Pathways for Expediting Joint Agricultural Development of China and BRI Countries

Gong Binlei (龚斌磊)*

China Academy for Rural Development (CARD) and School of Public Affairs, Zhejiang University, Hangzhou, China

Abstract: *Based on the agricultural panel data of 107 countries from 1962 to 2016, this paper establishes a global agricultural spatial production model, and explores pathways for mutually beneficial cooperation between China and the Belt and Road Initiative (BRI) countries in the agricultural sector. As shown in the empirical results, two-way spillover effects between China and BRI countries are all positive and significantly above world average of its kind, which builds the foundation of cooperation between both sides and reflects the BRI's vision and foresight. In the context of the BRI, there are two pathways for expediting agricultural development in China and BRI countries: First, both sides may benefit from greater spillover effects from each other's agricultural growth by promoting agricultural trade; second, China may gain from the overall spillover effects from agricultural development in BRI countries by promoting two-way trade, agri-technology aid and assistance in infrastructure projects for the common good of humanity.*

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1. Introduction

The Belt and Road Initiative ("BRI") is designed to promote cooperation between China and countries along the BRI routes based on their complementary advantages for mutual benefit. Mentioned five times in the Report to the 19th CPC National Congress, the BRI is a strategic priority for China's all-round opening up program with profound political, economic and cultural implications for China and BRI countries. As the cornerstone of trade along with ancient land and maritime Silk Road, agriculture remains a key aspect of the BRI in the new era, and plays an important role in promoting economic development, win-win cooperation and cultural exchanges between China and BRI countries. China's "No.1 central document" in 2018 calls for "deepening agricultural trade with BRI countries and

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* Corresponding author: Gong Binlei, email: gongbinlei@zju.edu.cn

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regions." The BRI presents opportunities for China to cooperate with BRI countries with respect to their agricultural resources and markets. It is of great practical significance, therefore, to identify pathways for agricultural cooperation between China and BRI countries, and provide an academic rationale for policy-making.

However, studies on the BRI with respect to agriculture remain scant. Shen and Xiao (2014) examines the BRI's strategic importance, and offers reflections on the BRI's priorities. Focusing on the BRI's risks and challenges, Zhang (2015) puts forward policy advice for deepening the BRI in terms of concepts, modes and strategies. Song (2014) stresses the significance of agricultural cooperation under the BRI, and offers an overview of superior agricultural resources in BRI countries. Zhang *et al.* (2015) sheds light on the potentials and priorities of agricultural cooperation between China and Central Asian countries. Yet these studies are preoccupied with macro description of the BRI's status quo and prospects without sufficient data support. With international trade data, Xu (2016) estimates trade complementarity between China and BRI countries without taking into account non-BRI countries under a global multilateral framework.

With global data, Li and Yan (2018) examine China's two-way trade advantages with BRI countries, but their study is focused on public security rather than agriculture. Among relevant studies based on global agricultural data, Coelli and Rao (2005) employ the data envelopement analysis (DEA) method to estimate agricultural productivity in 93 countries from 1980 to 2000; Headey *et al.* (2010) employs the stochastic frontier analysis (SFA) method to estimate agricultural productivity in 88 countries from 1970 to 2001. All these studies have employed the UN FAO's agricultural input and output data. Despite their coverage of major countries including BRI countries, these studies have failed to consider trade-related interactions between countries, not to mention a focus on China's strategic cooperation with BRI countries. The paucity of relevant academic literature presents a drawback to policy design. It is, therefore, of urgent practical and policy significance to measure agricultural interactions between countries, especially the spillover effects of agricultural production in China and BRI countries, and identify pathways to raise agricultural output in relevant countries.

Based on agricultural panel data of 107 major countries from 1962 to 2016, this paper establishes a two-dimensional agricultural production model to measure interactions between countries through agricultural production, focusing on the spillover effects on China and BRI countries. In addition, this paper specifies an agricultural productivity determination model to explore effective ways to raise agricultural productivity in China and BRI countries. Empirical result reveals positive spillover effects of global agricultural production, and the spillover effects between China and BRI countries are significantly above world average, which provides momentum for both sides to give each other priority in trade. Under the BRI, China and BRI countries face two options in developing agriculture by: (i) increasing agricultural trade for both sides to gain from the spillover effects of agricultural growth; (ii) assisting BRI countries in raising agricultural productivity and output through two-way trade, agri-technology aid and infrastructure construction assistance, which will increase overall agricultural spillover effects. This paper may offer the following innovations: (i) When constructing the agricultural production function, it takes into account both the mutual influence from geographical location and international trade to better depict agricultural input-output relationship in a more comprehensive manner, and estimate agricultural productivity more precisely; (ii) it uncovers China's advantages in cooperating with BRI countries under the global multilateral framework to provide theoretical and empirical evidence for the BRI; (iii) it identifies pathways for further promoting agricultural quality and efficiency in China and BRI countries.

2. Empirical Model Specification

This paper introduces the spatial econometric model into the global agricultural production function to control for the two-dimensional interactions between countries with respect to agricultural production, so as to estimate the spillover effects between China and BRI countries and compare the effects with world average level. The agricultural production function can estimate the total factor productivity (TFP) of agriculture in various countries. On this basis, this paper employs the agricultural productivity determination model to identify an effective path for raising agricultural TFP and output in China and BRI countries.

