Effects of International Trade on World Agricultural Production: Evidence from a Panel of 126 Countries 1962–2014

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1 Introduction

The General Agreement on Tariffs and Trade (GATT) was a multilateral agreement that had regulated international trade since 1948, aiming to substantially reduce tariffs and other trade barriers after World War II. Although some breakthroughs were achieved, the development of international trade was not satisfactory in the context of the Cold War. This situation changed dramatically in the 1990s after the dissolution of the Soviet Union. The lack of rivalry and tension between the major powers in the Eastern Bloc and the Western Bloc provided a great opportunity for international trade and global cooperation. The World Trade Organization (WTO) was formed as a replacement for the GATT in 1995 with the purpose of supervising and liberalizing international trade; it has a more permanent structure and is more powerful in dealing with international economic affairs.

Many economists (e.g., Tinbergen (1962), Disdier and Head (2008), and Michaels and Zhi (2010)) study the interactions and international trade across countries using a gravity model, where bilateral trade follows depends on economic sizes and distance between the two countries. Some other scholars (e.g., Henrekson (1994), Aghion and Griffith (2008), and Gong (2018c)), however, are more interested in the effect of international trade on economic growth, where productivity and efficiency analysis is usually adopted. Based on the latter approach, this article aims to evaluate the impacts of international trade on world agricultural production, especially the changes between the GATT and WTO periods. Moreover, we explore if this effect is different between GATT/WTO members and non-members, and between developed countries (DCs) and less developed countries (LDCs).

The new growth theory (e.g., Romer (1986) and Lucas (1988)) states that the international economic interflow is a major driver of economic growth. Hansson and Henrekson (1994) recommend using productivity growth instead of GDP growth as the proxy of economic growth to evaluate the impact of international trade, since international trade is a part of measured GDP. Moreover, new trade theory[2] believes international trade is a key factor for promoting technological progress and therefore functions as a productivity stimulus. Grossman and Helpman (1993) illustrate that international trade improves productivity through two channels: imports can bring not only commodities that cannot be produced domestically, but also the information needed to produce them, whereas exports can bring suggestions and requirements from foreign buyers that push exporters to update their technology and accumulate management skills from other countries. Aghion and Griffith (2008) point out that international trade can intensify the level of competition and innovation, which consequentially increases productivity.

Existing studies (e.g., Frankel and Romer (1999), Miller and Upadhyay (2000), Alcalá and Ciccone (2004), and Chanda and Dalgaard (2008)) often adopt a production function to estimate productivity and then evaluate the effect of international trade on the estimated productivity. The production function is usually assumed to be a conventional non-spatial model in the form $y_{it} = X_{it}\beta + \alpha_{it} + \varepsilon_{it}$ where y and X are output and inputs, while α_{it} is the productivity. In recent years, however, more and more economists consider cross-sectional dependence in the production function, as interactions and spillovers exist in the production process across units.[3] As a result, some scholars (e.g., Cohen and Paul (2004) and Gong (2017)) use the spatial

[2] The new trade theory, also known as the industrial-organization approach to trade, was initially expounded in a series of articles by P. R. Krugman (1979), Lancaster (1980), P. Krugman (1980), Helpman (1981), P. R. Krugman (1981) and Ethier (1982). P. Krugman (1992) and Markusen and Venables (1998) review and conclude the cores of the new trade theory.

[3] In agricultural sector, the spread of agricultural technologies through international trade is one of the drivers that may lead to positive spillovers. Moreover, free trade makes it possible for countries to generate more agricultural products with their competitive advantages. Given the same amount of total inputs, the total production can increase if a larger share of the output is from those productive agricultural products. On the other hand, however, trade dumping and destructive competition can be counterproductive (Brown-Kruse, 1991). Furthermore, externality problem occurs in agriculture across countries, such as excessive carbon emission that causes climate change, as well as overuse and pollution of water resources, can also generate negative spillover effects.

production function (or spatial cost function) $y_{it} = X_{it}\beta + \rho \sum_{j=1}^{N} \omega_{ij} y_{jt} + \alpha_{it} + \varepsilon_{it}$ in various industries where the output of a unit not only depends on its own input and productivity, but also on the output of other units. The elements ω_{ij} in the spatial weights matrix account for the dependence between units i and j, which is often measured through bilateral trade in cross-country analysis. Using the conventional non-spatial model, existing studies may have two disadvantages if cross-country interactions exist in world agricultural production. First, spillover effects due to international trade are overlooked when studying the effect of trade. Second, the ignorance of such spillovers further causes $\rho \sum_{j=1}^{N} \omega_{ij} y_{jt}$ to be mistakenly included in productivity, which leads to biased estimation in terms of the effect of international trade on productivity, because ω_{ij} includes information on international trade.

Considering these two puzzles, this article builds a spatial production function to model country-level agricultural production, where bilateral trade for each pair of nations is utilized to estimate the spillover effects due to international trade. In order to more comprehensively describe the overall interactions across countries, this article jointly considers geographic dependence and trade dependence using a model averaging method. Consequently, more accurate total factor productivity (TFP) can be derived, which allows us to better evaluate the unbiased effect of international trade on productivity. To summarize, this article explores the impacts of international trade on world agriculture through two channels: spillover effects and productivity growth.

There are four central contributions of this article: 1) it extends the effects of international trade on spillover effects, in addition to an unbiased effect on productivity using a spatial model; 2) it employs a model averaging method to jointly consider the geographic-wide and trade-wide dependence across countries; 3) it evaluates not only the effect of trade volume, but also the effects due to the characteristics and distributions of trade; and 4) it compares the aforementioned effects of international trade on agriculture between the GATT and WTO periods, between GATT/WTO members and non-members, and between DCs and LDCs.

Using a panel of 126 countries from 1962–2014, the empirical results show that: 1) international trade caused negative spillover effects in the GATT period (1962–1994), but positive spillover effects in the WTO period (1995–2014), which implies that international trade still retained some defects of a zero-sum game in the first period, but the advantages of international trade were enjoyed in the second period; 2) the existence of spillover effects due to international trade also implies the necessity to use spatial models, which not only capture cross-country interactions, but also avoid the biased estimation of TFP; 3) the weight assigned to international trade that explains cross-country dependence increased in the WTO period, indicating that trade is relatively more important than geographic proximity in global interactions; 4) more international trade had a very similar negative effect on productivity for DCs and LDCs in the GATT period, but a larger positive effect on productivity for DCs than LDCs in the WTO period; 5) the GATT did not provide a premium for its members, while the WTO offered significant benefits from international trade for its members; and 6) exports outperform imports in productivity enhancement and the diversification of trade partners is not beneficial in productivity growth. To summarize, international trade hindered agricultural growth due to negative spillover effects and the negative effect on productivity in the GATT period, but boosted agricultural growth due to the positive spillover effects and the positive effect on productivity in the WTO period.

The remainder of the article is structured as follows: Section 2 introduces the model and methodology, Section 3 provides data descriptions, Section 4 reports and analyzes the estimation results, and Section 5 concludes.

2 Model

This section first introduces a spatial production model that can separately measure the spillover effects due to international trade, as well as geographic proximity, across countries. Then, a model averaging method is adopted so that these two dimensions can be considered jointly, which derives more accurate total factor productivity (TFP). Finally, this article analyzes the impacts of international trade on TFP.

