Direct impacts and spatial spillovers: How does the multilateral resistance affect China-Africa agricultural trade?

Xie Jie, Liu Xuezhi*

The changes of one region's trade barriers will affect other regions' trade volume. These spatial correlations caused by explanatory variables also constitute another part of "the multilateral resistance", which tend to be ignored in traditional gravity equations. This paper takes this inconsistency between theoretical basis and empirical analysis as the breakthrough point of research. A multilateral gravity model is built, which has the feature of generalized spatial correlation. Then, frontier techniques of spatial econometrics are used to construct an empirical equation, and to conduct an empirical analysis, which scientifically estimate the magnitudes of bilateral direct impacts and the magnitudes of spatial spillovers on multilateral neighbors. The decomposition of the effects that provides reference for the directional operations of trade policy shows as follows: The negative factors that have significant spatial spillover effects would bring about multilateral resistance on China-Africa agricultural trade, which are caused by relatively poor social and economic conditions, corruption, and ethnic conflicts in some African countries. Energy production may cause crowding-out effects on agriculture of neighboring regions. In addition, the conflicts between African countries would hinder the development of agricultural trade between China and African countries not only because they have negative direct impacts on China-African agricultural trade but also because they have significant spatial spillover effects. When China promotes China-Africa agricultural trade by means of investment or aid, China should pay close attention to some direct or indirect impacts on the stable development of the China-African agricultural trade, which are caused by factors such as the developments of non-agricultural industries, peace, cultural consensus and efficient government.

Key words: direct impacts, spatial spillovers, multilateral resistance, China-Africa agricultural trade, generalized spatial multilateral gravity model

1. Introduction

For a long time, "multilateral resistance" has been either ignored in traditional

* Xie Jie, (email: x_j3027@sina.com), associate professor at School of Economics, Zhejiang Gongshang University, China; Liu Xuezhi, (email: liuxz420@126.com), Department of Development, Bank of Communications Headquarters, doctoral candidate at School of Finance and Statistics, East China Normal University.

gravity models of trade or not appropriately handled in empirical analysis, which is "border puzzle" in international trade theoretical research and empirical analysis. Anderson and Van Wincoop (2003) consider it crucial for gravity models of trade to involve properly "multilateral resistance terms". The "multilateral resistance terms" capture such a fact that bilateral trade depends not only on bilateral trade barriers but also on average trade barriers across all trade partners. The identification and explanation of multilateral resistance helps to estimate one nation's costs of overseas trade reasonably. The research of Anderson and van Wincoop is the start of thoughts constructing the micro-foundation for gravity model. Although Anderson and Van Wincoop proposed the idea of multilateral resistance, their discovery has not been appropriately dealt with in theoretical modeling or empirical equation specification so far. Africa has given the world of 21st century the dual impression of "famine and growth", being both among the regions with the highest economic growth rate and the regions suffering most severe food crisis. Rich resources and great development potential of Africa attract the whole world and all the great powers have strengthened their Africa-oriented strategies. The United States regards China's activities in Africa as part of global competition between China and US (Zhang, 2011). When the US resorts to "pivot to Asia" to divide China and its neighbors, China-Africa cooperation as a good example of South-South cooperation can be the leverage for multilateral relations, helping China to expand strategic space. The spatial differences of African nations in language, culture, politics, economy, religion and colonial influence, combined with great powers' conflicts of strategic interest in Africa, have provided opportunities of practice for the theoretical exploration of multilateral resistance.

Gravity model has the feature of displaying spatial effects, i.e. spatial correlation and spatial heterogeneity (Anselin and Bera, 1998). When there exist spatial effects, the appropriate identification technology is spatial econometrics, which can identify and detect spatial correlation (Anselin and Bera, 1998), and deal with the multi-direction of spatial correlation. Spatial econometrics can overcome the drawback of spatial terms omission in traditional econometric postulates (LeSage and Pace, 2008). LeSage and Pace (2008) develop traditional gravity model using spatial matrix to express spatial correlation and provide the method for maximum likelihood estimation. Behrens et al (2012) obtain a spatial econometric equation with linearization technique based on the gravity model built by Anderson and Van Wincoop (2003). Qian and Cai (2010) convert the gravity equation to an estimable spatial correlation model. Elhorst (2010) verifies that, general spatial econometrics mainly includes Spatial Lag Model (SLM) and Spatial Errors Model (SEM), the two of which are collectively referred to as general spatial econometric model (LeSage and Pace, 2010). SLM is also referred to as Spatial Auto Regressive Model (SAR). SLM is mainly about one region's explained variables dependent on neighboring regions' explained variables. For example, the export from country k to country j constitutes multilateral resistance for the export from country i to country j, which is in fact spatial competition effect caused by spatial correlation of explained variables. SEM assumes that spatial effects derive from some unknown causes. General spatial econometric model can explain part of the multilateral resistance, which is captured by spatially lagged explained variables of SLM.

The changes of one region's trade barriers will affect trade volume of both this region itself and other regions, and the spatial correlations caused by explanatory variables should also constitute a part of multilateral resistance in gravity model. In traditional econometrics, explanatory variable correlations cause multicollinearity, which is model misspecification. Early spatial econometric theories also hold that, when there exist spatially lagged correlations, spatial correlations of explanatory variables cannot be properly identified (Anselin et al, 2008). Based on the above understanding, spatial correlation terms of explanatory variables in gravity equations are often ignored or avoided (Qian and Cai, 2010; Behrens et al, 2012), which leads to the inconsistency between theoretical basis and empirical analysis. Multicollinearity is no longer model misspecification after spatial correlations of explanatory variables are incorporated into model specification (Elhorst, 2010). SDM contains both spatially lagged explained variables and spatially lagged explanatory variables, and one region's explained variables are not only affected by explanatory variables of this region but also dependent on explanatory variables and explained variables of other regions. Spatial correlations of both explained variables and explanatory variables are both logical conclusions of SDM, and there exists logical relationship of theoretical basis and empirical method between multilateral gravity equation and SDM. Explanatory variables can have direct impacts on the local region, and there will be indirect impacts if they have significant spatial spillovers on the neighboring regions. In trade gravity equations, direct impacts are equivalent to impacts of bilateral barriers and indirect impacts are equivalent to impacts of explanatory variables multilateral resistance. The value of SDM lies in its empirical estimate of the magnitude and significance of spatial spillovers, and policy analysts are likely to pay more attention to the magnitude of multilateral trade resistance caused by explanatory variables.

