Interstate Competition in Agriculture: Cheer or Fear? Evidence from the United States and China

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Abstract:

This article aims to evaluate the effects of multi-dimensional interstate competitions on agricultural production, which is achieved using spatial econometrics and model averaging methods. Using panel data, this article finds that interstate agricultural competition ought to be encouraged in the United States due to their positive impacts on spillovers and productivity but should be discouraged in China as it leads to negative spillovers and a decrease in productivity. U.S. agriculture enjoys the benefits of competition thanks to agricultural industrialization and a competitive market, whereas the planned system with government interference found in China has benefits as well as detriments.

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I. Introduction

There has been a great deal of debate in academia about whether competition is good or not; Google Scholar, for example, gives over 1.6 million results for the search "competition good or bad." Many, from Adam Smith to Richard Caves, believe that competition is productive and hence should be encouraged due to the well-known results of efficient resource allocation (Nickell 1996). In practice, however, competition can sometimes be destructive and counterproductive (Brown-Kruse 1991), and this has long been offered as a principal defect of the market system (Deneckere, Marvel, and Peck 1997), which may precipitate an undesirable "race-to-the-bottom" (Arya and Mittendorf 2011, Hanna 2010). In other cases, competition is claimed to have mixed effects; for example, in the banking sector, greater competition may be good for efficiency but bad for stability (Allen and Gale 2004).

Existing studies mainly focus on the effects of inter-firm or interregional competition on economic performance within a specific industry. Competition is usually measured by the number of competitors, market share, or market concentration (Nickell 1996, Greenhalgh and Rogers 2006), whereas performance is usually evaluated by the technical efficiency or total factor productivity derived from production function (Lafontaine and Sivadasan 2009, Stoyanov and Zubanov 2012, Chen and Lan 2017).

However, this conventional method may not apply to the study of interstate agricultural competition, as both the competition and its influences are multi-dimensional. On the one hand, interstate competition can be more intense between neighboring states as transportation costs are lower, which makes the movement of inputs and outputs simpler. In addition to geographic distance, the economic distance measured by trade volume also decides the level of competition.[1] The third variable that can decide the level of competition is similarity in industry structure; namely, a state dominated by crop production tends to have greater competition with other states also dominated by crops than with states dominated by livestock products for example.

On the other hand, interstate competition can affect agricultural production not only in the area of productivity but also through spillover effects. The conventional approach assumes that the input-output relation is fixed so that competition only affects productivity. In other words, the cross-sectional dependence and interstate interactions related to competition are overlooked or willfully ignored. As a result, spillover effects are not taken into account, and because the estimated total factor productivity (TFP) is inaccurate, we fail to capture the true data-generating process.

Considering competitions in all three of these dimensions, this article builds a model to more comprehensively describe the overall levels of competition faced by each state from all other states and then estimates the spillover effects brought about by interstate competition. Moreover, this article further explores the effects of competition on productivity, which can be more precisely estimated as we control the spillover effects. Methodologically, spatial techniques are utilized in the production function to capture the

1 For example, the strong mutual influence between the United States and China, regardless of the long geographical distance, is due to the large volume of bilateral trade. Besides bilateral trade, international trade with a third country also measures the levels of competition between two nations.

spillovers, and the model averaging method is adopted to combine the competitions in all three dimensions into multi-dimensional competition.

Empirically, this article aims to discover whether interstate competition is good or bad when it comes to agricultural production for the world's two largest agricultural producers by using panel data for the United States (lower 48 states during 1960–2004) and China (31 provinces during 1990–2015). Completely different results between the two countries are found. Competition should be encouraged in the United States as both significant positive spillover effects and TFP growth exist; both improve output with the given inputs due to competition. For China, however, more competition leads to negative spillover effects and a decrease in TFP, and therefore should be avoided. This article also finds evidence that intrastate competition increases TFP in the United States but decreases TFP in China. Moreover, soft power, such as education, is another major driver of productivity growth in the United States, whereas hard power, such as public expenditure and infrastructure development, is the key to productivity growth in China. This provides strong evidence that the government plays a more important rule in China's economic growth than it does in the United States, where the market system was established much earlier. We find that U.S. agriculture has enjoyed the benefits of the competition thanks to agricultural industrialization and a competitive market, whereas the enactment of the minimum grain purchase price policy and the lack of an authoritative third-party certificate makes China's agriculture a market of "lemons" and leads to an undesirable "race-to-the-bottom" that causes the negative effects of competition.

There are five central contributions of this article: 1) It contributes to the measure of competition from single-dimension to multi-dimension; 2) it extends the effect of competition on spillover effects in addition to a more accurate effect on productivity by employing spatial techniques; 3) it introduces a model averaging method to more comprehensively estimate the overall effect of competition; 4) it is the first article to study the multi-dimensional effects of multi-dimensional competition in the agricultural sector; and 5) it provides empirical evidence to the debate on competition from a new perspective that demonstrates that its effect not only varies across industries, but also across countries in the same industry.

The remainder of the article is structured as follows: Section 2 establishes the model, Section 3 presents data descriptions, Section 4 reports and explains the empirical results, and Section 5 draws a conclusion.

II. Model

This section introduces a spatial production model to measure interstate competition and the spillover effects, as well as a TFP determination equation to estimate the effect on productivity. We further discuss how to deal with the potential endogeneity problems.

A. Spatial Autoregressive Production Function

This article begins with a conventional non-spatial agricultural production function that follows a classic Cobb-Douglas formation:

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

where y_{it} measures the agricultural output in state *i* at time *t*, X_{it} is a $(1 \times K)$ input vector that identifies the input portfolio of state *i* at time *t*. β is a $(K \times 1)$ parameter vector that measures the input elasticities, and ε_{it} is an i.i.d. error term with zero mean and variance σ_{ε}^2. In the panel data setup, this article also includes P, a group of year dummy variables, and I, a group of state dummy variables, to control the change over time and state, respectively. Total factor productivity (TFP), usually measured by the Solow residual, can be calculated accordingly.

Everything is related to everything else, but closer things are more closely related to one another (Tobler 1979). If the cross-sectional interaction effects exist but are overlooked or consciously ignored by using Eq. (1), we may fail to capture the true input–output relation. In order to address any potential interstate dependence in the production process, this article establishes a spatial autoregressive production model that can identify the potential spillover effects across states. The Spatial Autoregressive Model (SAR), also known as the Spatial Lag Model, is one of the most widely used spatial models in economics (Cliff and Ord 1973, Ord 1975, Anselin 2013, LeSage and Pace 2009, Anselin 2001, Hardie, Narayan, and Gardner 2001). This model captures endogenous interaction effects by measuring the dependence in explained variable y

across states. As a result, the value of y in a state depends not only on its own inputs, but is also affected by the output in other states, which is known as spillover effects or externality. This article introduces the SAR model into the agricultural production function in the following form:

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

where ω_{ij} is the element in i-th row and j-th column of the $(N \times N)$ spatial weights matrix W, which measures the dependence between states i and j. Then ρ is an unknown parameter to be estimated that indices the existence, sign, and magnitude of the spillover effects.