2.1 Spatial Production Function and Trade-driven Spillover Effects

A non-spatial production function with Cobb-Douglas formation is adopted in many studies (e.g., Kingdon and Knight (2004), Waldkirch and Ofosu (2010), Pan and Christiaensen (2012), Andersson, Edgerton, and Opper (2013), and Chandra and Long (2013)) and has the form:

$$y_{it} = \alpha_0 + X_{it}\beta + \tau P + \gamma I + \varepsilon_{it}, \tag{1}$$

where y_{it} accounts for the agricultural output in country i at time t, X_{it} is a $(1 \times K)$ input vector that measures the input portfolio of country i at time t. β is a $(K \times 1)$ parameter vector of the input elasticities and ε_{it} is an i.i.d. disturbance with zero mean and variance σ_ε^2. P is a group of year dummy variables and I is a group of country dummy variables, which will capture the fixed effects over time and across countries, respectively.

However, the non-spatial agricultural production function relies on the assumption that agricultural production in each country is independent, which ignores cross-country interactions. In the context of globalization, this assumption is invalid and may lead to a biased input–output relation. This article introduces spatial techniques into the agricultural production function to address the potential spillover effects across nations. The Spatial Autoregressive Model (SAR) is one of the most popular spatial models utilized in econometrics (Anselin, 2001, 2013; Cliff & Ord, 1973; Hardie, Narayan, & Gardner, 2001; LeSage & Pace, 2009; Ord, 1975). SAR captures endogenous interaction effects by estimating the cross-sectional dependence on explained variable y. Consequently, in our study, the output of a nation depends not only on its own inputs and productivity, but it is also jointly decided by the output of other nations, known as spillover effects. This article employs the SAR model to the world agricultural production function at country level in the form:

$$y_{it} = \rho \sum_{j=1}^{N} \omega_{ij} y_{jt} + \alpha_0 + X_{it}\beta + \tau P + \gamma I + \varepsilon_{it}, \quad (2)$$

where ω_{ij} is the element in the i-th row and j-th column of the $(N \times N)$ spatial weights matrix W, which accounts for the cross-sectional dependence between nations i and j. Then ρ is a parameter to be predicted that measures the existence, sign and magnitude of the spillover effects. Endogeneity issues may occur in the production function, as some information available to the producers to adjust their input portfolios is unobservable to scholars (Ackerberg, Caves, & Frazer, 2015). The control function method recommended in Amsler, Prokhorov, and Schmidt (2016) is employed to test the endogeneity of the inputs, where lagged values of the inputs are utilized as instruments (Levinsohn & Petrin, 2003). For those inputs that are confirmed to be endogenous, this article introduces the instrumental variables (IV) method to correct the estimation bias.

In the first law of geography, Tobler (1979) says that everything is related to everything else, but closer things are more related than distant things. The spatial weights matrix W is the tool to define closeness across nations, measuring the magnitude of dependence and interactions according to the first law of geography. This article employs two methods to measure closeness from different perspectives.

1) Geographic closeness. Some studies (Curtis & Hicks, 2000; Roe, Irwin, & Sharp, 2002) adopt geographic proximity to measure the magnitude of cross-sectional dependence and interactions, as neighboring nations and nations that are closer in distance are more affected by each other (Kelejian, Murrell, & Shepotylo, 2013). In the world agricultural analysis, the geographic weight matrix (W_1) can be built where the elements ω_{ij}^1 are the inverse of the physical distance between nations *i* and *j*, such that closer nations have greater dependence (Gaigné, Le Gallo, Larue, & Schmitt, 2011; Isik, 2004). Mathematically, the elements in W_1 can be calculated by $\omega_{ij}^1 = (D_{ij})^{-1}$ where D_{ij} is the Euclidean distance between countries *i* and *j*.

2) Economic closeness. Some scholars (Druska & Horrace, 2004; Han, Ryu, & Sickles, 2016) use bilateral trade volume to account for the economic connection, which can explain the strong interactions between some nations (e.g., the United States and China), regardless of the great geographic distance. Two countries with a larger volume of agricultural trade are more closely connected and experience more interactions in the agricultural sector. The trade weights matrix (W_2) measures the total volume of the bilateral trade of agricultural products for each pair of countries. Mathematically, the volume of agricultural trade between countries *i* and *j* at time *t* is $\omega_{ijt}^2 = export_{ijt} + export_{jit}$, where $export_{ijt}$ accounts for the agricultural exports from nation *i* to nation *j* at time *t*. The elements ω_{ij}^2 in W_2 can be calculated by $\omega_{ij}^2 = \frac{1}{T}\sum_{t=1}^{T}(\omega_{ijt}^2)$ so that it reflects the average level of economic closeness during the sample period. Using this matrix can capture the spillover effects due to international trade on world agricultural production.

In summary, two candidates have been employed to measure cross-sectional interactions from different angles: geographic closeness and economic closeness. This article can therefore establish two spatial weights matrices (W_1 and W_2) to reflect multi-dimensional interactions in global agricultural production. In order to meet the requirements of a spatial weights matrix, W_1 and W_2 are then adjusted so that they are standardized by row and have zero diagonals. Finally, each of the two spatial weights matrices is introduced into Eq. (2) to measure the cross-country interactions in the corresponding dimensions. In other words, geographic-wide and trade-wide dependences can be separately captured.

Solving the spatial production model in Eq. (2), this article can estimate direct effects and indirect effects. The former measure the impacts of the country itself, whereas the latter are the impacts on other nations (Moussa & Laurent, 2015). Many scholars (Han, et al., 2016; LeSage & Pace, 2009) use indirect effects to interpret spillover effects. Mathematically, the direct effects are derived by averaging the diagonal elements of $(I - \rho W)^{-1}\beta$, while the indirect effects are predicted by averaging the row sums of the off-diagonal elements of $(I - \rho W)^{-1}\beta$. Therefore, the spillover effects due to interactions from different dimensions (geographic-wide and economic-wide) can be calculated, respectively.

It is worth noting that the economic-wide indirect effects can be regarded as spillover effects due to international trade, or trade-driven spillovers, since economic closeness is measured by bilateral trade. This article predicts that the spillover effects due to international trade are more positive, whereas the spillover effects due to geographic proximity have become less important in the past two decades, as globalization has become more popular. Moreover, the spillovers across countries can be either positive or negative in agriculture. On the one hand, technology spread can achieve positive spillover effects. On the other hand, negative spillovers exist because high agricultural production in one nation may reduce agricultural prices in other countries (or even cause destructive competition) and therefore lower the value of agricultural outputs in those countries. The sign of the overall spillover effects need to be estimated. Since globalization encourages more technology spread and better prevents destructive competition, this article forecasts that more positive spillovers can be observed in the WTO period.

2.2 Aggregation Method: Single- to Multi-dimensional Analysis

Let us denote F_1 and F_2 as the corresponding spatial production functions using W_1 and W_2 as the spatial weights matrix, separately. Since W_1 and W_2 may both reflect the interactions across countries to some extent, both F_1 and F_2 may partially capture the overall spillover effects from different perspectives. As a result, the overall spillover effects from cross-country interactions can be fully estimated only if we find an aggregation method to simultaneously take both dimensions into consideration. In other words, we need to convert the abovementioned two separate single-dimensional spatial analyses into a multi-dimensional analysis.