China-Africa agricultural trade has the dual effects of making use of both parties' advantages as a complement to each other, promoting regional development and ensuring food security. 70 percent of African population are engaged in agriculture (Diao et al, 2007). Agriculture is the pillar industry and development priority of most African countries as it plays an important role in the development, stability and anti-poverty of Africa. The Chinese government attaches great importance to the mutual beneficial cooperation with African countries in agriculture, makes great efforts to help African countries to turn their resource advantage into development advantage and realize sustainable development of agriculture. China-Africa agricultural trade not only helps to develop African economy, guard food security and promote anti-poverty cause

(Yang, 2007; Brautigam, 2012), but also alleviates the shortage of arable land and water resources in China (Zhu, 2008). China rose to Africa's largest trading partner in 2009. In recent years, China-Africa agricultural trade also develop rapidly. From 2009 to 2012, China's agricultural exports to Africa rose from $1.58 billion to $2.49 billion, increasing by 57.6%; China's agricultural imports from Africa rose from $1.16 billion to $2.86 billion, increasing by 1.46 times.[1] China mainly exports food crops such as wheat to Africa and imports non-food cash crops from Africa (Wang, 2014). Chinese enterprises also conduct investment activities such as prevalent variety cultivation, crops and cash crops production, and agricultural products processing in Africa. In 2012 China's direct agricultural investment in Africa reached $82.47 million,[2] which is still far below China-Africa agricultural trade volume. Exporting food to Africa is still the primary means of China to help alleviate famine of African countries, and to enhance grain self-supply ability of African countries, which will be a long-term aid strategy.

However, China's economic and trade activities in Africa touch traditional interests of Western powers, and China is labelled "agricultural imperialism" and "new resource colonialism". Europe has always regarded Africa as its "backyard", and "China's presence in Africa" makes it feel its traditional interests marginalized. To balance China's influence in Africa is also one of its strategic intentions of the United States. The various factors including mutual competition caused by conflicts of interests among nations, the cultural and religious influence of former colonial powers, conflicts of African strategic interests among great powers, the political and economic fluctuation risks of African nations, and the battle of "land grab" resulting from food crisis (Zhang, 2011), will inevitably bring multilateral resistance to China-Africa agricultural trade (Yan and Sha, 2011). If the multilateral resistance is not overcome, China-Africa agricultural investment that will reach a good scale gradually in the future will also be affected. Identification of the multiple resistance is the precondition for taking measures to cope with negative factors, promoting the stable development of China-Africa agricultural trade, and preventing Africa from falling victim to competition among great powers as in Cold War.

Empirical study is used to verify and correct current theories. Nowadays, with the empirical analytical methods and data set getting richer and richer, theoretical development should not be slowed down; empirical study and theory should supplement each other. If the theory can hardly explain reality, then we should keep exploring the inconsistency between them, overcome the limitations of empirical study, and develop economic theories with logical consistency, so as to advance our overall understanding of the inherent economic laws of the world. Considering the

[1] State Council Information Office (2013), China-Africa Economic and Trade Cooperation (2013).
[2] State Council Information Office (2013), China-Africa Economic and Trade Cooperation (2013).

lack of empirical analytical methods in the past, multilateral resistance coming from explanatory variables tends to be ignored. Research in SDM conducted by LeSage and Pace (2010) and Elhorst (2010) provides methods for empirical equation specification of multilateral gravity model. This paper makes some explorations about the consistency between theoretical basis and empirical analysis of multilateral gravity equations using frontier techniques offered by China-Africa agricultural trade. Gravity equation with generalized spatial correlations is first deduced, and then multiple factors that affect China-Africa agricultural trade are examined by using spatial econometric techniques for empirical equation specification and empirical estimation. In order to properly apply spatial econometrics to the analysis of spatial dependence among economic factors, this paper attempts to fill the gap of mishandling multilateral resistance coming from explanatory variables in gravity equations, and to improve theoretical basis and empirical analytical framework of gravity model, thus builds the dialectical connection from theoretical equation to empirical test in the hope of reaching consistency between theory and empirical study and integrating micro and macro. The empirical estimation built on relatively strong economic theoretical basis explains scientifically the magnitude of direct bilateral impacts and multilateral neighboring impacts, having both theoretical significance and practical implications for the targeting of trade policies.

2. Theory-based spatial multilateral gravity model

2.1. Multilateral gravity equation

Starting from the model proposed by Anderson and Van Wincoop (2003), we deduce a more generalized spatial multilateral gravity equation by gradually relaxing the assumptions. Anderson and Van Wincoop constructed a gravity equation containing rich multilateral trade resistance:

$$X_{ij} = \frac{Y_i Y_j}{Y^w}\left(\frac{\tau_{ij}}{p_i p_j}\right)^{1-\sigma} \tag{1}$$

Here, X_{ij} represents the nominal export from country i to country j; Y_i and Y_j represent the nominal GDP of export country i and import country j respectively; τ_{ij} represents bilateral trade costs; $\sigma > 1$ is elasticity of commodity substitution; price indexes p_i and p_j represent externalizing and internalizing multilateral resistance variables; $Y^w = \sum_j Y_j$. Set $\theta_j = Y_j / Y^w$, and the multilateral resistance terms that capture average trade barrier costs can be symmetrically represented as follows, externalizing: $p_i^{1-\sigma} = \sum_j p_j^{\sigma-1}\theta_j \tau_{ij}^{1-\sigma}$; internalizing: $p_j^{1-\sigma} = \sum_i p_i^{\sigma-1}\theta_i \tau_{ij}^{1-\sigma}$.