The spatial weights matrix W must be specified prior to estimating the spatial production function. Earlier studies (Roe, Irwin, and Sharp 2002, Curtis and Hicks 2000) usually used geographic distance as the indicator of dependence in the spatial weights matrix. In interstate studies, this means neighboring states are more related and affected by each other. More recently, the economic distance has been adopted as well (Druska and Horrace 2004). For example, Han, Ryu, and Sickles (2016) use bilateral trade volume to measure the economic connection among OECD countries. When economic distance is taken into consideration, it can explain the strong interactions between some countries (such as the United States and China) in spite of the great geographic distance. In one of the most cited spatial literature, LeSage (2008) states that one might replace geographical distance with measures of similarity, and the context of similarity would be in production processes or resource or product markets. For example, the similarity in the business and industry structure is another candidate for measuring cross-sectional dependence (Druska and Horrace 2004). Gong (2018b) uses the similarities among businesses to measure the interactions and competition across companies in the global oilfield market.

To summarize, three candidates have been introduced to measure cross-sectional dependence from different dimensions: geographic distance, trade volume, and similarity in industry structure. Accordingly, three spatial weights matrices ($W_1 - W_3$) can be built. In our intrastate agricultural analysis, the geographic weight matrix (W_1) can be established where the elements are the inverse of the physical distance between states so that closer states have greater dependence (Isik 2004, Gaigné et al. 2011).

Mathematically, the elements in W_1 can be calculated by $\omega_{ij}^1 = (D_{ij})^{-1}$ where D_{ij} is the Euclidean distance between states *i* and *j*.

In terms of the trade weights matrix (W_2), this article uses international trade data rather than interstate trade data as the latter is difficult to collect in both the United States and China. Interstate competition in the international market also causes interaction effects. For example, oil exporters Saudi Arabia and Iran have strong interaction and competition in crude oil, not because of their bilateral trade but rather because they compete in the global market. Similarly, the U.S. states in the "Corn Belt" have interactions in the soybean industry mainly due to their competition for market share in the international market. This article uses the overlapping volume of agricultural exports across states to build a trade weights matrix. Mathematically, the overlapping volume of agricultural exports between states *i* and *j* at time *t* is $\omega_{ijt}^2 = \min(E_{it}, E_{jt})$, where E_{it} represents the annual volume of agricultural exports in state *i*. The elements in W_2 can be measured by averaging annual values during the sample period $\omega_{ij}^2 = \frac{1}{T}\sum_{t=1}^{T}(\omega_{ijt}^2)$. As a result, two states with a large volume of agricultural exports are likely to face severe competition in the international market and therefore experience more dependence on each other.

Finally, the agricultural sector can be divided into different segments. In the United States, agricultural output is classified into three categories—crops, livestock products, and other farm-related outputs—according to the data from the United States Department of Agriculture (USDA). In China, farming, forestry, animal husbandry, and fisheries are the four segments in the agricultural sector, based on data from the National Bureau of Statistics of China. The similarity among the business between the two states can be measured by the homogeneity of their portfolios. Take U.S. agriculture as an example: If two states both produce crops rather than livestock products, the high similarity between them is likely to cause significant mutual influence as they directly compete with each other from demand of inputs to supply of outputs. This article adopts a cosine similarity method to calculate the similarities across states as it is a well-suited tool to measure the homogeneity of two portfolios (Getmansky et al. 2016) in many studies (e.g., in Hanley and Hoberg (2012), and Sias, Turtle, and Zykaj (2015)). Assuming agriculture can be divided into *N* segments, the industry structure in states *i* and *j* at time *t* can be denoted as

$R_{it} = (r_{it}^1, r_{it}^2, \ldots, r_{it}^N)$ and $R_{jt} = (r_{jt}^1, r_{jt}^2, \ldots, r_{jt}^N)$, where r_{it}^n is the share of output in the *n*-th segment over total agricultural output. The similarity between states *i* and *j* at time *t*, defined as the cosine similarity, can be calculated by $\omega_{ijt}^3 = (\sum_{n=1}^N r_{it}^n r_{jt}^n)/(\sqrt{\sum_{n=1}^N (r_{it}^n)^2}\sqrt{\sum_{n=1}^N (r_{jt}^n)^2})$, where ω_{ijt}^3 ranges from zero to unity. On the one hand, states *i* and *j* at time *t* have the exact same portfolio and achieve the highest similarity when $\omega_{ijt}^3 = 1$. On the other hand, the agricultural production in states *i* and *j* at time *t* is completely different and achieves the lowest similarity if $\omega_{ijt}^3 = 0$. The elements in the structure weights matrix W_3 can be calculated by averaging annual structure similarity during the sample period $\omega_{ij}^3 = \frac{1}{T}\sum_{t=1}^T(\omega_{ijt}^3)$. A smaller value of ω_{ij}^3 represents a lower proportion of two states' agricultural outputs in the overlapping segments. In other words, the similarity weight matrix W_3 measures the extent of direct competition between each pair of states.

In order to meet the qualification of spatial weights matrix, $W_1 - W_3$ are adjusted so that they are standardized by row and have zero diagonals. Finally, these three spatial weights matrices can be utilized to measure the interstate interactions in agriculture production from three different perspectives.

B. Interstate Competition and Spillover Effects

To some extent, all three of these spatial weights matrices can be used to measure interstate competition. In terms of geographic distance, neighboring states face more intense competition as the resources (including both inputs and outputs) can be transported less costly and more freely. In terms of trade volume, more severe competition exists between states with larger trade volume and market share in the international market. In terms of the similarity in agricultural structure, states with a similar portfolio have to compete for the same types of inputs as well as for the market share of the same types of outputs, in both the domestic market and the international market. Therefore, ω_{ij}^m is a proxy of competition intensity between states *i* and *j* at the *m*-th dimension.

For each of the three spatial weights matrices, the *i*-th row measures the levels of competition of each state in the eyes of state i. In other words, each row represents the similarities and importance of different opponents in the competitive landscape of a specific state. The *i*-th row answers the question "Who is on my list?" for state *i*. Conversely, the *i*-th column of a spatial weights matrix indicates the competition pressure from state *i* in the eyes of each and every state, which shows "Am I on others' lists?" Therefore, the sum of the *i*-th column of a spatial weights matrix measures the overall levels of interstate competition that state *i* faces from all other states in one dimension (Gong 2018b). More specifically, the time-invariant, geography-related interstate competition for state *i* is $comp_i^1 = \sum_j \omega_{ji}^1$, whereas the time-variant interstate competition for state *i* due to trade and industry structure is $comp_{it}^2 = \sum_j \omega_{jit}^2$ and $comp_{it}^3 = \sum_j \omega_{jit}^3$, respectively. Here ω_{ji}^1 is the element in the *j*-th row and *i*-th column of the time-invariant geographic weights matrix, whereas ω_{jit}^2 and ω_{jit}^3 are the elements of the time-variant trade and structure weights matrices, respectively. A greater value of $comp_{it}^m$ indicates that state i faces more intense interstate competition at time *t* at the *m*-th dimension.