In order to combine the interactions in both dimensions to utilize all available information and capture the true data generating process (DGP), the relative significance reflected by a series of weights, one for each dimension, must be decided. This article introduces the model averaging method, which assigns a weight to every candidate model according to its ability to explain the data when each model may to some extent specify the true DGP (Cho & Kasa, 2017; Malik & Temple, 2009). The weighted average estimation converts separate single-dimensional spatial analyses into a multi-dimensional analysis that fits the data the best and approximates the underlying mechanism. It is worth noting that model selection is a special case of the model averaging method, when all the weight is distributed to one candidate model.

This article uses a jackknife model averaging method proposed by Hansen and Racine (2012), which approaches the minimum expected square errors when the sample size approaches infinity. In recent years, many studies in productivity and efficiency analysis have employed the jackknife model averaging method. Shang (2015) reviews the family of model averaging methods and uses the jackknife method to study the productivity of 112 countries over the period from 1960–2012. Gong (2017) employs the jackknife method to estimate the interactions among 54 oilfield service companies over a thirteen-year period from 2002 to 2014. Gong (2018b) also adopts the jackknife method to predict the firm-level efficiency of the petroleum industry from 2009–2015.

More specifically, the jackknife method assigns weights according to the "leave-one-out" cross-validation criterion. The jackknife estimators of the output $\hat{y}^m = (\hat{y}_1^m, \dots, \hat{y}_N^m)'$ need to be derived, where $\hat{y}_i^m$ is the fitted value of nation i's output after its own observations are removed from the regression process of F_m using W_m as the spatial weights matrix. The weights w_m are assumed to be non-negative and sum to one, so the space $\Omega_2 = (w \in R^2 \colon w_m \geq 0, \sum_{m=1}^{2} w_m = 1)$. The jackknife weights $w^* = (w_1^*, w_2^*)$ are achieved by minimizing the cross-validation criteria over weight space:

$$w^* = \text{argmin}_{w=(w_1,w_2)\in\Omega_2} CV_n(w) = \frac{1}{n}\hat{e}(w)'\hat{e}(w), \tag{3}$$

where

$$\hat{e}(w) = y - \sum_{m=1}^{2} w_m \hat{y}^m.$$

Here $\sum_{m=1}^{2} w_m \hat{y}^m$ is the weighted average of the jackknife estimator, leaving $\hat{e}(w)$ as the weighted average residual. As a result, $w^* = (w_1^*, w_2^*)$ measures the jackknife weights assigned to each of the two single-dimensional spatial analyses, which reflect the relative importance of geographic and economic closeness on the mutual interference in the agricultural sector. Since

$w^* = (w_1^*, w_2^*)$ minimizes square residuals, the weighted average spatial production model in Eq. (4) is the best fit of the data.

$$y_{it} = \sum_{m=1}^{2} w_m^* (\rho_m \sum_{j=1}^{N} \omega_{ij}^m y_{jt} + X_{it}\beta_m + \varepsilon_{it}^m). \qquad (4)$$

The overall spillover effects due to multi-dimensional interactions can also be derived, which is the weighted average of the two single-dimensional spillovers. Mathematically, the overall spillover effects can be calculated by $\sum_{m=1}^{2} w_m^* [\,(I - \rho_m W_m)^{-1} \beta_m]$.

A second approach to derive the overall spillover effects can be constructed as follows. First, the weights $w^* = (w_1^*, w_2^*)$ are utilized directly to calculate the aggregated spatial weights matrix $W^* = \sum_{m=1}^{2} w_m^* W_m$. This new matrix reflects the overall level of interaction across countries, as each element in W^* is the weighted average of geographic and economic interactions between two nations. Second, this article introduces W^* into the spatial model in Eq. (2), which derives another estimate of the overall spillover effects $(I - \rho^* W^*)^{-1} \beta^*$. This measure of the overall spillover effects also considers interactions in both dimensions and is therefore comparable to the weighted average of the two indirect effects introduced in the previous paragraph. As a result, this article treats this second approach as a robustness check of the overall spillover effects.

In summary, this article employs each of the two spatial matrices (W_1 and W_2) to model the production process with the concern of geographic-wide and trade-wide interactions, which generate two single-dimensional spillover effects. The jackknife model averaging method is then applied to derive weights, which are utilized to estimate the overall spillover effects. Furthermore, the overall spillover effects can also be predicted directly using the weighted average spatial weights matrix W^*, which is adopted as a test to confirm the robustness of our estimation on spillover effects.

2.3 Effects of Trade on Total Factor Productivity

If a conventional non-spatial model is adopted, the spatial part $\rho \sum_{j=1}^{N} \omega_{ij} y_{jt}$ in Eq. (2) will be mistakenly included in total factor productivity (TFP), since TFP is a Solow residual. More importantly, the estimated effect of international trade on productivity is biased, as ω_{ij} in the spatial part includes information on international trade. The spatial production regression and model averaging method not only derive overall spillover effects, but also a more accurate TFP. In the first approach, aggregated TFP is the weighted average of the two TFPs derived by the two candidate models. In the second approach, however, aggregated TFP is estimated directly from the SAR model with W^* as the spatial weights matrix.

International trade may have impacts on agricultural production not only through spillover effects, but also through its influence on TFP. Hence, this article builds a TFP determination function in Eq. (5) to identify the effect of international trade on TFP.

$$TFP_{it} = \alpha + \beta_1 trade_{it} + \beta_2 exratio_{it} + \beta_3 H_{it} + \delta P + \rho R + \theta Z_{it} + \varepsilon_{it}, \qquad (5)$$

where TFP_{it} is the total factor productivity for nation i at time t. $trade_{it}$ measures the total value of the international trade of agricultural products for nation i at time t. $exratio_{it}$ accounts for the ratio of exports in total trade value in order to capture different effects of exports and imports on productivity. $H_{it} = \sum_j (\omega_{ijt}^2 \cdot \omega_{ijt}^2)$, the Herfindahl index of international trade, reflects the diversification of trade partners for nation i at time t, where ω_{ijt}^2 are the elements in the trade-wide spatial weight matrix. A lower value of H_{it} implies that the trade volumes of nation i are more evenly distributed to various trade partners, whereas a higher value of H_{it} shows that the trade portfolio is more diversified. To summarize, $trade_{it}$ controls the size of international trade, $exratio_{it}$ captures the characteristics of international trade, and H_{it} captures the distributions of international trade. P is a vector of year dummy variables to capture time fixed effects and R

vectors a group of region dummy variables to capture the region fixed effects. Finally, Z_{it} vectors a group of other TFP determinants to deal with the endogeneity problem, which will be further discussed.