Behrens et al (2012) build trade gravity model of N countries or regions. Behrens et al use price index in substitution equation (1) of spatial distribution of labor index to represent spatial multilateral resistance, and it can be written as:

$$X_{ij} = Y_i Y_j \frac{\left(\frac{X_{ij}\bar{Q}}{Y_i \tau_{ij}}\right)^{1-1/\sigma}}{\sum_k \frac{p_i}{p_k} Y_k \left(\frac{X_{kj}\bar{Q}}{Y_k \tau_{kj}}\right)^{1-1/\sigma}} = Y_j \frac{\tau_{ij}^{1/\sigma-1}\left(\frac{X_{ij}}{Y_i}\right)^{1-1/\sigma}}{\sum_k \frac{L_k}{L_i}\tau_{kj}^{1/\sigma-1}\left(\frac{X_{kj}}{Y_k}\right)^{1-1/\sigma}} \tag{2}$$

Here, taking advantage of the equilibrium relationship between price p and wage w $p_i / p_k = w_i / w_k$, and on account of the constraints by aggregate income $Y_j = L_j w_j$, equation (1) is transformed into equation (2); region i is endowed with consumers/laborers of quantity L_i who provide unit labor. As Behrens assumes there is only productive labor, L_i also represents the regional aggregate labor supply; $\overline{Q}$ represents aggregate demand under the assumption of market clearing. For the need of aggregation, j is expressed as k at times. Then, equation (2) can also be written as:

$$X_{ij} = Y_j^{\sigma}\left[\sum_k \frac{L_i}{L_k} X_{kj}^{\frac{1}{\sigma}-1}\left(\frac{\tau_{ij}Y_i}{\tau_{kj}Y_k}\right)^{\frac{1}{\sigma}-1}\right]^{\sigma} \Rightarrow X_{ij} = Y_j^{\sigma}\left[\sum_k \frac{L_k}{L_i} X_{kj}^{1-\frac{1}{\sigma}}\left(\frac{\tau_{kj}Y_k}{\tau_{ij}Y_i}\right)^{\frac{1}{\sigma}-1}\right]^{-\sigma} \tag{3}$$

Make a logarithmic expansion of equation (3), and we get equation (4):

$$\ln X_{ij} = \sigma \ln Y_j - \sigma \ln\left[\sum_k \frac{L_k}{L_i}\left(\frac{\tau_{kj}Y_K}{\tau_{ij}Y_i}\right)^{\frac{1}{\sigma}-1} X_{kj}^{1-\frac{1}{\sigma}}\right] \equiv \varphi(\sigma) \tag{4}$$

Here, on the market of region j, the export of region i is negatively correlated with the export of region k, which is obvious spatial competition.

2.2. Linearization and generalized spatial correlation model

In the vicinity of $\sigma = 1$, φ is given Taylor expansion, so that the nonlinear equation is transformed into its linear form, and we get a spatial correlation model that can be measured and estimated, thus we construct the logical relationship between theoretical gravity equation and empirical analysis. Equation (5) is obtained:

$$\begin{aligned}\ln X_{ij} = {} & \sigma \sum_k \frac{L_k}{L} \ln \frac{L_k}{L} + \sigma \ln Y_j - (\sigma - 1)\left[\ln \tau_{ij} - \sum_k \frac{L_k}{L} \ln \tau_{kj}\right] \\ & - \sigma\left[\ln w_i - \sum_k \frac{L_k}{L} \ln w_k\right] + \left[\ln Y_i - \sum_k \frac{L_k}{L} \ln Y_k\right] - (\sigma - 1)\sum_k \frac{L_k}{L} \ln X_{kj} + \varepsilon \end{aligned} \tag{5}$$

From the equilibrium relationship in equation (5), it may be presumed that, first, the trade volume between region i and j increases with j, GDP of destination country. Second, the trade volume between country j and j is subject to the relative trade barriers, which is measured through deviation of bilateral trade barriers τ_{ij} coming from population weighted average (The Third Item), i.e., relative market access. Third, trade is also subject to i, wage level of export country, which is also measured through population weighted average deviation (The Fourth Item); wage higher than average will increase production costs, and will make the enterprises of region i less competitive on the market of region j. Fourth, the trade flow between country i and j is also subject to Y_i, GDP of export country, measured through population weighted average deviation (The Fifth Item); experience tells us: large countries have more enterprises, which is because of "domestic market effect", and just as Behrens et al (2012) point out, there are also large countries which decrease other countries' export volume by providing export environment of considerable scale and attraction. Last, the trade volume between country i and j decreases with the increase in X_{kj}, sales volume of third country k to destination country (The Sixth Item); this is because the products of different countries are mutually substitutable, and the more substitutes resemble one another, the stronger the substitution effect is, accordingly the higher the value of σ is, which is explained as "spatial competition". "Spatial competition" is one kind of spatial dependence, which can be expressed by spatial lag coefficient $-(\sigma-1)\sum_k \frac{L_k}{L}$.

Here, ε is approximate residual item of first order Taylor expansion. Simplify equation (5) and we can get the following matrix expression:

$$X = \sigma S II + \sigma Y_j + (I-W)Y_i - (\sigma-1)(I-W)\tau - \sigma(I-W)w - (\sigma-1)WX + \varepsilon \tag{6}$$

Here, $X = (\ln X_{ij})$ is logarithmic trade flow matrix; $S = \sum_k \frac{L_k}{L}\ln\frac{L_k}{L}$ is entropy of population distribution (uniformity of spatial distribution); II is matrix with all elements being 1; Y_j is the logarithmic matrix of GDP of destination country; I is unit matrix; W is spatial weighted matrix; Y_i is the logarithmic matrix of GDP of export country; $\tau = (\ln\tau_{ij})$ is the logarithmic matrix of trade costs; $w = (\ln w_i)$ is the logarithmic matrix of wage of export country. Equation (6) is rewritten as generalized spatial correlation model:

$$X = \beta_0 II + \beta_1 Y_j + \beta_2 Y_i + \beta_3 \tau + \beta_4 w + \rho WX + \varepsilon \tag{7}$$

Here, WX is spatial lag operator, and ρ is spatial lag coefficient. $\beta_0 = \sigma S$ is constant term; $\beta_1 = \sigma$ being GDP coefficient of destination country, $\beta_2 = I - W = \theta_1 W$ being GDP coefficient of export country, set θ_1 as spatial correlation coefficient of exporter factors; trade cost coefficient being $\beta_3 = -(\sigma - 1)(I - W) = \theta_2 W$, set θ_2 as spatial correlation coefficient of trade costs; wage cost coefficient of destination country being $\beta_4 = -\sigma(I - W) = \theta_3 W$, set θ_3 as spatial correlation coefficient of destination country wage cost. If spatial error correction is taken into account, then $\varepsilon = \lambda W\varepsilon + \mu$, λ being spatial error correction coefficient. Equation (7) is rewritten as:

$$X = \beta_0 + \beta_1 Y_j + \theta_1 WY_i + \theta_2 W\tau + \theta_3 Ww + \rho WX + \varepsilon, \ \varepsilon = \lambda W\varepsilon + \mu \tag{8}$$

Here, WX coefficient represents the endogenous interaction among explained variables; WY coefficient represents the exogenous interaction among explanatory variables; $W\varepsilon$ represents the interaction among different space unit disturbance terms. The model by Behrens et al (2012) once more avoided spatial correlation of explanatory variables. Here in the first place we propose this more generic generalized spatial correlation equation which includes various special cases. An ideal simple model should accommodate all economic assumptions that need to be taken into consideration (Manski, 1993).