In spatial analysis, direct effects are the effects of the state itself, whereas indirect effects are the effects on other states (Moussa and Laurent 2015), which are often interpreted as spillover effects or externality (Han, Ryu, and Sickles 2016, LeSage and Pace 2009). After estimating Eq. (2), the direct effects are calculated by averaging the diagonal elements of $(I - \rho W)^{-1}\beta$, whereas the indirect effects are calculated by averaging the row sums of the off-diagonal elements of $(I - \rho W)^{-1}\beta$. Because the spatial weights matrix measures interstate competition, we can analyze whether interstate competition causes positive or negative spillover effects.

Suppose $F_1 - F_3$ are the matching spatial production functions using $W_1 - W_3$ as the spatial weights matrix; $W_1 - W_3$ may each include some useful information concerning cross-sectional dependence and competition, whereas $F_1 - F_3$ may each capture some characteristics of the spillover effects. Therefore, the overall impact of interstate competition on spillover effects cannot be fully considered without first finding an approach that will combine the results in all three dimensions.

In order to consider all three dimensions to then capture complete information and describe the true data generating process (DGP), the relative importance measured by a series of weights, one for each dimension, needs to be determined. The model averaging method assigns a weight to every candidate model based on its ability to explain the data when each candidate may partially specify the true DGP. As a result, the weighted average estimation is the best fit for the data. This article uses the model averaging method proposed by Buckland, Burnham, and Augustin (1997) that assigns weights based on the Akaike Information Criterion (AIC) of the competing models.

(3) $$w_m^* = \exp(-0.5 * AIC_m) / \sum_{m=1}^{3} \exp(-0.5 * AIC_m),$$

where w_m^* refers to the weight assigned to the *m*-th model (W_m, F_m). The AIC score can be computed by $AIC_m = 2k - 2\log(L_m)$, where k is the number of parameters to be estimated and L_m represents the maximized likelihood function for the *m*-th model.

The weights w_m^* reflect the ability of spatial competition in the *m*-th dimension to explain the data. The aggregated production function can then be calculated by $F^* = \sum_{m=1}^{3} w_m^* F_m$ so that all three dimensions are taken into consideration. Moreover, the weighted average of the three indirect effects estimated by the three candidate models is the overall spillover effects.

This article also uses the weights w_m^* to combine the three spatial weights matrices $(W_1 - W_3)$, which derives an aggregated spatial weights matrix $W^* = \sum_{m=1}^{3} w_m^* W_m$ that measures the overall level of competition across states. The elements in W^*, ω_{ij}^*, are the weighted average level of competition in all three dimensions between states i and *j*. Using this spatial weights matrix in Eq. (2) directly, we can estimate another measure of the overall spillover effects due to interstate competition in three dimensions, which is comparable to the aforementioned weighted average of the three indirect effects. Moreover, the overall interstate competition pressure for state i at time *t* can be calculated by $comp_{it} = w_1^* comp_i^1 + w_2^* comp_{it}^2 + w_3^* comp_{it}^3$.

To summarize, this article uses each of the three spatial matrices $(W_1 - W_3)$ to estimate the production function. This derives spillover effects and weights for each dimension, which makes it possible to calculate the weighted average spillover effects caused by interstate competition. On the other hand, the spillover effects can be estimated directly after we build the weighted average spatial weights matrix W^*. This article uses the latter approach as a robustness check to confirm the estimation result of the former approach.

C. Impact of Competition on Total Factor Productivity

Each of the two aforementioned approaches estimates not only aggregated spillover effects but also aggregated total factor productivity. In the former approach, aggregated TFP is the weighted average of the three TFPs estimated by the three candidate models. In the latter approach, aggregated TFP is derived from the SAR model, where the spatial weights matrix is the weighted average of the three spatial weights matrices.

In the spatial production function, interstate competition can affect agricultural production not only through the spillover effects but also through its effect on TFP. Therefore, this article establishes a TFP determination function in Eq. (4) to explore the impact of interstate competition.

(4) $$TFP_{it} = \alpha + \beta_1 comp_{it} + \beta_2 H_{it} + \sum_{j=2}^{N} \lambda_j r_{it}^j + \eta Z_{it} + \delta P + \rho R + \varepsilon_{it},$$

where TFP_{it} is the total factor productivity for state *i* at time *t*. Then $comp_{it}$ is a measure of the overall interstate competition pressure faced by state *i* at time *t*, which is discussed in the previous subsection. r_{it}^j is the share of output in the *j*-th segment over total agricultural output. H_{it} measures agricultural output diversification for the state *i* at time *t* by a Herfindahl index $H_{it} = \sum_{j=1}^{N} (r_{it}^j)^2$ over the *N* segments (Brümmer, Glauben, and Lu 2006). Z_{it} vectors other TFP determinants, including irrigated area, education, public expenditure, and per capita GDP to deal with the omitted variable problem, which is further discussed in the next subsection. *P* and *R* vector time and region dummies, respectively.

It is worth noting that the Herfindahl index H, to some extent, can reflect the level of intrastate competition, as it measures the industry structure within a state. States with a higher value of *H* have an industry structure that is specialized in one segment and are therefore more likely to experience more intensive intrastate competition as producers have more in-state opponents to compete with in both the input and output markets. In contrast, states with lower *H* values are more diversified in terms of their agricultural production, which decreases the pressure of intrastate competition due to having fewer competitors in the same segment.

To summarize, the industry structure information within a state is utilized to measure intrastate competition, whereas the industry structure information across states, as well as geography and trade information, is employed to measure interstate competition. The TFP determination equation can predict the effects of interstate competition and intrastate competition on agricultural productivity.

D. Endogeneity Problem

In the production function, endogeneity may be a problem as some information observed by the producers that is used to adjust the input portfolio is unavailable to economists (Ackerberg, Caves, and Frazer 2015). This article uses the control function method introduced in Amsler, Prokhorov, and Schmidt (2016) to test the exogeneity of the inputs. Following Levinsohn and Petrin (2003) and Gong (2018c), input prices and lagged values of input are utilized as instruments. This article uses the instrumental variables (IV) method to correct the estimation if any input is found to be endogenous.