2.1 Global Agricultural Spatial Production Model

Some studies (Wu, 2010; Wang *et al*., 2010; Pan, 2012; Gong, 2017; Gong and Zhang, 2019) introduce spatial correlation into the production function model to depict interactions between various production entities in the production process and estimate the spatial spillover effects. By introducing the general spatial model (GSM), this paper avoids any special form of model dependent on a priori hypothesis (for instance, spatial autoregressive model or spatial error model). In addition, the GSM can control for interactions between dependent variable y_{it} and error term ε_{it} of individuals. While the former reflects the flow and competition of agricultural goods between countries, the latter can control for the spatial correlation arising from some uncertainties such as climate.[1] Therefore, the global agricultural spatial production model employed in this paper can be expressed as follows:

$$y_{it} = \rho\sum_{j=1}^{N}\omega_{ij}y_{jt} + X_{it}\beta + \alpha + \gamma T + \delta P + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} = \lambda\sum_{j=1}^{N}\omega_{ij}\varepsilon_{jt} + v_{it} \tag{2}$$

In equations (1) and (2), y_{it} is the logarithm of country i's agricultural output in year t, and vector X_{it} denotes the logarithm of the consumption of various agricultural inputs; ω_{ij} is an element in column j and row i of the spatial weight matrix W, and reflects the correlation between country i and country j; ρ and λ measure the interactions of the explained variable and stochastic disturbance term between countries, respectively; α is intercept term, v_{it} is independent identically distributed stochastic disturbance term, and ε_{it} is spatial autocorrelation disturbance vector designated by the spatial weight matrix W and unknown coefficient λ. T is the dummy variable of time, and may measure progress in agri-technology, and P is the dummy variable of region. In equation (1), input factor may have the problem of endogeneity (Gong, 2018a). This paper employs the governing equation method developed by Amsler *et al.* (2016) for an endogeneity test of each input factor, and referencing Guan *et al.* (2009) and Gong (2016), corrects the input factor with endogeneity problem with its lagged term as instrumental variable.

This paper creates a spatial weight matrix W with the geographical distance and economic distance methods that are common in literature. First, correlation between any two countries is closely related to their geographical distance. Kelejian *et al*. (2013) believe that adjacent countries influence each other in more significant ways. Many academics (Curtis and Hicks, 2000; Roe *et al*., 2002) measure correlation between countries with geographical distance. In studies on world agricultural productivity, element ω_{ij}^{1} in column j and row i of the geographical weight matrix (W_1) is often a reciprocal of Euclidean distance between country i and country j (Gaigné *et al*., 2011; Isik, 2004). Second, the correlation between any two countries also has to do with the closeness of their economic exchanges, and is often measured by their two-way trade volume (Druska and Horrace, 2004; Han *et al*., 2016). Compared with geographical distance, economic distance may explain the correlation between countries with a relatively long-

[1] This paper has also attempted the Durbin model with spatial interaction effects between independent variables, but the result of Akaike information criterion (AIC) suggests that the GSM's goodness of fit is superior to the Durbin model's.

distance and close economic ties. For instance, China and the United States share close trade and economic exchanges despite their long geographical distance and thus influence each other in significant ways. In studies on world agricultural productivity, element ω_{ij}^{2} in column j and row i of the economic weight matrix (W_2) is often the average two-way trade volume between country i and country j during a certain period.

As a common practice, we standardize each row in the geographical weight matrix W_1 and economic weight matrix W_2 to make the sum of each row to be 1, and assign a value of 0 to all the elements on the diagonal line. Indirect effects on the geographical and economic dimensions are the mean values of the sums of outer rows on the diagonal line which are $\left(I-\rho_1 W_1\right)^{-1}\beta_1$ and $\left(I-\rho_2 W_2\right)^{-1}\beta_2$ respectively. Indirect effects reflect an individual's impact on other individuals. Many academics (LeSage and Pace, 2009; Gong, 2018b) regard the indirect effect as a variable of spillover effect. In agriculture, positive spillover effect mainly derives from technology spillover, and negative spillover effect is attributable to falling agricultural prices due to competition. Overall spillover effect is subject to the net value of the positive and negative effects.

The spatial production function based on either the geographical rate matrix W_1 or the economic weight matrix W_2 considers correlation between countries from a single dimension, and thus cannot provide a full picture of agricultural input-output relationship under both geographical and economic dimensions. The model averaging method is able to explain the agricultural input-output relationships of countries based on geographical and economic dimensions, assign different weights, and thus consider the relevance of both dimensions to obtain a more accurate estimate. Following Hansen and Racine (2012) and Gong (2018), this paper employs a jackknife-based model averaging method to assign weights to the two spatial models. Based on the "leave-one-out" cross-validation criterion, the jackknife model averaging method first estimates the jackknife fitted value $\hat{y}^{m}=\left(\hat{y}_1^{m},\ldots,\hat{y}_n^{m}\right)$ of agricultural output for each candidate model m, where $\hat{y}^{m}$ is the fitted value of a country's agricultural output derived from the agricultural production model with country i excluded from the samples. Assuming that weight w is the weight of geographical dimension, the jackknife weight w^* is the optimal weight under the cross-verification criterion.