Endogeneity may also be a problem in the TFP determination (i.e., Eq. (5)) because of omitted variables or simultaneity bias. In terms of the former bias, this article employs Z_{it} in Eq. (5), which vectors other TFP determinates adopted in the literature (Chen, Ming-Miin, Chang, & Hsu, 2008; Gong, 2018a), including the following: 1) the output share of crops in total agricultural products, $crops_{it}$; 2) the share of cropland in total agricultural land $cropland_{it}$; 3) the share of agricultural land that is irrigated, $irrig_{it}$; 4) the geographic Herfindahl index, $Hgeo_i = \sum_j (\omega_{ij}^1 \cdot \omega_{ij}^1)$, which is derived from W_1 and captures extra geographic allocation information; and 5) a group of dummy variables of low-income (LI_i, served as base group), lower middle-income (MI_L_i), upper middle-income (MI_U_i) and high-income (HI_i) countries. Causality can be another issue, as some TFP determinants may be affected by productivity as well, which leads to simultaneity bias. For instance, international trade in agriculture may be conversely affected by agricultural productivity and may therefore lead to reverse causation. This article uses the instrumental variable (IV) method to overcome this issue, where the population size (pop_{it}) recommended in Chanda and Dalgaard (2008), as well as the per capita agricultural production ($agri\_pc_{it}$) recommended in Madsen (2009), are employed as instruments for $trade_{it}$. Moreover, this article replaces all the independent variables with their lagged values to further deal with the causality problem. In order to break the potential serial correlation, independent variables that lagged two periods ($t-2$) are utilized, which can be regarded as a robustness check, as suggested in Guan, Kumbhakar, Myers, and Lansink (2009) and Gong (2018b).

This article also investigates whether there is a premium of international trade for GATT/WTO members. In other words, receiving membership in GATT or WTO can further enlarge the effect of international trade on productivity, which may be a strong incentive for non-members to join the league. Furthermore, this article aims to test if the impact of international trade and the premium for GATT/WTO members are different between less developed countries (LDCs) and developed countries (DCs). Accordingly, three interaction terms are added into the TFP determination equation, and the updated TFP determination function has the form:

$$TFP_{it} = \alpha + \beta_1 trade_{it} + \beta_2 trade_{it} \cdot mbr_{it} + \beta_3 trade_{it} \cdot DCs_{it} + \beta_4 trade_{it} \cdot mbr_{it} \cdot DCs_{it} + \beta_5 exratio_{it} + \beta_6 H_{it} + \theta_1 crops_{it} + \theta_2 cropland_{it} + \theta_3 irrig_{it} + \theta_4 Hgeo_i + \theta_5 MI\_L_i + \theta_6 MI\_U_i + \theta_7 HI_i + \delta P + \rho R + \varepsilon_{it}. \tag{6}$$

where mbr_{it} is a dummy variable for GATT/WTO membership, and DCs_{it} is a dummy variable for developed countries. Therefore, β_1 accounts for the impact of international trade for LDCs without GATT/WTO membership; β_2 measures if receiving a GATT/WTO membership can help these LDCs to achieve a premium of international trade; β_3 indicates whether the impact of international trade for DCs are different from LDCs, both without GATT/WTO membership; and β_4 tells whether the premium of becoming a GATT/WTO member is different between DCs and LDCs.

3 Data

The Economic Research Service of the United States Department of Agriculture (USDA-ERS) had published country-level agricultural input and output data[4] for 1961–2014. Gross agricultural output reported in USDA-ERS, Y_{it}, is originally from the Food and Agriculture Organization of the United Nations (FAO), which is the sum of the value of production of 189

[4] https://www.ers.usda.gov/data-products/international-agricultural-productivity/

crop and livestock commodities valued at constant, and global-average prices from 2004–2006 (in billion international 2005 $). There are six types of agricultural inputs: agricultural land ($land_{it}$, in million hectares of rain-fed cropland equivalents), agricultural labor ($labor_{it}$, in million economically active adults), livestock capital on farms ($livestock_{it}$, in thousand cattle equivalents), total stock of farm machinery ($machinery_{it}$, in million 40-CV tractor equivalents), fertilizer consumption ($fertilizer_{it}$, in million metric tons of N, P2O5, K2O), and total animal feed ($feed_{it}$, in million metric tons of crops and crop processing residues in dry-matter equivalents).

Data for bilateral trade are collected from NBER-UN and CEPII-BACI databases. The NBER-UN database documents a set of bilateral trade data by commodity for 1962–2000 in Feenstra, Lipsey, Deng, Ma, and Mo (2005), which is available on the NBER website. CEPII-BACI is the world trade database (BACI) developed by the French research center in international economics (CEPII) (Gaulier & Zignago, 2010), which provides bilateral values and quantities of trade for 1995–2014 using data originally from the United Nations Statistical Division (COMTRADE database). For both NBER-UN and CEPII-BACI databases, this article generates the bilateral trade of agricultural products data based on the definition of agricultural products given by the Agreement on Agriculture of the World Trade Organization (WTO). Similar to Boschma and Capone (2015) and Johnson and Noguera (2017), this paper uses NBER-UN and CEPII-BACI to generate trade data for 1962–1994 and 1995–2014, respectively. It is worth noting that the bilateral trade matrix (W_2), the trade Herfindahl index (H_{it}), and the country-level trade value and export ratio data ($trade_{it}$ and $exratio_{it}$) can be calculated using these two databases.

The data of other variables are collected as follows: 1) geographic spatial weight matrix (W_1) and geographic Herfindahl index ($Hgeo_i$) can be generated using the GeoDist datasets in CEPII, which provides the distance for pairs of countries; 2) the share of cropland in total agricultural land ($cropland_{it}$), the share of agricultural land that is irrigated ($irrig_{it}$), region dummy variables (R), and dummy variables of low-income, lower middle-income, upper middle-income and high-income countries (E_i), are all available from USDA-ERS, where our input and output data are collected; 3) the output share of crops in total agricultural products ($crops_{it}$) can be downloaded and computed from FAO's database; 4) GATT/WTO membership information (mbr_{it}) is available on the WTO website;[5] 5) Developed countries dummy variable (DCs_{it}) can be collected from the International Monetary Fund (IMF); 6) population size (pop_{it}) is collected from World Bank databases; and 7) per capita agricultural production ($agri\_pc_{it}$) can be computed using agricultural output from USDA-ERS and population data from World Bank databases.

Combining all the data mentioned above, this article is based on a balanced panel of 126 countries for 1962–2014 with a total of 6678 observations.[6] Table 1 provides summary statistics of the key variables in our panel data. On average, these 126 countries used 13.3 million hectares of agricultural land, 7.0 million workforce, 15,100 cattle equivalents of livestock capital, 0.2 million tractor equivalents of farm machinery, 0.8 million metric tons of fertilizer, and 6.7 million metric tons of feed to generate agricultural products that value 10.3 billion international dollars at 2005's constant price. In terms of trade, each nation, on average, had 5.9 billion dollars of international trade in agricultural products, the average export ratio is 0.51 and the trade Herfindahl index is 0.17. During the same period, 79% of the agricultural land is cropland, and

[5] Information of GATT members by 1994 and WTO members since 1995 are respectively available at https://www.wto.org/english/thewto_e/gattmem_e.htm and https://www.wto.org/english/thewto_e/whatis_e/tif_e/org6_e.htm.
[6] Inputs data in 1961 are used to check the endogeneity of inputs in the production function.

12% of the agricultural land is equipped for irrigation. The average ratio of crops in agricultural output is 60% and the remaining 40% is composed of livestock-related products. Finally, the sample countries, on average, had a population of 36 million and per capita agricultural products valued at 310 international dollars at 2005's constant price.