2.3. From bilateral barriers to multilateral resistance

We make some assumptions about the function form of trade costs τ_{ij} (please refer to the Fourth Item in equation (8)). By convention we define trade costs as logarithmic linear function of distance and other observation objects related to trade barriers, as in equation (9):

$$\tau_{ij} = d_{ij}^{\delta_1}(1 + tf_{ij})^{\delta_2} e^{\delta_3 exch + \delta_4 oda + \delta_5 gs + \delta_6 sc + \delta_7 excf + \delta_8 milt + \delta_9 ethn + \ldots} \tag{9}$$

Here, d_{ij} represents distance; tf_{ij} represents tariff; *exch*、*oda*、*gs*、*sc*、*excf*、*milt*、*ethn* … represent exchange rate, foreign aid, government stability, social and economic conditions, external conflicts, military and political conditions, ethnic tension, and so on.

In view of trade costs and spatial distance correlation, the item of trade costs in expression (7) can be decomposed into two: $\beta_3\tau = \beta_5\tau + \theta_4 W\tau$, where $\beta_5 = (\sigma - 1)$ and $\theta_4 = (\sigma - 1)$. Thus, equation (8) is rewritten as matrix:

$$X = \beta_0 + \beta_1 Y_j + \beta_5\tau + \theta_1 WY_i + \theta_3 Ww + \theta_4 W\tau + \rho WX + \varepsilon, \ \varepsilon = \lambda W\varepsilon + \mu \tag{10}$$

In equation (10), the negative effect of bilateral trade barriers on trade flow is reflected by $\beta_5 < 0$, and the negative effects of multilateral trade barriers on trade flow are determined by the nature of W (there is reciprocal relationship between every element of spatial weighted matrix and distance, except the diagonal elements).

3. Spatial econometric model specification and empirical analysis

3.1. Spatial panel model specification

According to Elhorst (2010), interaction parameter cannot be identified unless at least one interaction is excluded from the multiple spatial interactions. Moreover, spatial weighted matrix of spatially lagged explained variables should differ from that of spatial autocorrelation error terms (Anselin and Rey, 1997). IV/GMM estimators can use same weighted matrix to estimate spatially lagged explained variables and spatial auto-regression error terms (Lee, 2004), but cannot estimate models containing spatially lagged explanatory variables, as they have been used as instrumental variables (Elhorst and Fréret, 2009). A non-constraint panel SDM model may be applied, as it can be seen as the reduced form of a generalized spatial correlation equation, so we test whether this model can be degenerated (Elhorst and Fréret, 2009), and it is expressed as follows:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}'\beta + \sum_{j=1}^{N} w_{ij} x_{jt}'\theta + a_i + \kappa_t + \varepsilon_{it} \tag{11}$$

Here, y_{it} represents the explained variables of region i at the moment of t; x_{it} represents the explanatory variables of region i at the moment of t; $\sum_{j=1}^{N} w_{ij} y_{jt}$ represents the reciprocal effect of y_{it}, endogenous variables of neighboring regions to i, on y_{it}; $\sum_{j=1}^{N} w_{ij} x_{jt}'$ represents the reciprocal effect of x_{it}, exogenous variables of neighboring regions to i, on y_{it}; ρ is spatial auto-regression parameter, also referred to as spatial lag coefficient, representing spatial lag correlation; w_{ij} represents non-diagonal elements of spatial weighted matrix ($w_{ij} = d_{\min} / d_{ij}$, d_{ij} representing bilateral distance, d_{min} being the shortest among all the bilateral distances), and all the diagonal elements of matrix W are 0; β is explanatory variable coefficient matrix; θ is explanatory variable spatial correlation coefficient; a_i represents spatial individual effect; κ_t represents time individual effect; ε_{it} represents independent identically distributed error terms, which follow normal distribution of mean-zero and homoscedasticity. We use Wald statistics and likelihood ratio (LR) statistics to test two hypotheses: $H_0^1 : \theta = 0$, $H_0^2 : \theta + \rho\beta = 0$. The first hypothesis is used to test whether SDM can be degenerated into SLM; the second hypothesis is used to test whether SDM can be degenerated into SEM, and it is in fact equivalent to testing constraint condition: $\theta = -\rho\beta$. If test results reject both null hypotheses at the same time, then SDM cannot be degenerated.

3.2. Mechanism of feedback loop effect

We need to take spatial feedback loop effect into account when we make spatial econometric model estimation. Spatial econometric model expands information set as it includes information coming from observed values of neighboring regions. To see such results, SDM can be written as:

$$(I_n - \rho W) y = X\beta + WX\theta + \iota_n \alpha + \varepsilon = > y = \sum_{r=1}^{k} S_r(W) x_r + V(W) \iota_n \alpha + V(W) \varepsilon$$

$$S_r(W) = V(W)(I_n \beta_r + W\theta_r), \ V(W) = (I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots \quad (12)$$

The example of single dependent variable observed value in equation (13) clarifies the function of matrix $S_r(W)$. In the equation $S_r(W)$ is used to represent element i, j in matrix $S_r(W)$, and $V(W)_{\mathrm{i}}$ represents row i of $V(W)$.

$$y_i = \sum_{r=1}^{k} [S_r(W)_{i1} x_{1r} + S_r(W)_{i2} x_{2r} + , \cdots, + S_r(W)_{in} x_{nr}] + V(W)_i \iota\alpha + V(W)_i \varepsilon \quad (13)$$