$$w^{*}=\operatorname{argmin} CV_n\left(w\right)=\frac{1}{n}\hat{e}\left(w\right)^{'}\hat{e}\left(w\right)=\frac{1}{n}\left(y-w\hat{y}^{1}-\left(1-w\right)\hat{y}^{2}\right)^{'}\left(y-w\hat{y}^{1}-\left(1-w\right)\hat{y}^{2}\right) \tag{3}$$

In equation (3), $\hat{e}\left(w\right)$ is weighted average residual error, and w is the weight of geographical dimension; $1-w$ is the weight of economic dimension; $\hat{y}^{1}$ is the jackknife fitted value calculated with the geographical spatial production model; $\hat{y}^{2}$ is the jackknife fitted value calculated with the economic spatial production model. The above-mentioned jackknife model averaging method offers the following advantages: First, it can depict the agricultural production process and estimate agricultural TFP based on the impact of geographical and economic relevance on agricultural production; second, the geographical matrix and the economic matrix are employed in combination with the jackknife weight to calculate how various countries, including BRI countries specifically, influence agricultural production in China.

Based on the above specifications, this paper creates the following two-dimensional global agricultural spatial production model:

$$\begin{aligned} y_{it} &= w^{*}\left(\rho_1\sum_{j=1}^{N}\omega_{ij}^{1}y_{jt}+X_{it}\beta_1+\alpha_1+\gamma_1 T+\delta_1 P+\varepsilon_{it}^{1}\right) \\ &\quad +\left(1-w^{*}\right)\left(\rho_2\sum_{j=1}^{N}\omega_{ij}^{2}y_{jt}+X_{it}\beta_2+\alpha_2+\gamma_2 T+\delta_2 P+\varepsilon_{it}^{2}\right) \end{aligned} \tag{4}$$

$$\varepsilon_{it}^{m}=\lambda_m\sum_{j=1}^{N}\omega_{ij}^{m}\varepsilon_{jt}^{m}+v_{it}^{m},\ \forall m=1,2 \tag{5}$$

2.2 Global Agricultural TFP Determination Model

Agricultural TFP is an important indicator for agricultural competitiveness (Feng, 1990; Chen, 2006; Quan, 2009; Si, Wang, 2011; Yin *et al.*, 2016). Through equations (4) and (5), we can arrive at each country's agricultural productivity calculated with Solow residual $T\hat{F}P_{it} = \hat{w}^* \left(\hat{\alpha}_1 + \hat{\gamma}_1 T + \hat{\delta}_1 P + \hat{\varepsilon}^1_{it}\right) + \left(1 - \hat{w}^*\right)\left(\hat{\alpha}_2 + \hat{\gamma}_2 T + \hat{\delta}_2 P + \hat{\varepsilon}^2_{it}\right)$. By establishing the global agricultural TFP model, this paper aims to investigate the agricultural TFP effects of factors like R&D spending and trade, so as to identify how investment and policy-making should contribute to agricultural competitiveness in China and BRI countries. The following equation presents the global agricultural TFP model this paper intends to establish:

$$TFP_{it} = \alpha + \beta_1 R\&D_{it} + \beta_2 Trade_{it} + \tau Z + \gamma I + \varepsilon_{it} \tag{6}$$

In equation (6), TFP_{it} is the logarithmic form of country i's agricultural TFP in period t. $R\&D_{it}$ is country i's agricultural R&D spending stock in period t as a share of agricultural output. $Trade_{it}$ is country i's total international trade volume in period t. Z controls for the fixed effect of time, I controls for the fixed effect of region and ε is residual error.

Considering the possible interactions of agricultural TFP in various countries, this paper structures an integrated matrix with the geographical distance between countries and introduces the general spatial model (GSM) into the productivity determination model (equation (6)) to test whether spatial correlation is fully controlled for in the first step of the production function. In addition, equation (6) may have the endogeneity of omitted variables and reverse causality. The former problem is treated by introducing such control variables as the ratios of irrigation, crop farming and arable land. As for the latter problem, it is mentioned in literature that endogeneity may exist in international trade (Gong, 2018c). Following Chanda and Dalgaard (2008) and Madsen (2009), this paper solves the endogeneity problem of trade through the two-stage least square (2SLS) method with total population and per-capita agricultural output as instrumental variables.

3. Data Source and Descriptive Statistics

This paper collects the agricultural panel data of 107 countries from 1962 to 2016, which include 25 BRI countries. In 2016, these 107 countries represented 89% of the global agricultural output and 89% of world population. The agricultural input factors and output data of countries are all from the International Agricultural Productivity Database of the US Department of Agriculture and the UN FAO's Statistics Division (FAOSTAT). Specifically, agricultural output is calculated with constant 2005 international dollar[2]; labor input is the number of agricultural workforce; land input is calculated with equivalent arable land area; agri-machinery input is calculated with two-wheel 40-CV tractor equivalents; chemical fertilizer is calculated with the nutrient weight of N, P_2O_5, K_2O chemical fertilizers; livestock capital input is in "cattle equivalents" based on relative size and feeding requirement; animal feed input is calculated with the total metabolizable energy (ME) from all sources.