Table 1 Summary statistics

Variable Name	Notation	Unit	Mean	St. Dev.	Min	Max
agricultural output	Y	billion international $	10.3	34.9	0.0	591
agricultural land	$land$	million hectares	13.3	40.0	0.0	316
agricultural labour	$labor$	million active adults	7.0	33.0	0.0	391
livestock capital	$livestock$	thousand cattle equivalents	15.1	43.4	0.0	415
farm machinery	$machine$	million tractor equivalents	0.2	0.7	0.0	11.7
fertilizer consumption	$fertilizer$	million metric tons	0.8	3.4	0.0	51.4
animal feed	$feed$	million metric tons	6.7	23.3	0.0	371
agricultural trade value	$trade$	billion dollars	5.9	16.7	0.0	273
agricultural export ratio	$exratio$	--	0.51	0.26	0.0	1.0
trade Herfindahl index	H	--	0.17	0.12	0.04	0.93
geographic Herfindahl index	$Hgeo$	--	0.04	0.09	0.01	0.59
share of cropland	$cropland$	--	0.79	0.19	0.00	1.00
share of irrigated land	$irrig$	--	0.12	0.13	0.00	0.71
share of crops output	$crops$	--	0.60	0.23	0.01	1.00
GATT/WTO membership	mbr	--	0.68	0.47	0	1
developed countries dummy	DCs	--	0.18	0.38	0	1
population size	pop	million	36	127	0.06	1360
per capita agricultural output	$agri\_pc$	thousand international $	0.31	0.28	0.00	2.58

4 Estimation Results

This empirical study applies the models established in Section 2 to the balanced panel of 126 nations from 1961–2014 described in Section 3. First, the control function test shows that five inputs, including land, labor, machinery, fertilizer and animal feed, are endogenous, which are corrected by the IV method suggested in Amsler, Prokhorov and Schmidt (2016). Second, this article uses the Breusch-Pagan LM test (Breusch & Pagan, 1980) and the Pesaran CD test (Pesaran, 2004) to assess the cross-sectional dependence, both of which generate p-values of less than 0.05. Therefore, cross-sectional dependence exists. Third, this article adopts Moran's *I* test for spatial autocorrelation using geographic and trade spatial weights matrices W_1 and W_2, separately, both of which derive p-values of less than 0.05 and thus confirm the existence of spatial autocorrelation geographic-wide and trade-wide. Finally, this paper confirms that SAR model is the appropriate spatial model for the present dataset.[7] To summarize, it is necessary to consider geographic-wide and trade-wide dependence and employ W_1 and W_2 to estimate the world agricultural production function using spatial models. This section first analyzes the effect of international trade in the full sample period and then emphasizes the changes in the GATT period (1962–1994) and the WTO period (1995–2014).

[7] Weather and other variables that may cause spillover effects are included in the disturbance of the production function. Therefore, we can employ a General Spatial Model (GSM) rather than the SAR model, where the disturbance term is also assumed to be cross-sectional dependent, to check if the spillover exists. A GSM model has the form $y_{it} = \rho \sum_{j=1}^{N} \omega_{ij} y_{jt} + X_{it}\beta + \varepsilon_{it}$, where $\varepsilon_{it} = \lambda \sum_{j=1}^{N} \omega_{ij} \varepsilon_{jt} + u_{it}$. I have checked the results of GSM, which are fairly robust with the ones in SAR. Model selection result also suggests using SAR rather than GSM based on AIC scores. Therefore, weather shocks and other factors in the disturbance do not significantly affect the estimates.

4.1 Trade-driven Spillovers: Negative in the GATT Era and Positive in the WTO Era

Table 2 reports the estimation results of various spatial production functions in Eq. (2) across different periods. The first two columns describe agricultural production in the full sample period (1962–2014), whereas the next two columns and the last two columns provide results in the GATT period (1962–1994) and the WTO period (1995–2014), respectively. For each pair of columns that focus on the same period, the first column uses spatial weight matrix W_1 to control geographic autocorrelation, whereas the second column uses spatial weight matrix W_2 to control trade autocorrelation.

Table 2 Estimation results

	Full Period (1962–2014)		GATT Period (1962–1994)		WTO Period (1995–2014)	
	W_1	W_2	W_1	W_2	W_1	W_2
$land$	0.444***	0.450***	0.486***	0.490***	0.352***	0.343***
	(0.011)	(0.011)	(0.014)	(0.014)	(0.020)	(0.020)
$labor$	0.050***	0.042***	-0.023*	-0.026**	0.233***	0.242***
	(0.008)	(0.008)	(0.012)	(0.012)	(0.017)	(0.017)
$livestock$	0.272***	0.270***	0.326***	0.323***	0.166***	0.165***
	(0.010)	(0.010)	(0.013)	(0.013)	(0.016)	(0.016)
$machine$	0.069***	0.072***	0.059***	0.058***	0.087***	0.090***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.011)	(0.011)
$fertilizer$	0.059***	0.061***	0.050***	0.050***	0.018***	0.020***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
$feed$	0.106***	0.105***	0.102***	0.105***	0.144***	0.140***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.010)	(0.010)
time effects	controlled	controlled	controlled	controlled	controlled	controlled

nation effects	controlled	controlled	controlled	controlled	controlled	controlled
intercept	4.840***	5.001***	4.853***	4.996***	5.386***	5.104***
	(0.042)	(0.042)	(0.049)	(0.050)	(0.066)	(0.066)
ρ	0.147***	0.078***	0.056**	-0.060*	-0.032	0.529***
	(0.024)	(0.029)	(0.026)	(0.036)	(0.035)	(0.051)
indirect effect	0.172***	0.084***	0.059*	-0.056*	-0.031	0.346***
	(0.038)	(0.033)	(0.030)	(0.030)	(0.037)	(0.100)
sample size	6678	6678	4158	4158	2520	2520
jackknife w_m^*	0.16	0.84	0.35	0.65	0.00	1.00

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

For the full sample period, all six input elasticities are fairly robust in the first two columns in Table 2. The elasticities of land and livestock capital are the greatest (0.45 and 0.27, respectively), followed by the elasticity of animal feed (0.11), while the elasticity of machinery and fertilizer are the lowest (0.07 and 0.06, respectively). Moreover, the parametric ρ in both dimensions are statistically positive, indicating both positive geographic-wide spillover effects and positive trade-wide spillover effects. More specifically, the spillover effects, measured by indirect effects, are 0.172 due to geographic proximity and 0.084 due to bilateral trade, respectively. Finally, the jackknife model averaging weights assigned to the dependence in these two dimensions are 0.16 and 0.84, indicating that cross-country dependence is mainly related to international trade.

Comparing with the GATT period, the contributions of labor, animal feed and farm machinery to agricultural production were greater, whereas the importance of the other three inputs relatively decreased in the WTO period. During the GATT period, geographic spillover effects (ρ is 0.056 and indirect effects are 0.059) were positive, whereas international trade caused negative spillover effects (ρ is -0.06 and indirect effects are -0.056), which provides some evidence that international trade still retained some disadvantages of a zero-sum game, as in the old era. In the WTO period, however, international trade led to significant positive spillover effects (ρ is 0.529 and indirect effects are 0.346), which implies that the advantage of international trade was enjoyed in the agricultural sector. In the context of globalization and informatization, geographic spillover effects were negligible, which implies that geographical distance is no longer an obstacle to cross-country interactions and communications. Moreover, the jackknife weight assigned to trade-wide dependence rose from 0.65 in the GATT period to 1.00 in the WTO period, which further confirms that the importance of international trade was increasing and that geographical distance was no longer a barrier in the WTO era.