In the TFP determination equation, endogeneity may also be an issue due to omitted variables or causality. In order to solve the issue of omitted variables, this article introduces Z_{it} in Eq. (4), which vectors other TFP determinates used in literature, including the following: 1) the total sown area that is irrigated, $irrig_{it}$ in percentage (Gong 2018a); 2) the population completing high school education, $school_{it}$ in percentage (Jajri 2007, Mastromarco and Zago 2012); 3) public expenditure in agriculture, $expend_{it}$ in logarithms (Dong 2000, Nee and Sijin 1990); and 4) per capita GDP, GDP_{it} in logarithms (Ho 2012). Causality is another concern as some TFP determinants may be affected by productivity as well. For example, the level of public expenditure in agriculture may partially depend upon agricultural productivity. This article uses lagged values of TFP determinants in Eq. (4) to determine whether the estimation varies or not. Considering the serial correlation between these variables, this article uses independent variables that lagged two periods to break the potential dependence and independent variables that lagged three periods as a robustness check.

III. Data

The United States Department of Agriculture (USDA) had provided state-level agricultural input and output data[2] for the lower 48 states for 1960–2004.[3] Total agricultural output can be divided into three segments: livestock products (meat animals, dairy, poultry, and eggs), crops (food grains, feed crops, oil crops, vegetables and melons, fruits and nuts, and other crops[4]), and other farm-related outputs.[5] There are four types of agricultural inputs: labor (hired, self-employed, and unpaid family labor), land, capital (durable equipment, service buildings, and inventories), and intermediate inputs (feed and seed, energy, fertilizer and lime, pesticides, purchased services, and other intermediate goods). All of the inputs and outputs are given by their implicit quantities (in billions of dollars at 1996 constant prices). The data of other variables, including agricultural exports, irrigated land area, percentage of population completing high school, and federal government’s direct farm program payments, are also collected from the USDA, whereas data on GDP and population are available from the U.S. Bureau of Economic Analysis.

This article also collects provincial-level agricultural outputs and inputs of the 31 provinces in mainland China for 1990–2015. There are some differences between agricultural data in the United States and China. Firstly, China’s agricultural sector is divided into four segments: farming, forestry, animal husbandry, and fisheries. Secondly, we lack complete agricultural input data from the same data source in China. This article follows the traditional literature (e.g., Kalirajan, Obwona, and Zhao (1996), Chen (2006), Zhou and Zhang (2013), Liu et al. (2015), and Gong (2018a)) in selecting inputs and outputs for China’s agricultural data, aiming to make it as comparable to U.S. data as possible. Therefore, the output variable is the deflated gross value of agricultural output (in billions of dollars at 1996 constant prices). In terms of inputs, labor is measured as the size of the labor force (in millions) in the primary industry, land refers to the sown area (in millions of hectares) that reflects the actual utilization of the cultivated land, machinery is measured by the total power of agricultural machinery (in millions of

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2 https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/

3 Updates of the State-level statistics after 2004 are suspended in light of reduced resources and the discontinuance of key source data series.

4 This includes sugar crops, maple, seed crops, miscellaneous field crops, hops, mint, greenhouse and nursery, and mushrooms.

5 This includes output of goods and services from certain non-agricultural or secondary activities. These activities are defined as activities closely related to agricultural production for which information on output and input use cannot be separately observed.

kilowatts), and fertilizer refers to the sum of the gross weight of nitrogen, phosphate, potash, and complex fertilizers (in millions of tons). Because it is difficult to find other capital and intermediates data, this article includes labor, land, machinery, and fertilizers when studying China's agricultural production, which is also adopted in the aforementioned studies. Most of the data are from *China Statistical Yearbook*. Some data are supplemented (e.g., the labor statistics in 2013–2015) and adjusted (e.g., data of Chongqing and Hainan) using the *China Compendium of Statistics 1949–2008* and provincial-level statistical yearbooks. The data of other variables are collected as follows: 1) Data on irrigated land area and the government's expenditure on agriculture, forestry, and water affairs are also collected from the *China Statistical Yearbook*; 2) data on GDP and population are collected from the *China Statistical Yearbook* and the *China Compendium of Statistics 1949–2008*; and 3) agricultural export data are available on the website of the Ministry of Commerce of the People's Republic of China.

In terms of the public expenditure on agriculture, this article collects the federal government's direct farm program payments for the United States and the government's expenditure on agriculture, forestry and water affairs for China. In order to estimate the effect of public expenditure stocks (rather than flows) on agricultural productivity, this article introduces the unified perpetual inventory method (PIM) from Berlemann and Wesselhöft (2014) to convert flows data to stocks data, which is most often used in productivity analysis. Appendix A demonstrates the data-generating process of public agricultural expenditure stocks.

Table 1 summarizes state-level inputs and outputs in both the United States and China. Because the datasets for the two countries cover different time periods, the numbers cannot be directly comparable. During the period 1960–2004, the agricultural output for U.S. states more than doubled, on average, from 2.6 billion to 5.3 billion dollars at 1996 constant prices, which implies a real growth rate of 1.6%. In the input portfolio, labor decreased by almost two-thirds, land and capital maintained the same level, whereas intermediate inputs, on average, grew by more than 1% annually. In general, China achieved more rapid growth in agriculture based on the data from 1990 to 2015. The agricultural output increased more than four-fold, from 6.0 billion to 24.5 billion dollars, both at 1996 constant prices. The labor quantity in China also decreased, although at a slower pace than in the United States. Land area at the province-level slowly increased, from 4.8 million hectares in 1990 to 5.4 million hectares in 2015. Average utilization of machinery and fertilizer increased dramatically with growth rates of 5.6% and 3.5%, respectively.

[Insert Table 1 Here]

The total agricultural output reported in table 1 can be further divided into different segments. The USDA divides agriculture output into livestock products, crops, and other farm-related outputs, whereas the National Bureau of Statistics of China regards farming, forestry, animal husbandry, and fisheries as the four segments in the agricultural sector. Figure 1 provides the average output share by segment in the United States and China for selected years.

[Insert Figure 1 Here]

In the histogram on the left, the output share of crops among all agricultural products in the United States decreased from 47.7% to 43.6%, whereas the share of livestock products increased from 44.0% to 50.1% during the period 1960–2004. The trend of an increasing share of livestock products and a decreasing share of crops can also be witnessed in China as the output ratio of farming among all agricultural products decreased whereas the ratios of both animal husbandry and fishery increased during the period 1990–2015. However, the farming segment in China still accounted for 56.1% of agricultural outputs in 2015, which was the largest segment in China's agricultural sector.