Aside from the above input-output data, the global agricultural spatial production model also requires the geographical distance and bilateral trade data between countries to create the geographical weight matrix and the economic weight matrix. Geographical distances between countries are from the GeoDist database of the French research center in international economics (CEPII). Agricultural bilateral

[2] The "international donor" is a method of converting various currencies into a single currency in multilateral purchasing power parity comparisons (the World Bank's definition, see: https://datahelpdesk.worldbank.org/knowledgebase/articles/114944-what-is-an-international-dollar). Compared with the US dollar, the international dollar better reflects the level of agricultural output in various countries. Based on the International Agricultural Productivity Database of the US Department of Agriculture and the UN FAO's database (FAOSTAT), this paper reports the agricultural output of various countries.

trade data are from the NBER-UN database and the CEPII-BACI database. Aggregate international trade data are also from the NBER-UN and the CEPII-BACI databases. Agri-technology input (R&D) data are from the ASTI database of the International Food Policy Research Institute (IFPRI), the OECD's GERD database, Pardey and Roseboom (1989), Alston *et al*. (1999), and Pardey *et al*. (2016). Notably, agri-technology input can influence agricultural output in the current year and beyond. For instance, R&D input makes a new-generation agri-machinery more efficient, thus raising productivity over a long period. However, the above agricultural R&D data reflect the flow rather than the stock of agri-technology input over the years. Hence, this paper employs the perpetual inventory method to convert it into stock (Berlemann and Wesselhöft, 2014). Following Esposti and Pierani (2003), we employ a 20% world agricultural R&D depreciation rate. In addition, the ratio of irrigation and arable land is from the world agricultural productivity database of the US Department of Agriculture; the ratio of crop farming is from the UN FAO; total population data is from the World Bank; per-capita agricultural output is obtained after dividing total agricultural output by total population.

Table 1 shows agricultural data for 107 countries from 1962 to 2016. The mean value of total agricultural output calculated with 2005 constant price is 12.29 billion international dollars, and the ratios of crop farming and livestock are 63.6% and 36.4%, respectively. On average, each country had 8 million people employed in agriculture, 15.10 million hectares of arable land, 200,000 two-wheel 40-CV tractors, 900,000 tons of chemical fertilizer consumption, 14 million cattle equivalents of livestock capital, and 22.8 trillion calories of animal feed. These countries record 6.64 billion international dollars

Table 1: Descriptive Statistics of Key Variables

Variable	Unit of Measurement	Mean value	Standard deviation	Min.	Max.
Agricultural output	100 million international dollars (2005 constant price)	122.9	396.9	0	6,285
Labor input	Million people	8.0	35.7	0.0	391
Land input	Million hectares	15.1	43.9	0.0	333
Agri-machinery input	Million units	0.2	0.8	0.0	13.1
Chemical fertilizer input	Million tons	0.9	3.7	0.0	55.0
Livestock input	10 million cattle on hand equivalent	1.4	3.7	0	30.4
Fodder input	Trillion calories	22.8	75.8	0.0	1,113
Total agricultural trade volume	100 million international dollars (2005 constant price)	66.4	185.0	0.0	2,726
Agricultural R&D ratio	%	15.3	75.3	0.0	3,477
Irrigation ratio	%	10.6	11.7	0.0	71.3
Crop farming ratio	%	63.6	21.5	0.9	95.6
Arable land ratio	%	85.6	15.5	0.0	100
Total population	Million people	41.7	139.7	0.2	1,380
Per-capita agricultural output value	100 million international dollars (2005 constant price)	334.6	293.1	4.7	2,582

Source: Collected by authors.

in annual average agricultural trade by 2005 constant price. Agricultural R&D stock represents an average of 15.3% of agricultural output. On average, 10.6% of land is irrigated, and 85.6% of land is arable land. Per capita agricultural output value in these countries, whose average population is 41.70 million, is 334.6 international dollars.

4. Analysis of Estimation Results

Utilizing Amsler's *et al*. (2016) control function method, this paper finds that, after the residual errors of six types of input factors are included into the production function, the corresponding coefficients of the six residual errors are all significant at 5% (p-values of corresponding coefficients of residual errors for labor, land, agri-machinery, chemical fertilizer, livestock and fodder are 0.003, 0.004, 0.000, 0.000, 0.016 and 0.007, respectively), which indicates that endogeneity problem exists in all the six input factors. Referencing Guan *et al*. (2009) and Gong (2016), we make a correction with the lag terms of input factors as instrumental variables. Second, the Breusch-Pagan LM test result (z value is -3.003, and corresponding peak value is 0.003) and the Pesaran CD test result (Chi-square value is 77,348, and corresponding peak value is 0.000) are both significant at 1%, which indicates the existence of correlation in agricultural production between countries. Then, this paper establishes a spatial production function with the spatial weight matrix on geographical and economic dimensions, and Moran's I results thus obtained (geographical dimension: Moran's I = 0.033, p-value = 0.000; economic dimension: Moran's I = 0.029, p-value = 0.000) are all significant at 1%, which verifies the existence of spatial correlation in agricultural production between countries on both dimensions. Hence, it is necessary to estimate the agricultural production function with the spatial econometric model. Therefore, this paper utilizes the geographical weight matrix and the economic weight matrix in combination with the jackknife model averaging method to create a two-dimensional global agricultural spatial production model to estimate the spillover effects and agricultural TFP.