What is deduced from equation (13) does not seem like an independent data model, as the derivative of y_i to x_{ir} may be nonzero, and the value is determined by the element i, j of $S_r(W)$. And $\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij}$, the derivative of y_i to x_{jr}, does not equal β_r in least square method. Its implication: the changes of observed value explanatory variables of one region may have an impact on all observed value explained variables of other regions. SDM has logical features as explanatory variables and explained variables of other regions are taken into account by introducing Wy and WX. If explained variable matrix y reflects per-capita income of all regions and explanatory variables reflect regional features (for example, capital, industrial structure, population density and so on), regional differences in income depend on the income of neighboring regions partly, which are reflected by spatial lag matrix Wy and affected by spatial dependence of neighboring regions' features represented by WX. Self-derivation of region i is represented by $\frac{\partial y_i}{\partial x_{ir}} = S_r(W)_{ii}$, which measures the impact of changes in x_{ir} on observed value i explained variables. The impact includes feedback loop effect, i.e. observation object i affects observation object j, and observation object j also affects observation object i. Feedback loop may cover a much longer path: from observation object i to observation object j, continuing to observation object k, then returning to observation object i. Absolute value of ρ is smaller than 1, so data generation process assigns less high-order near neighbor influence to disturbance terms and the influence attenuate exponentially. Matrix W^2 reflects second-order near neighbor and nonzero diagonal elements included. Region i is the neighbor of its neighbor, so the near neighbor influence passed will also exert feedback effect on region i itself.

Empirical study focuses on two questions: the changes of one region and the impacts of these changes, the two of which are reflected by the column or row of matrix S_r (W). LeSage and Pace (2010) label the mean of row sum as average aggregate impact on an observation object and label the mean of column sum as average aggregate impact coming from an observation object. Matrix S_r (W) diagonal mean provides summary metrics for average direct impact, and average indirect impact is the subtraction of average direct impact from average aggregate impact. Abreu et al (2004) propose SLM as in equation (14), with β_r being direct impact, $W\rho\beta_r$ being indirect impact and item in brackets being elicited impact:

$$\frac{\partial y}{\partial x_r'} = I_n\beta_r + W\rho\beta_r + [\ W^2\rho^2\beta_r + W^3\rho^3\beta_r + \cdots\ ] \tag{14}$$

Direct impact is not equivalent to seeking partial derivative of y_i to x_{ir} individually, and indirect impact is not equivalent to seeking partial derivative of y_i to x_{ir} ($i\neq j$) individually. The definitions of direct impact and indirect impact correspond to series self-derivative and series cross partial derivative respectively, which include feedback loop effect. This method simplifies three labels (direct, indirect and elicited) into two (direct and indirect). Compared to SLM, aggregate impact coming from the changes of variable X_r in SDM presents great heterogeneity, because there is added matrix $W\theta_r$ in aggregate impact which is equivalent to range attenuation function. Contrary to the fact that every variable has identical global multiplier under SLM, it allows the existence of differences between spillover effects of changes in explanatory variables (LeSage and Pace, 2010). If this spatial econometric model is used to estimate theoretical equation (10), direct impact is equivalent to the impact magnitude of bilateral barriers and indirect impact is equivalent to the impact magnitude of explanatory variable multilateral resistance. Decomposition of the impacts based on SDM does not calculate magnitude of multilateral resistance coming from explained variables, but SDM can be used to estimate reaction coefficient representing the changes in this multilateral resistance. Policy analysts may need to pay more attention to magnitude of multilateral resistance coming from explanatory variables, which tends to be ignored because of the disconnection between empirical methods and theoretical basis, but to estimate and explain its significance can offer more practical guidance.

3.3. Spatial data source and model variables selection

The sample includes China and 39 African countries. Explained variables select China's agricultural export to African countries (*lnagrex*) as China-Africa agricultural trade proxy variable, and the data comes from China's Ministry of Agriculture. Explanatory variables include: country risk index coming from International Country Risk Guide (ICRG); energy production (*lnenergy*) and net official development aid (*lnoda*) coming from World Bank Database; China-Africa direct investment stock (*lnodis*) coming from *Statistical Bulletin of China's Outward Foreign Direct*

Investment 2004-2013; GDP weighted geographical distance (*lnecdis*) of which geographical distance comes from CEPII database and GDP comes from World Bank Database. GDP weighted geographical distance takes GDP and geographical distance in theoretical equations into consideration. Some ICRG indices are strongly correlated, so five representative country risk indices are selected: social and economic conditions (*sc*), investment environment (*inp*), external conflicts (*excf*), corruption (*crp*), and ethnic tension (*ethn*). As many African countries have substantially decreased or exempted tariffs in order to deal with food crisis or join WTO, and as tariff policies are relatively stable and constant in certain years, tariff is not incorporated into spatial panel model with time series feature. Per capita wage is related to both per capita GDP and GDP weighted geographical distance, so it is not included in the empirical model either. Though South Africa signed Currency Swap Agreement with China in 2015, most African countries still rely on US dollar for trade settlements, and due to the restraints of backward finance, domestic currencies of most African countries are not freely convertible, so bilateral exchange rate is not included in the system of explanatory variables.

Table 1
Model variable meaning and code

Explained variables	China-Africa agricultural export volume		
Code	*lnagrex*		
Explanatory variables	Energy production	Net official development aid	China-Africa direct investment stock
Code	*lnenergy*	*lnoda*	*lnodis*
Explanatory variables	GDP weighted geographical distance	Social economic conditions	Investment environment
Code	*lnecdis*	*sc*	*inp*
Explanatory variables	External conflicts	corruption	Ethnic tension
Code	*excf*	*crp*	*ethn*

Note: variable codes are English abbreviations or logarithmic English abbreviations.

3.4. Empirical analysis

Hausman Test of spatial panel proposed by Lee and Yu (2012) is applied to decide whether the spatial panel model is in random effect form or fixed effect form. As Hausman Test statistic value is 80.0344, and probability is 0.0000, we should choose fixed effect model. In order to decide whether SLM or SEM is more suitable to describe data than models without any spatial interaction, Lagrange multiplier (LM) test (Anselin et al, 1996) and Robust LM test (Anselin et al, 1996; Elhorst, 2014) are necessary. Test results are reported in Table 2.

