ij}^G = e^{-\delta D_{ij}}$ ), and technological distance (dis-similarity in technological specialization) using uncentered correlation of sectorial R&D expenditures across city pairs.

$$w_{ij}^T = \frac{\sum_k E_{ik} E_{jk}}{\sqrt{(\sum_k E_{ik}^2)(\sum_k E_{jk}^2)}}.$$

Taking the logarithmic form of production function, we setup a following spatial lag model with time-space recursive form like Anselin (2007), in which the dependence relies on a weighted average of neighboring and the value of itself in time  $t-1$ .

$$\ln P_{it} = \rho \sum_j w_{ij} \ln P_{jt} + \beta_0 \ln P_{it-1} + X\gamma + \mu_t + \varepsilon_{it},$$

<sup>2</sup> Given the (increasing) significant role of innovation in Shenzhen, Shenzhen is regarded as the innovation center of PRD in this study. To be specific, the whole city of Shenzhen is recognized as the National Independent Innovation Demonstration Zone (before Guangzhou), which is the first time in China. It also produces more patents than Guangzhou.



**Table 2:** Description of key variables

Variables	Measurement and instruments
Patent	The number of total patent applications
Patent stock	Perpetual inventory method: $A_{i,t} = (1 - \lambda)A_{i,t-1} + R_{it}$ , $\lambda = 15\%$
R&D expenditure (million RMB)	Split up the R&D expense of province using the share of each city in provincial total in terms of Government Expenditure for Science and Technology expenditure
Trade (million USD)	The sum of export and import (deflated by USA CPI)
FDI (million USD)	FDI stock
Employee	The number of persons employed at year-end
Pgdp (RMB)	GDP per capita

**Table 3:** Statistical descriptions of key variables

Variable	Obs	Mean value	Std. Dev.	Min	Max
Patent	1,620	4898.665	12387.49	16	145,165
Patent_stock	1,620	11320.26	29863.55	10.1	382,357
rd	1,620	2169.492	5984.502	2.75	90106.8
pgdp	1,620	24478.14	16302.26	3285.8	102,355
FDI	1,620	2479.371	5649.54	40,433	58034.8
Trade	1,620	10067.16	38810.01	2.35	421,562
Employee	1,620	256.4304	185.9565	22.6	1668.8

Source: China Statistical Book and municipal statistical bulletins.

where the dependent variable  $P_{it}$  denotes the innovation output of city  $i$  in year  $t$  measured as the number of total patent applications filed in each of the 270 regions in 7 years.  $W$  is the spatial weight matrix and  $\rho$  is the spatial autocorrelation coefficient. The one-lagged dependent variable is included in the specification in order to capture the lagged effect of innovative activity. Other controls include patent stock (Bilgin, Lau, & Karabulut, 2012), R&D expenditure (Shanga, Poonb, & Yuec, 2012), trade volume, FDI stock (Hanley, Liu, & Vaona, 2015), employees (Gogokhia & Berulava, 2021), and GDP per capita. Time fixed effects and individual fixed effects are also introduced in the specification. Table 1 describes the key variables in detail.

### 3.2 Data

This study adopts a municipal-level panel dataset over the period of 2007–2012. Since the patent data are not available from China Statistical Book, we manually collected the patent data from the statistical bulletins released by the prefectural governments of the three MEZs through their websites. 270 prefecture-level cities are included in the sample.<sup>3</sup> The data of other variables are acquired from China Statistical Book. Table 2 defines the variables of

main interest. Table 3 reports the statistical descriptions of key variables.

### 3.3 Method

For the sake of choosing a suitable empirical method, we compute the spatial autocorrelation statistics using Moran's  $I$  index to test the spatial correlation of dependent variable. The Moran's  $I$  index is given by:

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

where  $S^2$  is the sample variance,  $W_{ij}$  is the spatial weights matrix. The value of  $I$  is between 0 and 1, when the value is greater than 0, there is a positive spatial correlation, and when the value is less than 0, there is a negative spatial correlation.

Table 4 reports the Moran's  $I$  index by year and different distances. As seen in this table, innovation activity measured by patent or patent stock in all years shows positive

<sup>3</sup> Some prefecture-level cities are excluded from the data because of patent data unavailability. Most of them are from western under-developed regions.