4.1 Production Function and Spillover Effects

Table 2 provides the regression results of the spatial econometric model containing both geographical and economic dimensions. As shown in columns (1) and (2), the six types of agricultural input factors are all significant at 1% in both types of spatial econometric model. Based on the jackknife model averaging (JMA) method, we assign weights of 0.73 and 0.27 to the two types of spatial econometric model with geographical distance and economic distance as spatial weight matrixes. Based on such jackknife weights, we obtain the regression results of two-dimensional global agricultural spatial production model in column (3):

Labor elasticity coefficient is 0.125, which means that a 1% increase in a country's agricultural labor input may increase the home country's agricultural output by 0.125%;

Land elasticity coefficient is 0.352, which means that a 1% increase in a country's agricultural land will raise the country's agricultural output by 0.352%;

Agri-machinery elasticity coefficient is 0.042, which means that a 1% increase in a country's agri-machinery will raise the country's agricultural output by 0.042%;

Chemical fertilizer elasticity coefficient is 0.093, which means that a 1% increase in the country's chemical fertilizer consumption will raise the country's agricultural output by 0.093%;

Livestock elasticity coefficient is 0.275, which means that a 1% increase in a country's livestock on hand will increase the country's agricultural output by 0.275%;

Feed elasticity coefficient is 0.112, which means that a 1% increase in a country's fodder input will increase the country's agricultural output by 0.112%.

In comparison, column (4) provides the estimation results of the global agricultural production function without spatial correlation taken into account.

Table 2: Regression Results of the Spatial Econometric Model

Variable	Geographical spatial model	Economic spatial model	Two-dimensional spatial model	Traditional non-spatial model
	(1)	(2)	(3)	(4)
Labor input	0.136***	0.097***	0.125***	0.088***
	(0.009)	(0.009)	(0.009)	(0.009)
Land input	0.339***	0.387***	0.352***	0.390***
	(0.011)	(0.011)	(0.011)	(0.011)
Agri-machinery input	0.040***	0.049***	0.042***	0.047***
	(0.004)	(0.004)	(0.004)	(0.004)
Chemical fertilizer input	0.093***	0.094***	0.093***	0.094***
	(0.004)	(0.004)	(0.004)	(0.004)
Livestock input	0.279***	0.265***	0.275***	0.268***
	(0.010)	(0.010)	(0.010)	(0.011)
Feed input	0.113***	0.108***	0.112***	0.113***
	(0.006)	(0.006)	(0.006)	(0.006)
Year	Controlled	Controlled	Controlled	Controlled
Region	Controlled	Controlled	Controlled	Controlled
Intercept	5.214***	5.308***	5.239***	5.212***
	(0.048)	(0.041)	(0.046)	(0.040)
Number of samples	5,885	5,885	5,885	5,885
Jackknife model weight	0.73	0.27	—	—

Notes: Numbers in parentheses are the standard errors of regression coefficients; ***, ** and * denote significance at 1%, 5% and 10%, respectively. Columns (1) and (2) are econometric results obtained with different spatial weight matrixes in equation (1). Column (3) is the econometric result of equation (4). Column (4) is the result of traditional production function model without spatial correlation taken into account.
Source: Collected by authors.

Table 3 presents the overall spillover effects of global agricultural production. Specifically, the spillover effects in columns (1) through (3) are provided in the spatial econometric model in columns (1) through (3) of Table 2. Columns (1) and (2) of Table 3 reveal significant positive spillover effects of agricultural production on both geographical and trade dimensions. On the geographical dimension, countries with a shorter geographical distance enjoy convenient access to transportation that facilitates communication and technology diffusion. In addition, countries with a shorter distance share similar resource endowment, climate and culture, which makes it easier to adopt similar technologies. On trade dimension, agricultural import brings not only foreign agricultural goods but the information and technology for producing such goods. In exporting agricultural goods, a home country's producers must adopt new technology and raise management efficiency (Grossman and Helpman, 1993) to meet the needs of foreign buyers. In this sense, countries with a shorter geographical distance and greater bilateral trade will enjoy more positive spillover effects. As shown in column (3) of Table 3, when geographical and economic relevance are both taken into account, global agricultural production will have significant

Table 3: Global Agricultural Spillover Effects

Variable	Geographical spillover effect	Economic spillover effect	Weighted average spillover effect
	(1)	(2)	(3)
Labor input	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Land input	0.012**	0.018***	0.014**
	(0.005)	(0.009)	(0.006)
Agri-machinery input	0.001**	0.002***	0.001**
	(0.000)	(0.001)	(0.001)
Fertilizer input	0.003***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)
Livestock input	0.009***	0.012***	0.010**
	(0.004)	(0.006)	(0.005)
Fodder input	0.004***	0.005***	0.004***
	(0.001)	(0.002)	(0.001)
Total	0.034***	0.046***	0.037***
	(0.007)	(0.011)	(0.008)

Notes: Numbers in parentheses are the standard errors of regression coefficients; ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Source: Collected by authors.

positive spillover effects. That is to say, China's agriculture stands to gain from Chinese investment in the agricultural sector of other countries. This positive effect will increase amid China's growing bilateral agricultural trade with other countries. When the rest 106 countries see their agricultural output double, China's agricultural output will also increase by 3.7% under the spillover effect.