Null hypotheses of LM test and Robust LM test do not have spatially lagged effect or spatial error correlation. According to Table 2, except that spatial lag effect and spatial error correlation in spatial and time fixed effects model do not reject null hypothesis of LM test at 10% significance level, spatial lag effect and spatial error correlation in other types of models all reject null hypothesis of LM test at 1% significance level. Robust LM tests all reject null hypothesis at 5% significance level. Most types of models rejecting null hypotheses without spatial lag correlation or spatial error autocorrelation, spatial fixed effects SLM and SEM stand simultaneously, and time fixed effects SLM and SEM stand simultaneously; in spatial and time fixed effects model, all lack of spatial lag effect and spatial error correlation is not significantly rejected.

Table 2
LM test and Robust LM test of spatial lag correlation and spatial error autocorrelation

Model	Statistics	Hybrid OLS estimating model	*p*	Spatial fixed effects	*p*	Time fixed effects	*p*	Spatial and time fixed effects	*p*
Trade panel	Spatial lag LM	117.644	0.000	33.784	0.000	57.368	0.000	0.075	0.784
	Spatial error LM	52.978	0.000	7.769	0.005	15.132	0.000	2.223	0.136
	Spatial lag robust LM	80.940	0.000	31.743	0.000	74.713	0.000	17.814	0.000
	Spatial error robust LM	16.274	0.001	5.728	0.017	32.477	0.000	19.960	0.000

Note: *p* value is probability, and OLS represents least square method.

Table 3
LR test of joint significance of spatial fixed effects and time fixed effects

Model	Trade panel	
Statistics	*LR*	*p*
Spatial fixed effects	553.310	0.000
Time fixed effects	42.182	0.000

Note: *p* value is probability.

LR test is applied to decide whether fixed effects are jointly significant (Elhorst, 2014). Null hypothesis of LR test about the significance of spatial fixed effects $H_0^3 : \mu_1 = ... = \mu_N = \alpha$. Null hypothesis of LR test about the significance of time fixed effects $H_0^4 : u_1 = ... = u_N = \kappa$. According to Table 3, insignificant null hypothesis being rejected, model spatial and time fixed effects being significant, spatial fixed effects and time fixed effects are jointly significant and spatial panel model includes both a_i and κ_t.

According to Table 4, both Wald test and LR test reject null hypothesis that can be degenerated into SLM and SEM, so agricultural trade panel should select SDM. If SLM, SEM and SDM include spatial fixed effects but not time fixed effects, $\hat{\sigma}^2$, estimate of σ^2 obtained through direct method is biased (Baltagi, 2005), and the biased error can be corrected by $\hat{\sigma}_{TC}^2 = (T / T - 1)\, \hat{\sigma}^2$. If SLM, SEM and SDM include time fixed effects but not spatial fixed effects, $\hat{\sigma}^2$, estimate of σ^2 obtained through direct method is biased and the biased error can be corrected by $\hat{\sigma}_{NC}^2 = (N / N - 1)\, \hat{\sigma}^2$ (Lee and Yu, 2010a). When N is of quite great value, this correction will be futile.

Table 4
Test of whether agricultural trade panel SDM can be degenerated

	SDM degeneration test		SDM degeneration test (error correction)	
	Explanatory variables spatial lag effect	Spatial error autocorrelation effect	Explanatory variables spatial lag effect	Spatial error autocorrelation effect
Wald statistics	81.033	70.158	64.356	58.432
p	0.000	0.000	0.000	0.000
LR statistics	66.755	62.193	66.755	62.193
p	0.000	0.000	0.000	0.000

Note: *p* value is probability.

Table 5
Model estimation of agricultural trade panel SDM

Variable	Spatial fixed effects			Time fixed effects			Spatial and time fixed effects			Spatial and time fixed effects (error correction)		
	coeff-cient	*t*	*p*	coeff-cient	*t*	*p*	coeff-cient	*t*	*p*	coeff-cient	*t*	*p*
lnodis	0.165	2.711	0.007	0.143	1.953	0.051	0.182	3.042	0.002	0.180	2.766	0.006
lnecdis	-0.963	-2.813	0.005	0.788	6.198	0.000	-1.015	-3.043	0.002	-1.001	-2.755	0.006
lnenergy	-0.406	-3.009	0.003	0.043	1.179	0.239	-0.362	-2.902	0.004	-0.358	-2.634	0.008
lnoda	0.027	0.525	0.600	0.231	4.077	0.000	-0.010	-0.202	0.840	-0.007	-0.132	0.895
sc	0.033	0.237	0.813	-0.052	-0.387	0.699	0.071	0.521	0.602	0.073	0.490	0.624
inp	0.252	1.978	0.048	0.252	2.974	0.003	0.376	3.104	0.002	0.361	2.735	0.006
excf	-0.145	-1.495	0.135	0.272	2.625	0.009	-0.134	-1.504	0.133	-0.130	-1.341	0.180
crp	0.042	0.334	0.738	0.233	1.666	0.096	-0.054	-0.447	0.655	-0.055	-0.418	0.676
ethn	0.296	1.652	0.099	0.110	0.825	0.410	0.362	2.117	0.034	0.351	1.886	0.059
*W*lnodis*	-0.180	-0.719	0.472	0.788	1.510	0.131	0.022	0.054	0.957	-0.004	-0.008	0.993
*W*lnecdis*	-2.087	-1.077	0.282	2.887	2.123	0.034	-3.067	-1.213	0.225	-2.703	-0.983	0.326
*W*lnenergy*	0.021	0.021	0.983	-1.256	-3.088	0.002	-0.168	-0.163	0.870	-0.061	-0.055	0.957
*W*lnoda*	-0.354	-0.959	0.337	0.618	1.429	0.153	-0.859	-2.048	0.041	-0.859	-1.880	0.060
*W*sc*	-0.137	-0.119	0.906	2.303	3.027	0.003	0.416	0.346	0.729	0.423	0.324	0.746
*W*in*p	0.447	0.574	0.566	-0.240	-0.405	0.686	1.647	1.778	0.075	1.525	1.513	0.130
*W*excf*	-0.562	-0.823	0.411	2.493	3.254	0.001	-0.342	-0.473	0.636	-0.339	-0.431	0.667
*W*crp*	0.975	1.293	0.196	5.763	4.278	0.000	-0.377	-0.437	0.662	-0.355	-0.378	0.706
*W*ethn*	4.109	2.701	0.007	3.417	3.087	0.002	4.645	3.081	0.002	4.596	2.797	0.005
*W*lnagrex*	-0.441	-2.256	0.024	-0.259	-1.480	0.139	-0.832	-3.982	0.000	-0.629	-3.075	0.002
R^2	0.930			0.771			0.935			0.934		
LogL	-289.489			-472.673			-280.449			-280.449		

Note: *p* value is probability. Due to limited space names of the 39 countries are not listed here; the authors can provide the information is necessary.