Table 4: Moran's I index

		2007	2008	2009	2010	2011	2012
Geographic distance	Patent	0.017	0.018	0.021	0.022	0.021	0.020
	( <i>p</i> -value)	0.000	0.000	0.000	0.000	0.000	0.000
	Patent stock	0.013	0.014	0.016	0.017	0.019	0.020
Technological distance	( <i>p</i> -value)	0.000	0.000	0.000	0.000	0.000	0.000
	Patent	0.017	0.018	0.020	0.020	0.020	0.021
	( <i>p</i> -value)	0.000	0.000	0.000	0.000	0.000	0.000
	Patent stock	0.015	0.016	0.018	0.019	0.020	0.020
	( <i>p</i> -value)	0.000	0.000	0.000	0.000	0.000	0.000

Table 5: LM tests

Test	Geographic distance			Technological distance		
	Statistic	df	<i>p</i> -value	Statistic	df	<i>p</i> -value
LMERR	15.653	1	0.000	14.285	1	0.000
R-LMERR	1.334	1	0.193	1.730	1	0.188
LMLAG	31.035	1	0.000	41.007	1	0.000
R-LMLAG	33.716	1	0.000	48.453	1	0.000

significant spatial dependence. And this spatial correlation increases with year. However, the values of Moran index are very low, suggesting that the spatial correlation is weak. The reason why the values of Moran Index are low lies in

that the technical development across China is extremely uneven, which leads to the low average spatial technical dependence. Considering the existence of spatial correlation of dependent variable, we think that Spatial autoregressive (SAR) model outperforms other spatial models.

Furthermore, we check the spatial effects by executing several LM tests including LMERR, LMLAG, and robust R-LMERR and R-LMLAG. Table 5 reports the test results. According to Anselin et al. (1997), if LMLAG is more significant than LMERR in statistics, and R-LMLAG is significant while R-LMERR is not, it can be concluded that spatial lag model is the suitable model. Otherwise, spatial error model is more appropriate.

Table 6: Spillovers within all regions

	Geo-distance		Tech-distance	
	(1)	(2)	(3)	(4)
L.Inpatent	0.771*** (0.0238)	0.795*** (0.0243)	0.726*** (0.0107)	0.821*** (0.0109)
lnrd	0.0438** (0.0220)	0.0198* (0.0225)	0.0170* (0.00964)	0.0169* (0.00992)
lnpgdp	0.0573 (0.0910)	0.371*** (0.0935)	0.118*** (0.0398)	0.0285 (0.0417)
lnFDI	0.101*** (0.0285)	0.00650 (0.0292)	0.0206 (0.0126)	0.0316* (0.0130)
Intrade	0.00890 (0.0196)	0.0126 (0.0200)	−0.0142* (0.00860)	0.0123 (0.00885)
lnemployee	−0.00664 (0.0757)	−0.0155 (0.0775)	−0.103*** (0.0332)	−0.0393 (0.0343)
rho		0.109*** (0.334)		0.251*** (0.310)
lnpatent_stock	0.333*** (0.200)	0.437*** (0.121)	0.403*** (0.239)	0.328*** (0.121)
sigma2_e		0.0659*** (0.00212)		0.0129*** (0.000414)
Observations	1,350	1,350	1,350	1,350
R-squared	0.37	0.359	0.449	0.708
Number of cities	270	270	270	270

Note: Robust standard errors in parentheses. \*\*\**p* < 0.01, \*\**p* < 0.05, and \**p* < 0.1.

**Table 7:** Spillovers within three MEZs

	JJJ		YRD		PRD	
	(1) GD	(2) TD	(3) GD	(4) TD	(5) GD	(6) TD
L.Inpatient	1.132*** (0.0236)	0.800*** (0.0242)	0.719*** (0.0107)	0.825*** (0.0109)	0.750*** (0.0469)	0.749*** (0.0471)
lnrd	0.0963*** (0.0172)	0.0221** (0.0177)	0.0375 (0.00757)	0.0700** (0.00781)	0.0470* (0.0259)	0.0475* (0.0258)
lnpgdp	1.144*** (0.0908)	0.363*** (0.0934)	0.122*** (0.0398)	0.0303 (0.0418)	0.955*** (1.076)	0.413*** (1.024)
lnFDI	0.275*** (0.0285)	0.00409 (0.0292)	0.0407*** (0.0126)	0.0322** (0.0130)	0.0155 (0.0141)	0.0550*** (0.0203)
lntrade	−0.0234 (0.0195)	0.0130 (0.0201)	0.0317*** (0.00861)	−0.0123 (0.00887)	0.0403 (0.0279)	0.0398 (0.0279)
lnemployee	0.0242 (0.0755)	−0.0127 (0.0776)	0.144*** (0.0333)	−0.0380 (0.0344)	0.0198 (0.0378)	0.0148 (0.0379)
rho	0.102*** (0.197)	0.245*** (0.239)	0.474*** (0.328)	0.644*** (0.308)	0.507*** (0.122)	0.782*** (0.132)
lnpatent_stock	0.334*** (0.125)	0.338*** (0.126)	0.336*** (0.0718)	0.320*** (0.0267)	0.344*** (0.127)	0.342*** (0.127)
sigma2_e	0.0515*** (0.00206)	0.0660*** (0.00212)	0.00851*** (0.00385)	0.0129*** (0.00416)	0.00536*** (0.00410)	0.0245*** (0.00327)
Observations	91	91	182	182	105	105
R-squared	0.106	0.217	0.236	0.502	0.313	0.318
Number of cities	13	13	26	26	15	15