The question is how to identify countries with which cooperation will benefit China the most. In other words, will priority cooperation with and investment in BRI countries contribute more to China's agricultural development? To answer this question, we should separately examine the spillover effects of various countries on China, i.e. how agricultural growth in the countries will contribute to China's agricultural development in different ways. Table 4 shows the average spillover effects of BRI and non-BRI countries. Most BRI countries are geographically close to China and exert greater spillover effects on China. Given the geographical spillover effects from trade, a twofold increase in the agricultural output of a BRI country will lead to an average increase of 0.0362% in China's agricultural output, which is almost twice the average effect of non-BRI countries (0.0192%). Given the fixed geographical distance between countries, BRI countries exert greater and more lasting geographical spillover effects on China. Agriculture investment and cooperation in these countries will generate more positive effects on agriculture in China.

Given the economic spillover effects from trade, a twofold increase in agricultural output in a BRI country will raise agricultural output in China by 0.0106%, which is roughly consistent with non-BRI countries' effect on China. On both geographical and economic dimensions, BRI countries' effects on agriculture in China (0.0468%) are more significant than those of non-BRI countries (0.0311%), and

Table 4: Average Spillover Effects of Other Countries on China

Variable	Geographical spillover effects	Economic spillover effects	Overall spillover effects
	(1)	(2)	(3)
Global average	0.0232%	0.0116%	0.0348%
BRI countries	0.0362%	0.0106%	0.0468%
Non-BRI countries	0.0192%	0.0119%	0.0311%
p value of t-test between BRI and non-BRI countries	0.0000***	0.8090	0.0420**

Notes: Numbers in parentheses are the standard errors of regression coefficients; ***, ** and * denote significance at 1%, 5% and 10%, respectively.
Source: Collected by authors.

Table 5: China's Average Spillover Effect on Other Countries

Variable	Geographical spillover effect	Economic spillover effect	Overall spillover effect
	(1)	(2)	(3)
Global average	0.0162%	0.0583%	0.0745%
BRI countries	0.0258%	0.0615%	0.0873%
Non-BRI countries	0.0132%	0.0574%	0.0706%
p value of t test for differences between BRI and non-BRI countries	0.006***	0.769	0.033**

Notes: Numbers in parentheses are the standard errors of regression coefficients; ***, ** and * denote significance at 1%, 5% and 10%, respectively.
Source: Collected by authors.

Welch double-sample t-test reveals significant statistical difference between the two. Therefore, China's cooperation with BRI countries will influence China's agricultural development in a more positive way.

Results in Table 4 suggest that China is motivated to give priority to cooperation with BRI countries. The next question is whether BRI countries are motivated to give priority to agricultural cooperation with China. To answer this question, we should reversely investigate China's spillover effects on various countries. Table 5 provides China's average spillover effects on BRI countries and non-BRI countries. Result suggests that when geographical and economic dimensions are taken into account, China's average spillover effect on BRI countries (0.0873%) is higher than China's average spillover effect on non-BRI countries (0.0706%) and the Welch double-sample t-test indicates significant statistical difference between the two. Compared with non-BRI countries, BRI countries gain more from, and are thus more motivated to engage in, strategic cooperation with China. Notably, China's economic spillover effects on other countries (as shown in Table 5) are significantly higher than the economic spillover effects of other countries on China (as shown in Table 4). The main reason is that with significant agricultural trade volume, China is the most important trading partner for a majority of countries around the world.

Table 4 and Table 5 show significant geographical spillover effects between China and BRI countries, which are constant over time and can be taken advantage of sustainably. On the other hand, the economic spillover effects between China and BRI countries are insignificant during this paper's study period (1962-2016), but such spillover effects vary with time. Recent years have seen a sharp rise in agricultural trade between China and BRI countries. In 2018, China's agricultural trade with BRI countries totalled 76 billion US dollars, up 12.0% YoY, which was 6.5 percentage points higher than the growth rate of agricultural trade between China and non-BRI countries.[3] Therefore, we have reason to believe that the economic spillover effects between China and BRI countries are about to appear and further reinforce the overall spillover effects.