IV. Estimation Results

This empirical study applies the described models above to a balanced panel of the lower 48 states in the United States over a period of 45 years, from 1960–2004, and a balanced panel of 31 provinces in China over a period of 37 years, from 1978–2015, separately. First, the control function test shows that all four inputs are exogenous in the agricultural production function for both the United States and China. Second, this article uses the Breusch-Pagan LM test (Breusch and Pagan 1980) to assess the cross-sectional dependence, which generates a chi-square of 4909 for the U.S. data and a chi-square of 2192 for the China data. Because both chi-squares correspond to a p-value of less than

0.01, cross-sectional dependence exists for both datasets. Therefore, spatial techniques are necessary in the agricultural production function for both the United States and China. Furthermore, the Moran's I index is significantly different from zero when each of three spatial weights matrices is employed for the two countries, which further verifies the existence of spatial autocorrelation in all the three dimensions for both the United States and China.

A. Production Functions

Table 2 reports the estimation results of various spatial production functions. The first three columns describe agricultural production in the United States during the sample period, where competition is considered in geography, trade, and industry structure, one for each column. Analogously, the next three columns present agricultural production in China. In table 2, the model averaging weights obtained using data of the United States are 0.395, 0.494, and 0.111 for the three spatial models using $W_1 - W_3$ as the spatial weights matrices, respectively. For China's agricultural production, the corresponding weights are 0.412, 0.410, and 0.178, respectively. To summarize, competition in industry structure is relatively less important than competition in geography and trade in both countries.

[Insert Table 2 Here]

The input elasticities estimated in various spatial models are all statistically significant and fairly robust. Using the model averaging weights, this article concludes that the elasticity of labor, land, capital, and intermediate inputs are 0.10, 0.10, 0.05, and 0.61 respectively for U.S. agricultural production during the sample period. Furthermore, the elasticity of labor, land, machinery, and fertilizer are 0.15, 0.26, 0.06, and 0.20 in China's agricultural sector, respectively. Compared with agricultural production in the United States, the contribution of labor and land to agricultural outputs is greater in China.

B. Effect on Spillovers: Positive in the United States and Negative in China

The spatial models and the model averaging weights estimated in table 2 can help us derive the indirect effects of the inputs, which, in literature, are interpreted as spillover effects. Table 3 presents both the direct and indirect effects of all four inputs for the

United States in the first two columns and for China in the next two columns. The first column provides the weighted average levels of the direct and indirect effects derived from all three spatial models on the U.S. data, as does the third column on the China data. The second and fourth columns, however, use a spatial model with a weighted average spatial weights matrix to estimate the overall direct and indirect effects, which can be regarded as a robustness check of the first and third columns. Both methods are discussed in Section 2.

[Insert Table 3 Here]

We will focus on the indirect effects in order to reveal the spillover effects in agricultural production. For the United States, all four inputs have significantly positive indirect effects, which implies the existence of positive externality across states in the sample period. Moreover, this result is robust as both of the first two columns derive positive indirect effects. For China, however, the indirect effects of all four inputs are significantly negative in both the third and fourth columns, which provides evidence of negative externality. In other words, interprovincial competition discourages provincial agricultural output in China during the sample period.

C. Levels of Interstate Competition

In terms of interstate competition, this article uses the model averaging weights w_m^* to combine the three spatial weights matrices ($W_1 - W_3$) into an aggregated $W^* = \sum_{m=1}^{3} w_m^* W_m$. The average of the i-th column of W^* measures the overall competition faced by state i from all other states. Table 4 presents the levels of interstate competition faced by each of the lower 48 states in the United States and each of the 31 provinces in mainland China. It is worth noting that the average levels of competition for both nations are equal to one due to the standardization of the spatial weights matrices. Therefore, across-state comparisons are allowed but across-country comparisons are invalid.

[Insert Table 4 Here]

Table 4 adopts the classification system defined by the United States Census Bureau and divides the lower 48 states into four regions: nine states in the Northeast, twelve states in the Midwest, sixteen states in the South, and eleven states in the West. States in the Midwest experienced the severest competition with an average level of competition of

1.23. Intense competition was also witnessed in the South as the average level was above one (the national average) there as well. The average levels of competition in the West and the Northeast were relatively low, indicating that these states, on average, experienced less pressure in competition. For each region, table 4 sorts the corresponding states by their levels of competition. Finally, the top four states that faced the most intense competition were Arkansas, Illinois, Iowa, and California, whereas the last four states in this list were Vermont, New Hampshire, Nevada, and Maine.

Under the division system defined by National Bureau of Statistics of China, the 31 provinces in mainland China can be divided into four regions: Western, Central, Eastern, and Northeast China. Table 4 shows that the ten provinces in Eastern China, on average, faced the most intense competition in agriculture, followed by the three provinces in the Northeast and then the six provinces in Central China, whereas the twelve provinces in Western China experienced the least amount of competition. The provinces in each region are also sorted by their levels of competition. It is worth noting that all but one province in both Western and Central China have competition levels that are less than one, whereas all but two provinces in Northeast and Eastern China have competition levels over one.

D. Effect on Productivity: Positive in the United States and Negative in China

A differing perspective for evaluating the impact of competition on agriculture is to estimate its effect on agricultural TFP. Table 5 does this by reporting the estimated results of the TFP determination equation. The first column is the main model for the United States. The second column replaces the independent variables with their lagged values in two periods to take care of the potential causality. The third column, however, replaces the dependent variable with the TFP that was estimated by the other approach introduced in this article in order to test the robustness of the TFP derived from the main approach. The same order applies to the next three columns that report the results of China's agricultural TFP determination. To summarize, the estimation results are fairly robust for both the United States and China. Therefore, this article makes predictions based on the first column for the United States and the fourth column for China.

[Insert Table 5 Here]

In terms of the U.S. agricultural TFP, the effect of interstate competition is significantly positive, indicating that more competition faced by a state from all other states is likely to improve its own agricultural productivity rather than being detrimental. Moreover, this effect is also economically significant. Take the region that experienced the least amount of competition as an example: States in the Northeast, on average, could improve their productivity by 22% if the level of competition increased to the national average. The effect of intrastate competition is also significantly positive, which implies that specialization within a state can boost productivity growth in the United States. Suppose all states have the same industry structure as the national average, which is shown in figure 1; the value of H, in figure 1, increased from 0.428 in 1960 to 0.445 in 2004, which implies a trend of specialization and leads to a 1.5% increase in TFP, other things being equal.

In an across-segment comparison, the segments of livestock products and other farm-related products are significantly more productive than the crops segment. More specifically, a one percentage point increase in the share of livestock products that replaces crops production can improve productivity by 0.35%, whereas a one percentage point increase in the ratio of other farm-related products that replaces the share of crops can raise productivity by 0.49%. This article also concludes that a larger irrigation system, higher levels of education, and an increase in per capita GDP all have significantly positive impacts on productivity, whereas the effect of public expenditure is negligible.