4.2 Effect on Productivity: Negative in the GATT Era and Positive in the WTO Era

The previous subsection estimates the spatial production functions with different spatial weights matrices and their corresponding jackknife model averaging weights, which can derive total factor productivity (TFP). Table 3 reports the estimated results of the TFP determination equation. The result of the full sample period is given in the first two columns, while the results of the GATT and WTO periods are separately listed in the next two columns and the last two columns. For each pair of columns that cover the same period, the first column reports the result of IV regression without the interaction terms (i.e., Eq. (5)) to estimate the average effect of international trade on productivity, whereas the second column reports the IV results with the interaction term (i.e., Eq. (6)) so that the different impact of international trade between GATT/WTO members and non-members, as well as the different impact of international trade between DCs and LDCs can be captured. More regression results and more robustness checks are provided in the Appendix, all of which are fairly robust.

Table 3 TFP determination regression results

TFP Determinants	Full Period (1962–2014) (1)	Full Period (1962–2014) (2)	GATT Period (1962–1994) (3)	GATT Period (1962–1994) (4)	WTO Period (1995–2014) (5)	WTO Period (1995–2014) (6)
$trade$	-0.003	-0.011	-0.034*	-0.035*	0.043***	0.029*
	(0.012)	(0.012)	(0.018)	(0.018)	(0.016)	(0.016)
$trade \cdot mbr$	--	0.004***	--	0.002	--	0.004**
	--	(0.001)	--	(0.002)	--	(0.002)
$trade \cdot DCs$	--	0.007	--	0.000	--	--
	--	(0.009)	--	(0.010)	--	--
$trade \cdot mbr \cdot DCs$	--	0.000	--	-0.002	--	0.021***
	--	(0.009)	--	(0.010)	--	(0.002)
$exratio$	0.128***	0.110***	0.032	0.022	0.552***	0.536***
	(0.028)	(0.029)	(0.039)	(0.040)	(0.047)	(0.047)
H	0.225***	0.241***	0.363***	0.379***	0.280***	0.272**
	(0.065)	(0.065)	(0.092)	(0.093)	(0.106)	(0.106)
$crops$	-0.174***	-0.177***	-0.121***	-0.118***	-0.285***	-0.278***
	(0.025)	(0.025)	(0.035)	(0.035)	(0.039)	(0.038)
$cropland$	1.249***	1.245***	1.362***	1.351***	1.163***	1.124***
	(0.044)	(0.044)	(0.065)	(0.065)	(0.064)	(0.063)
$irrig$	1.414***	1.394***	1.681***	1.662***	1.412***	1.378***
	(0.060)	(0.061)	(0.092)	(0.093)	(0.082)	(0.081)
$Hgeo$	1.866***	1.886***	2.105***	2.115***	1.755***	1.780***
	(0.068)	(0.068)	(0.096)	(0.096)	(0.100)	(0.098)
MI_L_i	0.186***	0.181***	0.237***	0.230***	0.117***	0.112***
	(0.023)	(0.023)	(0.035)	(0.035)	(0.032)	(0.032)
MI_U_i	0.302***	0.308***	0.385***	0.382***	0.246***	0.252***
	(0.027)	(0.027)	(0.040)	(0.040)	(0.037)	(0.036)
HI_i	0.757***	0.727***	0.879***	0.872***	0.708***	0.600***
	(0.032)	(0.032)	(0.048)	(0.048)	(0.042)	(0.043)
time effects	controlled	controlled	controlled	controlled	controlled	controlled
region effects	controlled	controlled	controlled	controlled	controlled	controlled
intercept	3.712***	3.789***	3.846***	3.850***	3.691***	3.900***
	(0.146)	(0.147)	(0.211)	(0.213)	(0.227)	(0.224)
sample size	6678	6678	4158	4158	2520	2520

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively. There is no estimation for the coefficient of $trade \cdot DCs$ in Column 6, as all the developed countries are WTO members in the WTO period.

This article estimates the impacts of international trade on TFP from three dimensions, including the size of trade ($trade_{it}$), the characteristics of trade ($exratio_{it}$) and the distributions of trade H_{it}. First and foremost, we are interested in the effect of trade volume when the characteristics and distributions of trade are controlled. On average, a one percent increase in the total volume of international trade could decrease agricultural TFP by 0.034 percent during the GATT period, but can increase agricultural TFP by 0.043 percent during the WTO period. Therefore, the size of trade had a negative effect on TFP in the first period, but a positive effect on TFP in the second period. During the full period, this effect is economically and statistically insignificant from zero, indicating no effect of international trade on productivity.

Furthermore, this article is interested in the difference between GATT/WTO members and non-members, as well as between DCs and LDCs, in terms of the effects of international trade on productivity across periods. In the GATT period, these four groups have no significant difference, as the coefficients of all three interaction terms in Column 4 were insignificantly different from zero, which implies that DCs and LDCs both had identical and negative impact of international trade on productivity, and GATT members enjoyed no extra benefit from international trade compared with non-members. In the WTO period, LDCs without WTO membership can achieve a 0.029 percent increase in agricultural TFP from a one percent increase in the total volume of international trade. This increase can further improve by 0.004 percent for LDCs who received WTO membership, which implies that WTO accession helps LDCs to receive a small premium on productivity from international trade. Moreover, we cannot identify the premium of WTO membership for DCs, since all the DCs are WTO members. But on average, a one percent increase in the total volume of international trade can increase agricultural TFP by 0.054 percent for DCs, which is much larger than the one for LDCs. These findings show that there is no difference between LDCs and DCs and no difference between members and non-members in the GATT period, whereas the WTO provided small premium from international trade to its members and greater improvement in productivity due to international trade is witnessed for DCs than for LDCs in the WTO period.

In terms of the characteristics of trade, exports are more preferred than imports, as the ratio of exports in trade has a positive effect on TFP. On average, a one percentage point increase in export ratio can raise TFP by more than 0.1 percent over the full period. However, this difference between exports and imports is only found in the WTO period. In terms of the distributions of trade, the diversification of trade partners can discourage TFP growth, as a negative effect of trade Herfindahl index is observed. Having more trade partners may expand trade volume, but when trade volume is controlled, the diversification of trade partners is not preferred. However, the disadvantage of having more trade partners diminished over time.

In terms of output portfolio, crops-related products are on average less productive than livestock-related products. During the full sample period, a one percentage point decrease in output share of crops, on average, increased TFP by 0.177 percent. Moreover, the advantage in productivity of livestock-related products is enlarged from the GATT period to the WTO period. Considering the quality of land, cropland is more productive than pasture, and irrigated land is more productive than non-irrigated land. Moreover, both of the advantages of cropland and irrigated land are fairly consistent in the GATT period and the WTO period.

This article also finds that the TFP level for low-income, middle-income, and high-income countries are significantly different. Compared with low-income countries, lower middle-income countries on average were about 20 percent more productive, upper middle-income countries on average were 30 percent more productive, while high-income countries on average were around

75 percent more productive over the full period. Moreover, the productivity gap between low-income and lower middle-income countries diminished by half, from more than 20 percent in the GATT period to about 10 percent in the WTO period. The gap between lower and upper middle-income countries, however, dropped only slightly, from 15 percent in the GATT period to 13 percent in the WTO period. Finally, the gap between upper middle-income and high-income countries also decreased slightly, from about 50 percent in the GATT period to roughly 45 percent in the WTO period.