4.2 TFP and Its Determinants

As shown in Tables 4 and 5, China and BRI countries have the motivations to prioritize cooperation with each other for mutual benefit. This paper is concerned with a more important question: With the aim of strengthening strategic cooperation, which steps can be taken to jointly expedite agricultural development in China and BRI countries? As Tables 4 and 5 suggest, China should increase agricultural trade with BRI countries for both sides to benefit from greater spillover effects of agricultural growth. Another priority is to increase agricultural productivity to generate greater overall spillover effects at constant unit spillover effect and input factors. Figure 1 describes global average agricultural TFP and its growth from 1962 to 2016. As shown in the figure, global agricultural TFP growth has averaged 0.7% annually, which is similar to the estimate (0.8%) of the US Department of Agriculture.[4] TFP growth is a result of international commitments to raise productivity. Global agricultural productivity increased by close to 40% over 1962. That is to say, with the same amount of production factors, agricultural output was two fifths higher in 2016 than in 1962. During the same period, world population increased from 3.127

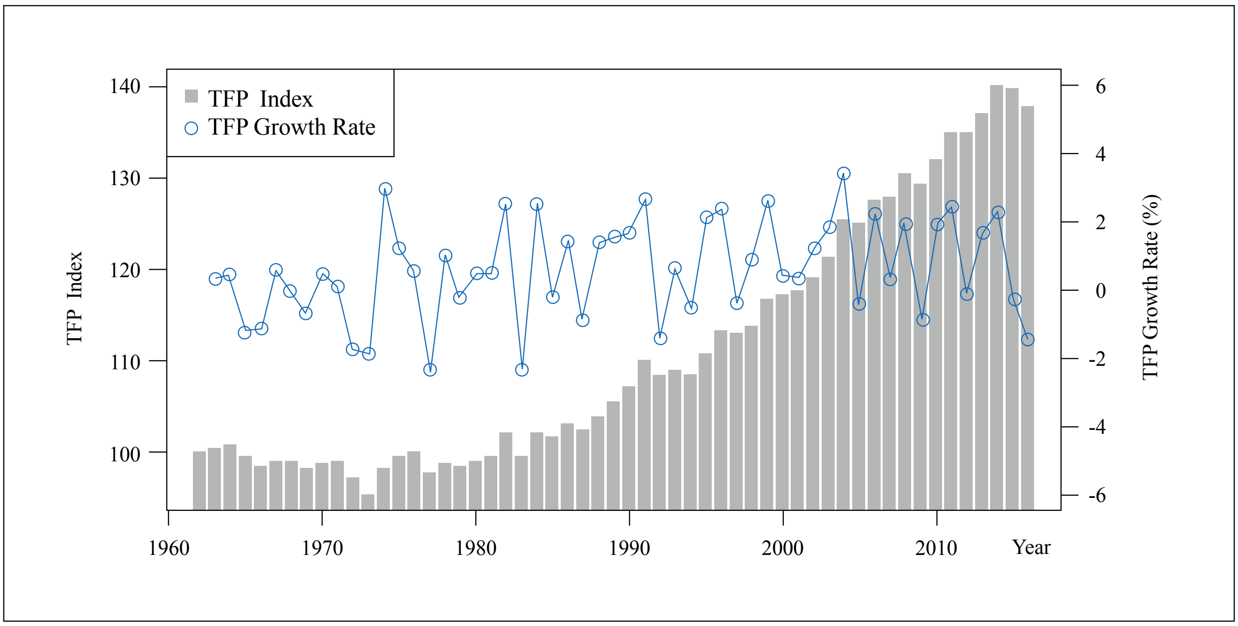

Figure 1: Global Average Agricultural TFP and Growth Trend

Source: Collected by authors.

[3] Data is from the 2018 BRI Agricultural Trade Development Report released by the Agricultural Trade Promotion Center of China's Ministry of Agriculture and Rural Affairs

[4] Data is from the US Department of Agriculture (https://www.ers.usda.gov/data-products/international-agricultural-productivity/).

billion to 7.444 billion. Rising agricultural productivity is vital to feed the world's population. With the limited production factors and environmental capacity, productivity will play an increasingly important role in boosting agricultural output.

The regression results provided by Table 6 in the agricultural productivity determination model are intended to investigate how to increase agricultural TFP and output. Specifically, Model 1 (the first three columns) is the traditional productivity determination model, and Model 2 (the latter three columns) is the spatial productivity determination model. In each model, the first column reports OLS estimation results, the second column reports the first-step estimation results of 2SLS, and the third column reports