Applying OLS to the estimation of spatial model, which will lead to inconsistent estimate of regression parameter of spatially lagged explanatory variables model, inconsistent estimate of spatial parameter, inconsistent estimate of standard error. So parameter estimation is made based on maximum likelihood estimation (MLE) provided by Lee (2004), Lee and Yu (2010b). See Table 5, in the four models, time fixed effects model has relatively more significance coefficients. See also LM test in Table 2, time fixed effects model rejects relatively more significantly hypothesis void of SLM or SEM at 1% significance level. When SLM and SEM stand simultaneously, we need to test whether SDM can be degenerated into SLM and SEM. According to Table 4, SDM cannot be degenerated. On the basis of the above results, model estimation of times fixed effects SDM is relatively more effective. In the four models, China-Africa direct investment accumulation (*lnodis*) significantly promotes China-Africa agricultural trade (*lnagrex*). As far as the other three models other than time fixed effects model are concerned, GDP weighted geographical distance (*lnecdis*) is negatively correlated with agricultural trade. Only in time fixed effects model, net official development aid (*lnoda*) promotes China-Africa agricultural trade significantly.

It needs to be specified in terms of the impacts of country risk variables: the higher ICRG risk index, the lower that country's risk; if ICRG index is positively correlated with trade in the model, there is significant negative correlation between high country risk and trade volume. So in time fixed effects model, investment environment, external conflicts, and higher risk of corruption have significant negative effects on agricultural trade.

In time fixed effects model, estimation coefficient of spatially lagged explanatory variables that include W represents multilateral trade resistance coming from explanatory variables. Agricultural trade (*lnagrex*) is also negatively affected by energy production (*lnenergy*) of neighboring regions; social and economic conditions (*sc*), external conflicts (*excf*), corruption (*crp*), higher risk of ethnic tension (*ethn*) in neighboring regions will bring negative impacts on agricultural trade of the local region. GDP weighted geographic distance (*lnecdis*) has positive impacts on near neighbors; when GDP is of quite high volume, hindering effect of distance tends to decrease, and trade volume of home country hindered by distance may also transfer to trade volume of the near neighbor, which near neighbor is relatively close to source country of trade. The spatial interaction between W and factors such as China-Africa direct investment stock (*lnodis*), net official development aid (*lnoda*), and investment environment (*inp*) is not significant, and there are no obvious spatial spillover effects of China-Africa direct investment accumulation, international official development aid, and investment environments of African countries. This leaves policymakers to reflect: How to enhance regional effects of direct investment and official development aid in Africa? How can Africa improve its overall investment environment?

Except for time fixed effects model, spatial lag impacts of explained variables of the other three models are significant; there exists spatial competition among neighboring regions in agricultural trade, which represents multilateral trade resistance coming from explained variables. There is little difference between the results of spatial and time effects model estimation and those of spatial and time effects model estimation after error correction, and considering that the model has high value of *N* and low value of *T*, the difference mainly comes from the impact of error correction of spatial fixed effects.

Although the test of Table 3 reveals that spatial fixed effects and time fixed effects of agricultural trade panel are jointly significant, test of Table 2 does not support the validity of SLM and SEM under both spatial and time fixed effects, instead the test of Table 2 support that spatial fixed effects SLM and SEM stand simultaneously and that time fixed effects SLM and SEM stand simultaneously. As SLM and SEM do not always stand under both spatial and time fixed effects, it is not necessary to test whether its SDM can be degenerated into SLM or SEM, and the scenario under spatial and time fixed effects is not taken into account in subsequent decompositon calculation of SDM direct impacts and indirect impacts. Taken the tests of Table 2, Table 4 and Table 5 together, model estimation of time fixed effects SDM is relatively more effective, so only the decomposition results of time fixed effects SDM are reported here in Table 6.

Table 6
Decomposition estimation and test II of agricultural trade pane SDM impacts: time fixed effects panel

	Direct impacts			Indirect impacts			Aggregate impacts		
	Coefficient	*t*	*p*	Coefficient	*t*	*p*	Coefficient	*t*	*p*
lnodis	0.132	1.801	0.079	0.629	1.415	0.165	0.761	1.615	0.114
lnecdis	0.761	6.300	0.000	2.212	1.900	0.065	2.973	2.467	0.018
lnenergy	0.058	1.556	0.128	-1.046	-2.829	0.007	-0.988	-2.556	0.015
lnoda	0.224	4.197	0.000	0.463	1.313	0.197	0.687	1.852	0.072
sc	-0.080	-0.602	0.551	1.889	3.185	0.003	1.809	2.814	0.008
inp	0.258	3.037	0.004	-0.230	-0.456	0.651	0.028	0.052	0.959
excf	0.244	2.309	0.026	2.012	2.833	0.007	2.255	3.059	0.004
crp	0.164	1.165	0.251	4.727	3.696	0.001	4.891	3.624	0.001
ethn	0.068	0.523	0.604	2.773	3.018	0.005	2.841	2.993	0.005

Note: *p* value is probability. Aggregate impacts=direct impacts +indirect impacts; indirect impacts are also referred to as spillovers, and aggregate impacts are also referred to as superimposed impacts.