In terms of China's agricultural sector, the impacts of interstate and intrastate competition on TFP are significantly negative. On the one hand, interstate competition impedes productivity growth; for example, states in Eastern China that faced the severest pressure of competition can enjoy an 8% increase in TFP if their levels of competition can be decreased to the national average. On the other hand, the negative effect of intrastate competition should, theoretically, push Chinese provinces to be more diversified in their agricultural production. The realized agricultural development in China indeed follows this trend of diversification, which is shown in figure 1. During the period 1990–2015, the average value of H in China decreased from 0.477 to 0.414. Assuming all provinces have the same industry structure at the national average, further diversification can increase TFP by 8% during the sample period, other things being equal. In across-segment comparison, the fishery segment is the most productive, followed by farming and animal husbandry, whereas forestry is the least productive segment. This article also concludes that irrigation and public expenditure have significant positive impacts on productivity whereas the effects of education and per capita GDP are negligible.

E. Comparison between the United States and China

Based on the previous analysis, this article finds positive spillover effects in agricultural production for the United States but negative spillover effects for China. Moreover, the directions of the effects of interstate and intrastate competition on productivity are consistent for the same country: Both are positive for the United States, and both are negative for China. The trend of in the United States of specialization in agriculture and the trend of diversification in China's agricultural sector both provide evidence of the predicted effects of intrastate competition for the two nations. To summarize, agricultural competition is welcomed and should be encouraged in the United States, both in state and across state borders, as both positive externality and productivity growth are found. However, the development of China's agriculture, both in province and across province borders, can benefit more from the adoption of diversification and a differentiation strategy under the current circumstances.

In terms of other agricultural TFP determinants, this article also finds some differences between the two countries. In the United States, the level of education, measured by population ratio, that completes high school and the overall economic development measured by per capita GDP have significantly positive effects on productivity, but this is not observed using the data on China. Considering that agriculture accounts for less than 2% of U.S. GDP, the positive effects of per capita GDP imply that there are spillover effects to agriculture from other industries. In contrast, the effects of irrigation and public expenditure on productivity in China are greater than those in the United States. These findings show that soft power (e.g., education) and spillovers (from other industries) are the main drivers of TFP growth in the United States under the market system, whereas hard power, such as public investment and infrastructure, is the driving force in China, where the government plays a more important rule in economic growth.

The next big assignment is to find the reasons and drivers behind the difference. In the United States, many agricultural products are regarded as a commodity, which means the quality is essentially uniform across producers. The homogenous characteristics of a commodity can lower the transaction cost and are more easily used as inputs in the production of other goods or services. The homogeneity attribute makes it easier to enjoy the positive spillover effects that are brought about by knowledge and R&D. Such spillover effects have long been found in the manufacturing sector, where industrial agglomeration occurs. It is worth noting that an important prerequisite is that the manufacturing sector produces commodities. Moreover, the spillover effects exist both in state and across state borders. For example, the seeds of corn and soybeans used in the Corn Belt are very similar, which is a key to uniform quality and leads to similar requirements of other intermediate inputs, such as fertilizers and pesticides. Therefore, many innovations, such as GMO techniques, on seeds, fertilizers, and pesticides can be spread rapidly across the state border and thus produce both intrastate and interstate positive spillovers. Furthermore, the deal price is related to quality on the basis of the market price. Hence, farmers and producers still have the incentive to compete on quality in order to earn the premium price. The consumers, on the demand side, are also willing to pay a premium for high-quality products, such as organic food. Finally, agricultural TFP in the United States is also promoted by the improvement in per capita GDP, which measures the overall development level, and the average level of education, which measures the human capital.

In China, a planned system with government interference still exists in the agricultural sector after almost four decades of rural reforms. To date, China still implements the policy of a minimum grain purchase price. Farmers can sell crops to nationally owned agricultural enterprises at a fixed price that is higher than international market price regardless of the quality. This higher-than-market price also means that any high-quality products cannot receive a premium if sold on the market. Because the government purchases crops without any regard for quality control, it is analogous to a market for "lemons" (Kahna 2013, Angelucci, Karlan, and Zinman 2015). Under this circumstance, low-quality products that cost less dominate the market under Gresham's Law. Such destructive competition can cause negative externality and hinder productivity growth.

The lack of classification also leads to massive loss in those nationally owned agricultural enterprises as these unclassified crops are stored in the same place regardless of their quality. This makes it harder to guarantee food safety and quality, and local crops are unable to compete with imported goods.

Moreover, the majority of Chinese consumers still prefer low-priced food and are unwilling to pay a premium for high-quality food. As a result, low-quality agricultural products—the “lemons” —drive out the good, which has caused many severe food safety issues in recent years. Although these issues have awakened an awareness of food quality and safety, the lack of an authoritative third-party certificate, such as the organic food certified by the USDA in the United States, prevents consumers from finding and rewarding trustworthy food. Furthermore, the development of other sectors measured by per capita GDP and the growth in human capital measured by schooling data have no significant effect on TFP. However, the government interference is not all bad. The public expenditure in agriculture and the development of farm-related infrastructure, such as an irrigation system, pushes productivity forward both rapidly and significantly.

To summarize, in the United States, agricultural production is more like manufacturing. The commodity’s character of uniform quality guarantees the basic quality of the products and expands the spillover effects. In order to survive in the market system with the current market price, producers have to compete with their opponents, which is likely to boost productivity in the competitive market. In short, the U.S. agricultural sector has many similar elements to the manufacturing sector and competitive market, which guarantees the desirable benefits brought about by competition, as found in literature. China’s agricultural production is a typical market of “lemons,” as no authoritative third-party certificate helps consumers to distinguish between a high-quality product (a “peach”) and a “lemon.” The nationally owned agricultural enterprises, although they may be able to distinguish the difference, will not punish the “lemon” and reward the “peach” in the context of the minimum grain purchase price that is higher than market price. The presence of information asymmetry drives out the good and leads to an undesirable but inevitable “race-to-the-bottom.” However, the lesson that the United States can learn from China is how to make public expenditure effective when it comes to boosting productivity. Moreover, the irrigation system in China is also much more valid for stimulating growth than that in the United States.

V. Conclusion and Policy Implications

This article builds a model to more comprehensively describe the overall effect of interstate competition on spillover effects in addition to the impact on productivity, which is achieved by the combination of spatial production functions and the model averaging method. This model is then utilized to explore whether interstate competition in agriculture should be encouraged or discouraged in the United States and China, respectively. To the best of our knowledge, this is the first article to study the multi-dimensional effects of multi-dimensional competition in the agricultural sector and therefore contributes to the debate on competition by utilizing the evidence of different effects across countries for the same industry.

More specifically, interstate competition should be encouraged in the United States due to its positive impacts on spillovers and TFP, but should be discouraged in China as it leads to negative spillovers and a decrease in TFP. Moreover, intrastate competition increased TFP in the United States but depressed TFP in China. The major drivers of agricultural productivity growth in the two countries are also found to be totally dissimilar, which provides evidence of a centrally planned system with more government interference in China compared with the market system in the United States. To summarize, U.S. agriculture enjoyed benefits from competition thanks to agricultural industrialization and a competitive market, whereas a planned system with government interference in China has both good and bad sides. Based on these findings, this article provides three policy implications.