Table 6: Regression Results of Agricultural Productivity Determination Model

	Model 1			Model 2		
	OLS	2SLS		OLS	2SLS	
		Step 1	Step 2		Step 1	Step 2
	(1)	(2)	(3)	(4)	(5)	(6)
log (total agricultural trade volume)	0.028^{***}	—	0.037^{***}	0.027^{***}	—	0.030^{***}
	(0.003)	—	(0.012)	(0.003)	—	(0.009)
Ratio of agricultural R&D	0.022^{***}	-0.085^{***}	0.023^{***}	0.021^{***}	-0.095^{***}	0.025^{***}
	(0.008)	(0.029)	(0.008)	(0.007)	(0.028)	(0.007)
Ratio of irrigation	1.102^{***}	3.076^{***}	1.074^{***}	1.124^{***}	2.601^{***}	1.131^{***}
	(0.063)	(0.237	(0.072)	(0.062)	(0.243)	(0.065)
Ratio of crop farming	-0.332^{***}	-0.202	-0.332^{***}	-0.392^{***}	-0.094	-0.384^{***}
	(0.034)	(0.130)	(0.034)	(0.033)	(0.130)	(0.031)
Ratio of arable land	1.480^{***}	1.292^{***}	1.476^{***}	1.428^{***}	0.728^{***}	1.292^{***}
	(0.049)	(0.191	(0.049)	(0.055)	(0.202)	(0.045)
Instrumental variable 1: Total population	—	0.321^{***}	—	—	0.334^{***}	—
	—	(0.017)	—	—	(0.017)	—
Instrumental variable 2: Per capita agricultural output	—	1.655^{***}	—	—	1.434^{***}	—
	—	(0.127)	—	—	(0.129)	—
Year	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Region	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Intercept	3.802^{***}	11.558^{***}	3.685^{***}	5.211^{***}	9.848^{***}	4.451^{***}
	(0.092)	(0.316)	(0.168)	(0.122)	(0.377)	(0.162)
Spatial auto-regression coefficient ρ	—	—	—	-0.023		-0.017
	—	—	—	(0.077)		(0.074)
Error variance coefficient λ	—	—	—	0.056		0.053
	—	—	—	(0.055)		(0.059)
Number of samples	5,885	5,885	5,885	5,885	5,885	5,885

Notes: Numbers in parentheses are the standard errors of regression coefficients; ***, ** and * denote significance at 1%, 5% and 10%, respectively.
Source: Collected by authors.

the estimation results of the second-step 2SLS. Results indicate that after the instrumental variable method is employed to treat the endogeneity problem of international trade, there is an increase in the estimated value of the positive effect of international trade on agricultural productivity, and the agricultural productivity effects of other variables remain constant.

In model 2, the p-value of Moran's index I is greater than 0.1, and the regression results in Table 6 indicate that the spatial autoregression coefficient ρ and the error variance coefficient λ are both insignificant. Therefore, there is no significant spillover effect in the productivity determination model. In addition, the OLS estimation results of model 2 are all approximate to the results of model 1, which further proves that spatial correlation is fully controlled for in the two-dimensional global agricultural spatial production model. Based on the above reason, this paper selects model 1 as benchmark model, and reaches the following conclusions with results from column (3): First, a twofold increase in agricultural trade will lead to a 3.7% rise in the home country's TFP under constant factor input. Second, an increase in agricultural R&D input as a share of agricultural output by a percentage point will lead to a 0.023% rise in agricultural TFP. Third, an increase in the ratios of irrigation and arable land by each percentage point will lead to a 1.074% and 1.476% rise in agricultural TFP, respectively. Lastly, an increase in the ratio of crop farming by each percentage point will reduce agricultural TFP by 0.332%. That is to say, the livestock industry is more efficient than crop farming. The above results suggest that agricultural TFP can be increased significantly by boosting agricultural trade and R&D and increasing the ratios of irrigation, livestock and arable land.

Based on the above findings, China can promote bilateral trade and assistance in agri-technology and infrastructure construction to help BRI countries ramp up agricultural output through BRI strategic cooperation. Trade and technology assistance should provide more support to livestock farming in these countries. While expediting agricultural development in BRI countries and creating a conducive external environment for China, these measures will also benefit China's agriculture through spillover effects for mutual benefit.

5. Conclusions and Policy Advice

By establishing a global agricultural production function reflecting both geographical and economic dimensions, this paper estimates the spillover effects of agricultural production in 107 countries and explores pathways and measures for China and BRI countries to seek beneficial cooperation. Results indicate that positive spillover effects exist in agricultural production in various countries and that the spillover effects between China and BRI countries are significantly higher than world average of its kind. Such strong spillover effects underpin cooperation for mutual benefit, and reflect the BRI's vision and foresight. There are two options for China to step up agricultural cooperation with BRI countries: First, China may increase agricultural trade with BRI countries for both sides to benefit from greater spillover effects from agricultural growth; second, China may assist BRI countries in raising agricultural TFP and output and thus increase overall spillover effects on agriculture in China through bilateral trade, agri-technology aid and assistance in irrigation and other infrastructure projects. Notably, China is no longer preoccupied with seeking rapid growth in agricultural output. Given the limited production factors and environmental capacity, efficiency and quality are the new priorities for China's agricultural development. Under given agricultural output, positive spillover effects and agricultural productivity growth may reduce the use of agricultural production factors. For instance, less consumption of chemical fertilizers may ease environmental pressures, and the conservation of labor and land will release resources for the secondary and tertiary industries.

Based on this paper's research conclusions, we can arrive at the following policy advice: First, China should increase agricultural trade with BRI countries, and enhance the spillover effects and agricultural TFP. China and BRI countries share complementary strengths in agriculture and may bring into play synergy between labor-intensive and resource-intensive agriculture and between precision and extensive agriculture. China's eastern, central and western regions may engage in agricultural cooperation with Central Asia, Southeast Asia, South Asia, West Asia, Eastern Europe and North Africa, and promote trade in grains, livestock, palm oil, vegetables and tropical fruits based on their comparative advantages for mutual benefit. Second, China should cooperate with BRI countries with respect to agri-technology and infrastructure projects like irrigation. Such cooperation will not only increase China's agricultural productivity and national income but create a favorable environment for China and for the common good of humanity.

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