5 Conclusion and Policy Implications

This article aims to evaluate the effects of international trade on global agricultural production. A spatial production model and a model averaging method are adopted to estimate country-level agricultural production when cross-country interactions due to geographical proximity and bilateral trade are jointly considered. This model not only captures the trade-driven spillover effects, but also leads to unbiased total factor productivity (TFP). This article then estimates the effects of the size, characteristics, and distributions of international trade on TFP, which is the second impact of trade on agriculture, in addition to the spillover effects.

Using a panel of 126 countries from 1962–2014, this article evaluates the overall impact of international trade during the full sample period and then analyzes the changes and differences between the GATT period and the WTO period when the macro environment of international trade varied dramatically. In the GATT period, international trade caused negative spillover effects and hindered productivity growth. These results show that international trade and cooperation were not beneficial, probably due to the Cold War, where rivalry and tension between powers in the Eastern Bloc and the Western Bloc prevented the development of globalization. In the WTO period, however, international trade not only generated positive spillover effects, but also improved the level of productivity. Moreover, the GATT did not offer extra benefits for its members, whereas the WTO provided a premium through international trade to its members. Such findings provided evidence that the benefits of international trade and WTO accession are currently being enjoyed in agricultural production and should be further encouraged in the context of globalization. Finally, the impact of international trade on productivity is identical for DCs and LDCs in the GATT period, but DCs enjoyed much larger benefits due to international trade than LDCs in the WTO period. Based on these empirical findings, this article generates the following policy implications.

Firstly, this article finds that WTO members, on average, enjoyed a greater positive effect of international trade on TFP compared with the non-member group, indicating the benefits of WTO accessions. Some countries are afraid of the negative impacts on agriculture brought by WTO accessions, but the empirical result suggests that those governments should reconsider the premium of becoming a member, especially the countries that already have a large volume of international trade.

Secondly, significant spillover effects and productivity growth in the agricultural sector have been brought about by international trade and enjoyed by both WTO members and non-members since the mid-1990s. Therefore, globalization and free trade should be encouraged and supported. Conversely, the consequences of anti-globalization and protectionism should be re-evaluated.

Thirdly, the coefficient of the trade Herfindahl index (H_{it}) is negative in both the GATT and WTO periods, which implies that the diversification of trade partners is not beneficial. In other words, major trade partners are more important than minor ones. As a result, governments should pay more attention to consolidating the relationships with their major partners where more cooperation and connection has already been established.

Finally, less developed countries benefited much less than developed countries from international trade in the WTO period. Since international trade brought severer competition, LDCs should pay more attention on how to learn from the imported commodities and how to update their technology for the exported products, which aims to encourage innovation and consequentially increases productivity.

To summarize, significant positive spillovers are enjoyed due to globalization, major trade partners are more important, and developed countries benefited more from international trade. All these findings provide some evidence why US President Donald Trump should not initiate US-China trade war, which may have negative effects on the economic growth for both countries.

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Appendix Robustness Checks

A. Endogeneity Concern

Table A.1 provides the OLS estimation, IV estimation, and IV estimation with lagged regressors of the TFP determination regression with endogeneity concern during the full period from 1962–2014. Columns (3) and (6) of Table A.1 are consistent with columns (1) and (2) of Table 3, respectively. Analogously, Tables A.2 and A.3 separately report detailed robustness checks for the GATT period (1962–1994) and the WTO period (1995–2014). To summarize, OLS and IV estimations have some variation, but IV and IV-Lag results are fairly robust, which implies that the endogeneity problem has been taken care of.

Table A.1 Detailed TFP determination regression results in the full period

TFP Determinants	Full Period (1962–2014)					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV-Lag.2	OLS	IV	IV-Lag.2
$trade$	0.009**	-0.006	-0.003	-0.006	-0.013	-0.011
	(0.004)	(0.011)	(0.012)	(0.005)	(0.011)	(0.012)
$trade \cdot mbr$	--	--	--	0.004***	0.004***	0.004***
	--	--	--	(0.001)	(0.001)	(0.001)
$trade \cdot DCs$	--	--	--	0.010	0.008	0.007
	--	--	--	(0.009)	(0.009)	(0.009)
$trade \cdot mbr \cdot DCs$	--	--	--	-0.002	0.000	0.000
	--	--	--	(0.009)	(0.009)	(0.009)
$exratio$	0.111***	0.129***	0.128***	0.106***	0.110***	0.110***
	(0.027)	(0.027)	(0.028)	(0.027)	(0.028)	(0.029)
H	0.247***	0.200***	0.225***	0.245***	0.216***	0.241***
	(0.053)	(0.063)	(0.065)	(0.054)	(0.064)	(0.065)
$crops$	-0.178***	-0.178***	-0.174***	-0.182***	-0.181***	-0.177***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
$cropland$	1.238***	1.266***	1.249***	1.243***	1.262***	1.245***
	(0.037)	(0.043)	(0.044)	(0.038)	(0.043)	(0.044)
$irrig$	1.402***	1.425***	1.414***	1.386***	1.404***	1.394***
	(0.057)	(0.059)	(0.060)	(0.057)	(0.059)	(0.061)
$Hgeo$	1.873***	1.856***	1.866***	1.891***	1.878***	1.886***
	(0.066)	(0.067)	(0.068)	(0.066)	(0.067)	(0.068)
MI_L_i	0.172***	0.189***	0.186***	0.173***	0.184***	0.181***
	(0.019)	(0.023)	(0.023)	(0.020)	(0.023)	(0.023)
MI_U_i	0.285***	0.305***	0.302***	0.299***	0.311***	0.308***
	(0.022)	(0.026)	(0.027)	(0.022)	(0.026)	(0.027)
HI_i	0.732***	0.759***	0.757***	0.706***	0.726***	0.727***
	(0.025)	(0.031)	(0.032)	(0.025)	(0.031)	(0.032)
time effects	controlled	controlled	controlled	controlled	controlled	controlled
region effects	controlled	controlled	controlled	controlled	controlled	controlled
intercept	3.583***	3.725***	3.712***	3.738***	3.805***	3.789***
	(0.096)	(0.142)	(0.146)	(0.097)	(0.142)	(0.147)

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.2 Detailed TFP determination regression results in the GATT period