Note: Robust standard errors in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , and \* $p < 0.1$ .

As shown in Table 5, the statistical values of LMLAG and R-LMLAG are greater than that of LMERR and R-LMERR, and R-LMLAG is significant, while R-LMERR is not. The test result suggests that spatial lag model is a better option.

## 4 Empirical Results

Given that the panel data is used and the lagged dependent variable is included in the vector of controls, the dynamic panel data SAR model with time fixed effects and individual fixed effects is adopted for empirical analysis and estimated with ML method.<sup>4</sup> We employ Hausman test to select between fixed effect model and random effect model. The rejection of null hypothesis of Hausman test indicates the acceptance of fixed effect model.

### 4.1 Spillovers within All Regions

We first look at the spillovers within all regions as presented in Table 6. Columns 1 and 3 report within estimators

of dynamic panel data model estimated by system generalized method of moments (GMM) for reference. Column 2 reports the estimation results using geographic distance as spatial weights matrix. Column 4 employs technological distance as spatial weights matrix. As shown in this table, the spatial autoregressive parameters  $\rho$  (rho) in columns 2 and 4 are significant at 1% level, suggesting there are remarkable spillovers between cities in China. However, the magnitude of the spatial parameter weighted by geographic distance is much lower than that weighted by technological distance, which means that technological similarity plays a more important role on the spillovers than geographic proximity and the spillovers between cities with higher technological similarity are stronger. One reason is that cities with lower technological distance have higher absorptive ability, which promotes the spillover effect. The results confirm the findings of previous studies on absorptive ability.

Concerning other controls, the 1-year lagged patent, patent stock, GDP per capita, and R&D expenditure are found to have significant impact on the number of patent applications. While the FDI, trade volume, and the number of employees seem to have no significant relationship with regional innovation.

<sup>4</sup> The command `xsmle` is used in stata 15.



**Table 8:** Decomposition of knowledge spillovers

kstd	Knowledge spillover by technological distance knowledge spillover: $\sum_{j=1, j \neq i}^N w_{jt-1}^T \ln P_{jt-1}$
ksgd	Knowledge spillover by geographical distance 1) Geographical distance: $w_{ij}^G = e^{-\delta D_{ij}}$ (keep the geographical distance < 800 km; distance decay 0.03). 2) Knowledge spillover: $\sum_{j=1, j \neq i}^N w_{jt-1}^G \ln P_{jt-1}$
ksgdc	Knowledge spillover by geographical distance from three core cities (Beijing, Shanghai, and Shenzhen): $W_{iN}^G \ln P_{N,t-1}$
kstdc	Knowledge spillover by technological distance from 3 core cities (Beijing, Shanghai, and Shenzhen): $W_{iN}^T \ln P_{N,t-1}$
nksgdc	Knowledge spillover by geographical distance from three core cities (Beijing, Shanghai, and Shenzhen) to its neighbors within the same zone; neighbor dummy* ksgdc
nkstdc	Knowledge spillover by technological distance from three core cities (Beijing, Shanghai, and Shenzhen) to its neighbors within the same zone; neighbor dummy* kstdc

## 4.2 Spillovers within Three MEZs

In the next step, the spillovers within three MEZs are examined in this section as demonstrated in Table 7. Columns 1, 3, and 5 report the estimation results using geographic distance as spatial weights and the rest uses

technological distance. As reported in this table, the spatial autoregressive parameters  $\rho$  (rho) in all columns are found to be significant, which means that spillovers exist across all these three metropolitan regions. More importantly, the magnitude of spatial coefficient (rho) of the PRD is the largest, followed by the YRD, and the JJJ.