First, government interference is not always detrimental. In literature, we find that there is a market defect and market failure especially in areas where externality exists. The U.S. government should learn from the Chinese government how to make public expenditure in agriculture more effective to provide the necessary public goods and thereby boost productivity growth. Moreover, the farm-related infrastructure, such as watering and irrigation systems, has been managed by the government for more than two thousand years in China. The positive effect of irrigation on TFP in China is 20 times larger than that in the United States, which is a space where the U.S. government and producers can improve.

Second, China has many more lessons to learn from the United States as the government's inappropriate interference is the key to the market of "lemons" and the "race-to-the-bottom." For one, the Chinese government should reform the policy of a minimum grain purchase price. The guaranteed price should be no higher than the market price and include a quality-monitoring system. In addition, the Chinese government should establish an authoritative third-party certificate system, such as the USDA in the United States, to provide valid, trustworthy information to consumers. To summarize, the Chinese government should help consumers distinguish between the "peach" and the "lemon."

Third, the Chinese government should also help drive out "lemons" in the context of raising food safety issues in China. Agricultural industrialization and commercialization is a good example set by the United States, where the commodity character of agricultural products guarantees food quality. Moreover, this transformation can also bring about the positive spillovers and productivity growth found in the United States. The strong manufacturing system and nationally owned agricultural buyers provide a good foundation for such a transformation in China. To summarize, the Chinese government not only needs to distinguish between the "peach" and the "lemon" but also reward the former and punish the latter, which can change the situation from a "race-to-the-bottom" to a "race-to-the-top."

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TABLE 1 – SUMMARY STATISTICS

Variable	Unit	First Year		Last Year		Real Growth
		Mean	S.D.	Mean	S.D.	Rate
The United States (1960–2004)						
Output	billions of $1996	2.6	2.5	5.3	5.5	1.6%
Labor	billions of $1996	3.4	2.6	1.3	1.2	-2.2%
Land	billions of $1996	0.8	0.8	0.7	0.7	-0.3%
Capital	billions of $1996	0.6	0.5	0.5	0.5	-0.4%
Intermediate	billions of $1996	1.3	1.2	2.1	2.0	1.1%
China (1990–2015)						
Output	billions of $1996	6.0	4.4	24.5	17.2	5.8%
Labor	million person	10.9	8.7	8.7	6.5	-0.9%
Land	million hectares	4.8	3.2	5.4	3.8	0.5%
Machinery	million kilowatts	9.3	7.6	36.0	33.0	5.6%
Fertilizer	million tons	0.8	0.7	1.9	1.5	3.5%

TABLE 2 – ESTIMATION RESULTS

Determinants	The United States (1960–2004)			China (1990–2015)		
	W_1	W_2	W_3	W_1	W_2	W_3
Labor	0.094	0.101	0.096	0.145	0.152	0.144
	(0.009)	(0.009)	(0.009)	(0.044)	(0.044)	(0.043)
Land	0.091	0.097	0.105	0.266	0.263	0.260
	(0.018)	(0.018)	(0.017)	(0.060)	(0.060)	(0.058)
Capital	0.040	0.058	0.062	0.066	0.063	0.065
	(0.019)	(0.019)	(0.019)	(0.025)	(0.025)	(0.024)
Intermediate	0.600	0.612	0.599	0.198	0.198	0.193
	(0.013)	(0.013)	(0.013)	(0.036)	(0.036)	(0.035)
Time Effects	controlled	controlled	controlled	controlled	controlled	controlled
State Effects	controlled	controlled	controlled	controlled	controlled	controlled
Intercept	0.433	-0.430	16.869	-0.574	-0.657	4.207
	(0.249)	(0.250)	(0.245)	(0.240)	(0.240)	(0.232)
Weight w_m^*	0.395	0.494	0.111	0.412	0.410	0.178

Notes: In China's production function, capital refers to machinery and intermediate refers to fertilizer.

TABLE 3 – DIRECT AND INDIRECT EFFECTS OF THE INPUTS

Determinants	The United States (1960–2004)		China (1990–2015)	
	(1)	(2)	(3)	(4)
Labor				
Direct Effect	0.098	0.098	0.148	0.150
	(0.009)	(0.009)	(0.047)	(0.041)
Indirect Effect	0.010	0.032	-0.016	-0.002
	(0.001)	(0.004)	(0.005)	(0.001)
Land				
Direct Effect	0.096	0.092	0.264	0.267
	(0.016)	(0.018)	(0.063)	(0.064)
Indirect Effect	0.008	0.030	-0.030	-0.003
	(0.002)	(0.007)	(0.008)	(0.001)
Capital				
Direct Effect	0.051	0.048	0.064	0.067
	(0.016)	(0.020)	(0.022)	(0.023)
Indirect Effect	0.004	0.015	-0.008	-0.001
	(0.001)	(0.007)	(0.003)	(0.000)
Intermediate				
Direct Effect	0.607	0.607	0.197	0.198
	(0.012)	(0.013)	(0.035)	(0.033)
Indirect Effect	0.061	0.196	-0.022	-0.003
	(0.007)	(0.021)	(0.005)	(0.000)

TABLE 4 – LEVELS OF INTERSTATE COMPETITION IN THE UNITED STATES AND CHINA

The United States (1960–2004)							
Northeast	**0.74**	**Midwest**	**1.23**	**South**	**1.05**	**West**	**0.89**
Pennsylvania	1.13	Illinois	1.37	Arkansas	1.43	California	1.34
New York	0.91	Iowa	1.35	Texas	1.25	Colorado	1.10
Massachusetts	0.83	Nebraska	1.32	North Carolina	1.23	Washington	1.04
New Jersey	0.76	Kansas	1.32	Kentucky	1.18	Arizona	1.01
Connecticut	0.75	Indiana	1.30	Alabama	1.13	Idaho	0.99
Rhode Island	0.61	Ohio	1.25	Mississippi	1.11	Oregon	0.92
Vermont	0.59	Minnesota	1.24	Georgia	1.09	Montana	0.86
New Hampshire	0.58	Missouri	1.23	Tennessee	1.06	Utah	0.73
Maine	0.51	Wisconsin	1.14	Florida	1.03	New Mexico	0.66
		South Dakota	1.12	Oklahoma	1.02	Wyoming	0.61
		North Dakota	1.11	Virginia	1.01	Nevada	0.53
		Michigan	1.06	Louisiana	0.97		
				South Carolina	0.91		
				Maryland	0.89		
				Delaware	0.76		
				West Virginia	0.66		
China (1990–2015)							
Western China	**0.84**	**Central China**	**0.93**	**Eastern China**	**1.21**	**Northeast**	**1.04**
Shaanxi	0.98	Anhui	1.02	Tianjin	1.40	Liaoning	1.15
Chongqing	0.92	Hubei	0.97	Beijing	1.40	Jilin	1.09
Yunnan	0.92	Jiangxi	0.92	Shanghai	1.33	Heilongjiang	0.89
Gansu	0.91	Shanxi	0.92	Shandong	1.32		
Guangxi	0.89	Henan	0.91	Zhejiang	1.29		
Inner Mongolia	0.86	Hunan	0.86	Guangdong	1.18		
Sichuan	0.84			Fujian	1.12		
Ningxia	0.83			Jiangsu	1.12		
Guizhou	0.82			Hebei	1.09		
Xinjiang	0.77			Hainan	0.87		
Qinghai	0.75						
Tibet	0.64						