TFP Determinants	GATT Period (1962–1994)					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV-Lag.2	OLS	IV	IV-Lag.2
$trade$	0.012*	-0.037**	-0.034*	-0.015**	-0.038**	-0.035*
	(0.006)	(0.017)	(0.018)	(0.007)	(0.017)	(0.018)
$trade \cdot mbr$	--	--	--	0.003*	0.003*	0.002
	--	--	--	(0.002)	(0.001)	(0.002)
$trade \cdot DCs$	--	--	--	-0.002	0.000	0.000
	--	--	--	(0.010)	(0.010)	(0.010)
$trade \cdot mbr \cdot DCs$	--	--	--	-0.003	-0.002	-0.002
	--	--	--	(0.010)	(0.010)	(0.010)
$exratio$	0.003	0.037	0.032	-0.013	0.025	0.022
	(0.038)	(0.038)	(0.039)	(0.038)	(0.039)	(0.040)
H	0.485***	0.317***	0.363***	0.516***	0.337***	0.379***
	(0.070)	(0.089)	(0.092)	(0.071)	(0.090)	(0.093)
$crops$	-0.127***	-0.125***	-0.121***	-0.121***	-0.122***	-0.118***
	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.035)
$cropland$	1.226***	1.338***	1.362***	1.202***	1.324***	1.351***
	(0.050)	(0.063)	(0.065)	(0.052)	(0.063)	(0.065)
$irrig$	1.546***	1.641***	1.681***	1.514***	1.618***	1.662***
	(0.084)	(0.089)	(0.092)	(0.085)	(0.090)	(0.093)
$Hgeo$	2.154***	2.096***	2.105***	2.164***	2.108***	2.115***
	(0.091)	(0.093)	(0.096)	(0.092)	(0.094)	(0.096)
MI_L_i	0.174***	0.235***	0.237***	0.160***	0.226***	0.230***
	(0.027)	(0.033)	(0.035)	(0.027)	(0.034)	(0.035)
MI_U_i	0.313***	0.384***	0.385***	0.302***	0.381***	0.382***
	(0.031)	(0.039)	(0.040)	(0.031)	(0.039)	(0.040)
HI_i	0.786***	0.879***	0.879***	0.777***	0.870***	0.872***
	(0.035)	(0.046)	(0.048)	(0.036)	(0.047)	(0.048)
time effects	controlled	controlled	controlled	controlled	controlled	controlled
region effects	controlled	controlled	controlled	controlled	controlled	controlled
intercept	3.430***	3.903***	3.846***	3.397***	3.907***	3.850***
	(0.128)	(0.203)	(0.211)	(0.134)	(0.205)	(0.213)

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Table A.3 Detailed TFP determination regression results in the WTO period

TFP Determinants	WTO Period (1995–2014)					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV-Lag.2	OLS	IV	IV-Lag.2
$trade$	0.021***	0.041***	0.043***	0.014**	0.028*	0.029*
	(0.007)	(0.015)	(0.016)	(0.008)	(0.014)	(0.016)
$trade \cdot mbr$	--	--	--	0.004**	0.004**	0.004**
	--	--	--	(0.002)	(0.002)	(0.002)
$trade \cdot DCs$	--	--	--	--	--	--
	--	--	--	--	--	--
$trade \cdot mbr \cdot DCs$	--	--	--	0.024***	0.022***	0.021***
	--	--	--	(0.002)	(0.002)	(0.002)
$exratio$	0.539***	0.538***	0.552***	0.587***	0.523***	0.536***
	(0.043)	(0.044)	(0.047)	(0.043)	(0.044)	(0.047)
H	0.177*	0.251**	0.280***	0.125**	0.250**	0.272**
	(0.090)	(0.099)	(0.106)	(0.090)	(0.100)	(0.106)
$crops$	-0.282***	-0.282***	-0.285***	-0.278***	-0.273***	-0.278***
	(0.037)	(0.037)	(0.039)	(0.036)	(0.036)	(0.038)
$cropland$	1.209***	1.174***	1.163***	1.163***	1.132***	1.124***
	(0.058)	(0.061)	(0.064)	(0.057)	(0.060)	(0.063)
$irrig$	1.431***	1.417***	1.412***	1.391***	1.379***	1.378***
	(0.077)	(0.078)	(0.082)	(0.076)	(0.076)	(0.081)
$Hgeo$	1.703***	1.734***	1.755***	1.732***	1.764***	1.780***
	(0.094)	(0.095)	(0.100)	(0.092)	(0.093)	(0.098)
MI_L_i	0.140***	0.119***	0.117***	0.152***	0.114***	0.112***
	(0.027)	(0.030)	(0.032)	(0.027)	(0.030)	(0.032)
MI_U_i	0.271***	0.247***	0.246***	0.301***	0.254***	0.252***
	(0.031)	(0.035)	(0.037)	(0.031)	(0.034)	(0.036)
HI_i	0.738***	0.709***	0.708***	0.641***	0.596***	0.600***
	(0.034)	(0.040)	(0.042)	(0.035)	(0.040)	(0.043)
time effects	controlled	controlled	controlled	controlled	controlled	controlled
region effects	controlled	controlled	controlled	controlled	controlled	controlled
intercept	3.948***	3.693***	3.691***	4.428***	3.888***	3.900***
	(0.139)	(0.214)	(0.227)	(0.143)	(0.210)	(0.224)

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively. There is no estimation for the coefficient of $trade \cdot DCs$ in Columns 4–6, as all the developed countries are WTO members in the WTO period.

B. Robustness of the Cobb-Douglas Production Formation and Total Factor Productivity

This article introduces two approaches to derive Total Factor Productivity (TFP) in Section 2. In the first approach, aggregated TFP is the weighted average of the two TFPs derived from the two spatial production functions that separately use W_1 and W_2 as the spatial weights matrix. This estimation, denoted as TFP_{it}, is used in all previous TFP determination regressions. In the second approach, however, aggregated TFP is estimated directly from the spatial production function with W^* as the spatial weights matrix, which is denoted as TFP_robust_{it} and can be employed to check the robustness of TFP_{it}.

Both TFP_{it} and TFP_robust_{it} are estimated under the assumption that the production function follows a Cobb-Douglas (C-D) formation. In order to check the validity of this formation hypothesis in Eq. (2), this article also assumes a Transcendental Logarithmic (T-L) production function which includes not only the inputs, as in the C-D model, but also their square terms and interaction terms. The two approaches to derive TFP are then utilized again to predict TFP_TL_{it} and $TFP\_robust\_TL_{it}$, which are comparable with TFP_{it} and TFP_robust_{it}, respectively.

In order to check the robustness of the production formation, as well as the TFP, this article follows Gong (2018b) to calculate the correlation of the TFPs derived from various models in Table A.4. All the correlation coefficients in the table are above 0.85, which implies a strong uphill (positive) linear relationship across the TFPs derived in the four models. Moreover, Table A.5 presents the estimation results of three regressions, where TFP_{it} is the independent variable and the other three estimations of TFP (TFP_robust_{it}, TFP_TL_{it}, and $TFP\_robust\_TL_{it}$) are the dependent variables, one for each regression. The coefficients of TFP_{it} in different models are all significant, which also confirms the robustness of the TFPs under different methods. To summarize, the robustness of the Cobb-Douglas production formation and the TFP derived from various approaches are confirmed.

Table A.4 Correlations of the TFP across models

	TFP_{it}	TFP_robust_{it}	TFP_TL_{it}	TFP_robust_T
TFP_{it}	1	0.9998	0.8717	0.8677
TFP_robust_{it}	0.9998	1	0.8689	0.8646
TFP_TL_{it}	0.8717	0.8689	1	0.9994
$TFP\_robust\_TL_{it}$	0.8677	0.8646	0.9994	1

Table A.5 Regressions of the TFP across models

	TFP_robust_{it}	TFP_TL_{it}	$TFP\_robust\_TL_{it}$
TFP_{it}	1.005***	0.675***	0.671***
	(0.000)	(0.005)	(0.005)
intercept	-0.045***	2.316***	2.361***
	(0.002)	(0.027)	(0.027)

Note. Standard errors are given in parentheses. Asterisks *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.