**Table 9:** Spillover from three core cities

	Beijing		Shanghai		Shenzhen	
	(1) GD	(2) TD	(3) GD	(4) TD	(5) GD	(6) TD
lnPatent_stock	0.448*** (0.0468)	0.449*** (0.0468)	0.464*** (0.0446)	0.463*** (0.0451)	0.450*** (0.0468)	0.449*** (0.0472)
lnrd	0.0389* (0.0258)	0.0394* (0.0258)	0.0448** (0.0260)	0.0495** (0.0260)	0.0370* (0.0259)	0.0375* (0.0258)
ksgdc	0.120 (0.197)		0.157*** (0.559)		0.159*** (1.076)	
kstdc		0.138* (0.016)		0.252* (0.0148)		0.255*** (0.0141)
nksgdc	−0.0027*** (0.132)		0.311*** (0.521)		0.413*** (1.024)	
nkstdc		0.114*** (0.0229)		0.445** (0.0356)		0.550*** (0.0203)
Intrade	0.0385 (0.0279)	0.0392 (0.0279)	0.0502* (0.0282)	0.0501* (0.0281)	0.0403 (0.0279)	0.0398 (0.0279)
lnFDI	−0.00259 (0.0377)	−0.00243 (0.0377)	0.0143 (0.0367)	0.0181 (0.0373)	−0.00198 (0.0378)	−0.00148 (0.0379)
lnemployee	−0.0781 (0.122)	−0.0783 (0.122)	−0.100 (0.122)	−0.0714 (0.121)	−0.0797 (0.122)	−0.0782 (0.122)
lnpgdp	0.334*** (0.125)	0.338*** (0.126)	0.245*** (0.117)	0.317*** (0.124)	0.344*** (0.127)	0.342*** (0.127)
L.patent	0.749*** (1.384)	0.814*** (1.392)	0.387*** (0.784)	0.816*** (0.446)	0.863*** (1.405)	0.868*** (1.405)
City-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,350	1,350	1,350	1,350	1,350	1,350
R-squared	0.313	0.313	0.311	0.311	0.313	0.313
Number of cities	270	270	270	270	270	270

Note: Robust standard errors in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , and \* $p < 0.1$ .

A comparison of the coefficient magnitudes reveals that spillovers between cities in the PRD are the greatest among the three economic zones. This result may be explained as follows. First, there is higher concentration of manufacturing industries in the PRD, which gives birth to more innovation activities, because manufacturing activities are inherently associated with more innovations. Second, the PRD is composed of cities from the same province, which means a higher proximity in geography, institution, and technology. Higher proximity is definitely helpful to the spillovers between cities. Finally, there are two metropolises in the PRD including Guangzhou and Shenzhen. Guangzhou is a cultural and political center where lots of universities are located. Shenzhen is an immigrant city and the manufacturing base. Different orientations of Guangzhou and Shenzhen lead to complementarity rather than competition. The complementarity will increase innovation cooperation and spillovers in this area. On the contrary, a counter-intuitive fact is that the spillovers among JJJ are the lowest. One possible explanation is that Beijing, the national capital, attracts the innovation resources and talents from neighboring cities like a vortex because of its political and educational resources, which reduces the absorptive ability of neighboring cities.<sup>5</sup> Furthermore, looking at results within groups, we also find that spatial coefficients weighted by technological distance are larger than that weighted by geographic distance in all three economic zones.

### 4.3 Spillovers from Three Core Cities

Moreover, we continue to investigate the spillovers from three core cities with the most patents including Beijing, Shanghai, and Shenzhen, which can help us to explore the mechanism of the heterogeneous regional spillovers studied in last section. To this end, we setup an empirical model as given by:

$$\ln P_{it} = \alpha \sum_{\substack{j=1 \\ j \neq i}}^N w_{ij} \ln P_{jt-1} + \beta_0 \ln P_{it-1} + X\gamma + \iota_i + \mu_t + \varepsilon_{it},$$

where  $\sum_{j=1}^N w_{ij} \ln P_{jt-1}$  denotes the spillovers from three core cities to others containing four items as described

in Table 8. *ksgdc* represents knowledge spillover by geographical distance from three core cities to rest of the cities. *kstdc* indicates knowledge spillover by technological distance from three core cities to other cities. *nksgdc* captures knowledge spillover by geographical distance from three core cities to its neighbors within the same economic zone. It is defined as the interaction term of neighbor dummy and *ksgdc*. Similarly, *nkstdc* means knowledge spillover by technological distance from three core cities to its neighbors within the same economic zone. It is also the interaction term of neighbor dummy and *kstdc*.