TABLE 5 – TFP DETERMINATION REGRESSION RESULTS

TFP Determinants	The United States (1960–2004) (1)	(2)	(3)	China (1990–2015) (4)	(5)	(6)
$comp$	0.858	0.859	0.865	-0.388	-0.416	-0.396
	(0.023)	(0.023)	(0.023)	(0.071)	(0.077)	(0.071)
H	0.902	0.932	0.911	-1.298	-1.297	-1.350
	(0.070)	(0.073)	(0.071)	(0.357)	(0.377)	(0.356)
r^2	0.348	0.361	0.330	-1.090	-1.173	-1.074
	(0.024)	(0.025)	(0.025)	(0.396)	(0.423)	(0.394)
r^3	0.485	0.555	0.493	-0.336	-0.338	-0.336
	(0.137)	(0.139)	(0.138)	(0.199)	(0.209)	(0.199)
r^4	--	--	--	1.080	1.093	1.063
	--	--	--	(0.339)	(0.359)	(0.338)
$irrig$	0.009	0.009	0.008	0.172	0.196	0.176
	(0.002)	(0.002)	(0.002)	(0.051)	(0.054)	(0.051)
$school$	0.334	0.347	0.345	0.022	0.021	0.022
	(0.038)	(0.039)	(0.039)	(0.023)	(0.023)	(0.023)
$expend$	-0.002	-0.002	-0.0004	0.354	0.349	0.349
	(0.003)	(0.003)	(0.003)	(0.012)	(0.012)	(0.012)
GDP	0.096	0.092	0.103	-0.050	-0.059	-0.044
	(0.019)	(0.019)	(0.019)	(0.035)	(0.037)	(0.035)
Time Effects	controlled	controlled	controlled	controlled	controlled	controlled
Region Effects	controlled	controlled	controlled	controlled	controlled	controlled
Intercept	0.782	0.792	-1.823	-0.140	-0.006	-0.614
	(0.066)	(0.068)	(0.067)	(0.319)	(0.338)	(0.318)
R^2	0.79	0.78	0.75	0.90	0.89	0.89

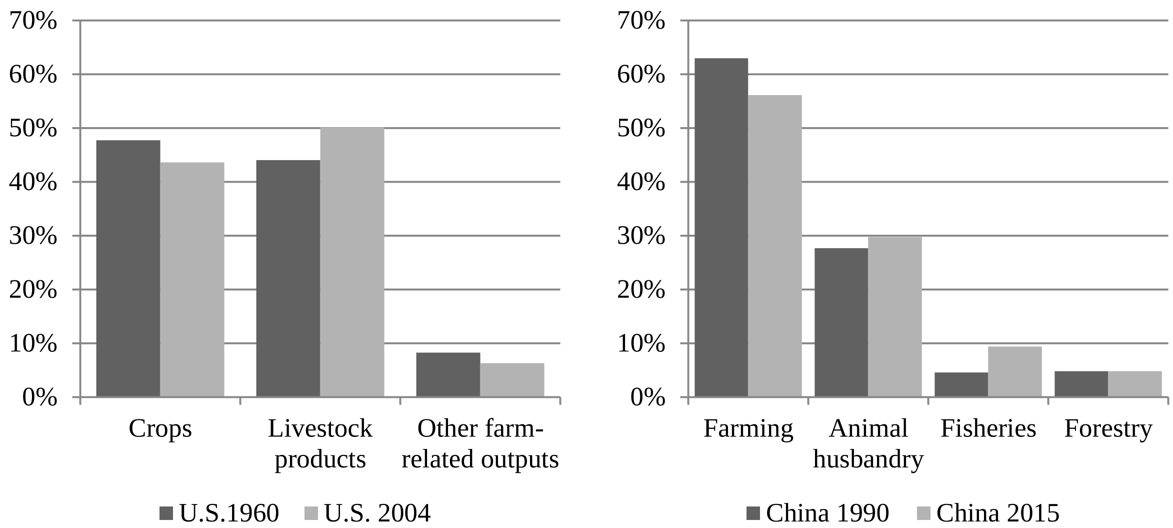

FIGURE 1. AVERAGE OUTPUT SHARE BY SEGMENT IN THE UNITED STATES AND CHINA

Appendix A Public Expenditure and Perpetual Inventory Method

The perpetual inventory method (PIM) is the most widely employed approach to convert investment from flows data to stocks data in many statistical offices. In the spirit of de la Fuente and Doménech (2006), Berlemann and Wesselhöft (2014) combine three PIMs into a unified approach in order to prevent the drawbacks of the various methods. The PIM interprets investment stock as an inventory of investment flows. The aggregate stock falls at the depreciation rate per period. Therefore, the stock of public expenditure in period t is a weight sum of the history of the public expenditure flows: $Finance_t = \sum_{i=0}^{\infty}(1-\delta)^i \cdot I_{t-(i+1)}$, where $Finance$ is the stock in public expenditure, I is the annual flows in public expenditure, and δ is the depreciation rate.

This article collects annual flows in public expenditure from 1960–2016 for the United States. Firstly, we calculate the average annual growth rate for each state during the period and assume public expenditure grow at the same speed during the period for 1900–1959. This helps us estimate the public expenditure back to 1900. Then we set 1990 as period 0 and calculate the stock of public expenditure in our sample period from 1960 to 2004. This article uses a farm-related depreciate rate of 11.79% given by Bureau of Economic Analysis to estimate the stocks $Finance_t$ for each of the 48 lower states.

This article also collects annual flows in public expenditure from 1978 to 2015 for China. Because the expenditure in 1978 is negligible, we assume zero public expenditure before 1978. This assumption has an ignorable effect on public expenditure stock estimation, as public expenditures before 1978, if not equal to zero, are almost zero following two decades of depreciation. Moreover, this article uses a depreciation rate of 5.6% in Chen (2014) to estimate expenditure stocks $Finance_t$ for each of the 31 provinces from 1990 to 2015.