The specification is a dynamic panel model rather than spatial model. The coefficient  $\alpha$  measures the direction and importance of spillover like a normal coefficient rather than spatial autoregressive parameter. The dependent variable and other controls are defined as spatial model. System GMM method is implemented to estimate the coefficients and fixed effect model is adopted as suggested by the Hausman tests.

Table 9 reports estimation results of the spillovers from three core cities. Columns 1, 3, and 5 report the estimation results weighted by geographic distance. Columns 2, 4, and 6 report the estimation results weighted by technological distance. As illustrated in this table, the spillover effect of Beijing to the rest is found to be insignificant when using geographic distance as weights, but it is significant when taking technological similarity into account as suggested by the estimation results in columns 1 and 2. Moreover, an unexpected finding is that there are significantly negative spillovers from Beijing to neighbors weighted by geographic distance, but they turn to be significantly positive when weighted by technological distance. The negative spillovers of Beijing to neighbors could explain the lowest spillovers to great extent within JJJ found in Section 4.2, which can be ascribed to the high cluster of innovation resources in Beijing. As expected, the spillovers from both Shanghai and Shenzhen to the rest of the cities or their neighbors are found to be significant and positive. In addition, the spillovers from Shenzhen are the strongest among three core cities, which are consistent with biggest spillovers within the PRD.

## 5 Conclusion

Over the past few years, China has seen its economy go through a fundamental restructure and transition. Innovation has become unprecedentedly important for its economic growth. In view of this, using a prefectural level data, we shed light on the knowledge spillovers

<sup>5</sup> The education advantage of Beijing can be described as follows. First, 8 of top 39 universities listed in “985 project” launched in May, 1998 are in Beijing. Second, the admission rate of Peking University and Tsinghua University, the top 2 universities, in Beijing is 0.913% in 2018, while national average of this rate is 0.072%.

within three MEZs by adopting spatial econometric methods. We first examine the spillovers within all regions, and then the spillovers within three MEZs, and finally the spillovers from three core cities. The results show that there are pronounced spillovers between cities in China, which is stronger between cities with high techno-proximity. Moreover, spillovers within three MEZs are found to be stronger but unequal. Spillovers between cities in the PRD are the greatest among the three economic zones, while the spillovers within JJJ are the lowest. Eventually, Shenzhen outperforms Shanghai and Beijing in knowledge spillovers, whereas Beijing may even adversely affect the innovation of neighbors.

Our study may have some policy implications. First, as suggested by the results, spillovers are stronger between cities with higher techno-proximity. The government should encourage R&D of less-developed regions through subsidies or tax preferences to improve their absorptive ability and reduce the local administrative protectionism to facilitate the technical cooperation. Moreover, spillovers within metropolitan areas are stronger. The government should allocate more resources to central areas to foster more innovations and promote regional economic integration to realize the free flow of new products and technologies. Finally, given the greater spillovers from core cities, more lighthouses should be cultivated by government. However, the economic zones should have different innovative strategies and should be treated with different industrial policies. The government should upgrade the industrial structures of Tianjin and Hebei to absorb the technological spillovers from Beijing. An innovation Community could be formed in YRD to realize regional technical integration. The national innovation demonstration zone should be improved to increase the innovations in PRD. The Greater Bay Area in this area should focus on technology development and finance for innovative startups and green energy solutions.

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## References

Abramovitz, M. (1986). Catching up, forging ahead, and falling behind. *Journal of Economic History*, 46(2), 385–406.

- Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, 31(7), 1069–1085.
- Anselin, L., Acs, Z. J., & Varga, A. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics*, 42, 422–448.
- Anselin, L. (2007). Spatial econometrics in RSUE: Retrospect and prospect. *Regional Science and Urban Economics*, 37(4), 450–456.
- Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review*, 86(4), 253–273.
- Audretsch, D. B., & Feldman, M. P. (1996). Innovative clusters and the industry life cycle. *Review of Industrial Organization*, 11, 253–273.
- Autant-Bernard, C., & LeSage, J. P. (2019). A heterogeneous coefficient approach to the knowledge production function. *Spatial Economic Analysis*, 14(2), 196–218.
- Bilgin, M. H., Lau, C. K. M., & Karabulut, G. (2012). Technology transfer and enterprise performance: A firm-level analysis in China. *Journal of Business Economics and Management*, 13, 489–498.
- Boschma, R. A. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39(1), 61–74.
- Bond-Smith, S., McCann, P., & Oxley, L. (2018). A regional model of endogenous growth without scale assumptions. *Spatial Economic Analysis*, 13(1), 5–35.
- Coe, D. T., Helpman, E., & Hoffmaister, A. W. (1997). North-South R&D spillovers. *The Economic Journal*, 107(440), 134–149.
- Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review*, 39(5), 859–887.
- Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35, 128–152.
- Damijan, J. P., Rojec, M., Majcen, B., & Knell, M. (2013). Impact of firm heterogeneity on direct and spillover effects of FDI: Micro-evidence from ten transition countries. *Journal of Comparative Economics*, 41, 895–922.
- Girma, S., Gong, Y., & Holger, G. (2008). Foreign direct investment, access to finance, and innovation activity in Chinese enterprises. *World Bank Economic Review*, 22, 367–382.
- Gogokhia, T., & Berulava, G. (2021). Business environment reforms, innovation and firm productivity in transition economies. *Eurasian Business Review*, 11, 221–245.
- Griffith, R., Harrison, R., & Van Reenen, J. (2006). How special is the special relationship? Using the impact of US R&D spillovers on UK firms as a test of technology sourcing. *American Economic Review*, 96(5), 1859–1875.
- Griliches, Z. (1979). Issues in assessing the contribution of R&D to productivity growth. *Bell Journal of Economics*, 10, 92–116.
- Grossman, G., & Helpman, E. (1990). Trade, innovation, and growth. *American Economic Review*, 80, 86–91.
- Hanley, A., Liu, W. H., & Vaona, A. (2015). Credit depth, government intervention and innovation in China: Evidence from the provincial data. *Eurasian Business Review*, 5, 73–98.
- Hu, A. G. Z., & Jefferson, G. H. (2002). FDI impact and spillover: Evidence from China's electronic and textile industries. *World Economy*, 25, 1063–1076.
- Huang, Y., & Zhang, Y. (2019). The innovation spillovers from outward and inward foreign direct investment: A firm-level spatial analysis. *Spatial Economic Analysis*, 15(1), 43–59.

- Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D, evidence from firms' patents, profits, and market value. *American Economic Review*, 76(5), 984–1001.
- Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108, 577–598.
- Keller, W. (2002). Trade and the transmission of technology. *Journal of Economic Growth*, 7(1), 5–24.
- Kazakis, P. (2019). On the nexus between innovation, productivity and migration of US university graduates. *Spatial Economic Analysis*, 14(4), 1–21.
- Li, X. (2009). China's regional innovation capacity in transition: An empirical approach. *Research Policy*, 38(2), 338–357.
- Liu, W.-H. (2014). Relevance of own R&D and sources of knowledge transfer for industrial innovation in China. *The Developing Economies*, 52(1), 1–25.
- Liu, F. C., Simon, D. F., Sun, Y. T., & Cao, C. (2011). China's innovation policies: Evolution, institutional structure, and trajectory. *Research Policy*, 40(7), 917–931.
- Ma, R., & Liu, W. (2019). Spatial concentration of innovation activities in China and the role of mega-economic zones. *China & World Economy*, 27, 24–43.
- Moreno, R., Paci, R., & Usai, S. (2005). Spatial spillovers and innovation activity in European regions. *Environment and Planning*, 37(10), 1793–1812.
- Narula, R., & Dunning, J. H. (2000). Industrial development, globalization and multinational enterprises: New realities for developing countries. *Oxford Development Studies*, 28(2), 141–167.
- Parrado, R., & Cian, E. D. (2014). Technology spillovers embodied in international trade: Intertemporal, regional and sectoral effects in a global CGE framework, *Energy Economics*, 41, 76–89.
- Shanga, Q., Poonb, J. P. H., & Yuec, Q. (2012) The role of regional knowledge spillovers on China's innovation. *China Economic Review*, 23, 1164–1175.
- Torre, A., & Gilly, J. P. (2000). On the analytical dimension of proximity dynamics, *Regional Studies*, 34(2), 169–180.
- Wang, Y., Sutherland, D., Ning, L., & Pan, X. (2015). The evolving nature of China's regional innovation systems: Insights from an exploration–exploitation approach. *Technological Forecasting and Social Change*, 100, 140–152.
- World Bank/Development Research Center of the State Council, the People's Republic of China. (2019). *Innovative China. New drivers of growth*. Washington: World Bank Group.