We find direct impacts approximate to SDM explanatory variables coefficient when we take direct impacts into consideration. The difference between 0.272, *excf* estimation coefficient and 0.244, direct impacts estimation, is 0.028, representing feedback effect which is the effect fed back after the neighboring regions are impacted by the local region. As the difference between estimation coefficient and direct impacts is small, feedback effect is small and is not likely to have economic significance. As opposed to the proximity between direct impact estimated value and SDM coefficient, there is big difference between spatial lag coefficient of SDM and indirect impact estimated value. For example, estimated value of *excf* indirect impacts is 2.012, but coefficient of spatial lag variable *W. excf* is 2.493, the difference being 0.481. If we mistake spatial lag variable coefficient of *excf* for indirect spillover effects, we will get wrong explanations. Elhorst and Fréret (2009) point out, taking the sum of coefficient estimation of certain variable *a* and spatial lag variable *W.a* of SDM as aggregate effects will also lead to wrong conclusions. As data generation process of SDM contains infinite series expansion of spatial matrix, spatial lag variable coefficient reflects potential changes, but it does not contain feedback loop effect (effects of W^2 and higher power of W), i.e. effect of near neighbors higher than second order. Therefore, to calculate indirect effects, i.e., spillovers, the method introduced in section 3.2 is needed.

According to Table 6, direct investment directly promotes agricultural trade, and indirect spillover effects are not significant. The reason for difference from panel model estimation is the consideration of feedback loop effect here. Feedback loop effect taken into account, direct impacts and spillover effects of GDP weighted distance are both significantly positive. In this global village which is getting smaller and smaller, globalization has boiled down to increasingly lower transportation costs (Alessandria and Choi, 2014); on the other hand, the larger GDP a country and its neighbors have, the greater resultant local market effects. Energy production has significant negative spillover effects on agricultural trade, which can be understood as the magnitudes of effects of multilateral resistance coming from explanatory variables; hence, we should guard against crowding-out effect on industries of near neighbors. Official development aid has brought significant direct impacts on agricultural trade. Negative factors such as social and economic conditions, corruption, and ethnic tension have brought significant spatial spillover effects, which can also be understood as the magnitude of effects of multilateral resistance coming from explanatory variables, with corruption having the greatest effects and ethnic conflict the second largest; social and economic stability and ethnic conflicts of in one country will spread to and influence its neighbors, as minority groups in this country are often the dominant ethnic group in the neighboring country; corruption is contagious across nations. Negative direct impacts and spillover effects of external conflicts are significant, and multilateral resistance effects of external conflicts are huge. In other words, peace, cultural consensus and efficient government play an important role in the stable development of China-Africa agricultural trade.

4. Conclusions

Estimation of generalized spatial correlation gravity model has rich policy implications, as it not only includes explanation of the magnitude of direct impacts coming from explanatory variables, autocorrelation explanation of explained variables spatial lag, but also includes the explanation of spillover effects coming from spatially lagged explanatory variables. This study builds a strong economic theoretical basis for the application of this model so that we can apply mainstream economic theories to the explanation of the series of near neighbor multilateral impacts and their magnitude. The application of this model enables us not only to identify the changes of multilateral resistance that China-Africa agricultural trade is faced with but also to explain what are the near neighbor impacts of the multilateral resistance and their magnitude. Because of the existence of spatial feedback loop effect of near neighbor impacts, bilateral direct impacts and spatial spillover effects can be estimated on the basis of model direct impacts coefficient and spatial lag coefficient. Bilateral direct impacts and spatial spillover effects scientifically explain the magnitudes of bilateral direct impacts and multilateral near neighbor impacts. Negative spatial spillovers are multilateral resistance effect, and both spatial lag correlations of explained variables and spatial lag correlation of explanatory variables can cause multilateral resistance. Generalized spatial correlation gravity model can identify the magnitude of impacts of multiple near neighbor factors on local region, which has great practical implications in the present world where various relations are interwoven and interpenetrated with each other.

Based on empirical analysis, this paper has reached not only the general conclusion that China-Africa investment significantly promotes China-Africa agricultural trade but also some unique conclusions: there are other multiple factors affecting China-Africa agricultural trade and creating corresponding direct impacts and spillover effects. Decomposition of impacts is an important feature function of generalized spatial correlation multilateral gravity model, which will provide guidance for the targeting of trade policies. Both China's investment in Africa and official development aid that African countries get promote directly China-Africa agricultural trade. Negative factors such as backward social and economic conditions, corruption and ethnic tension in certain African countries have significant spatial spillovers, bring multilateral resistance to the development of China-Africa agricultural trade. Energy production may have crowding-out effect on agricultural production of near neighbors. Moreover, conflicts among African countries have negative direct impacts on China-Africa agricultural trade, and bring significant spatial spillovers. When China promotes China-Africa agricultural trade by means of investment or aid, China should pay close attention to some direct or indirect impacts on the stable development of the China-African agricultural trade, which are caused by factors such as the development of non-agricultural industries, peace, cultural consensus and efficient government.

References

Abreu, M., Groot, H. L. F., & Florax, R. J. G. M. (2004). Space and growth: A survey of empirical evidence and methods. Tinbergen Institute Working Paper, No.TI 04-129/3.

Alessandria, G., & Choi, H. (2014). Do falling iceberg costs explain recent US export growth? *Journal of International Economics*, *94*(2), 311-325.

Anderson, J.E., & Van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, *93*(1), 170-192.

Anselin, L., & Bera, A. K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. *Statistics Textbooks and Monographs*, 155, 237-290.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics. 26*(1), 77-104.

Anselin, L., & Rey, S. (1997). Introduction to the special issue on spatial econometrics. *International Regional Science Review*, 20,1-7.

Anselin, L., Le Gallo, J., & Jayet, H. (2008). Spatial panel econometrics. In Matyas, L., & Sevestre, P. (eds.), *The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice*, 3rd edn. Dordrecht: Kluwer Academic Publisher, 627-662.

Baltagi, B. (2005). *Econometric analysis of panel data,* 3rd edn. Chichester: John Wiley & Sons, 13.

Behrens, K., Ertur, C., & Koch, W. (2012). Dual gravity: Using spatial econometrics to control for multilateral resistance. *Journal of Applied Econometrics*, *27*(5), 773-794.

Braudigam, D. (2012). *The dragon's gift: The real story of China in Africa (translated by Shen Xiaolei & Gao Mingxiu),* Social Sciences Academic Press (China).

Diao, X., Hazell, P. B. R., Resnick, D., & Thurlow, J. (2007). The role of agriculture in development: Implications for Sub-Saharan Africa. Research Report 153, International Food Policy Research Institute (IFPRI).

Elhorst, J. P., & Fréret, S. (2009). Evidence of political yardstick competition in France using a two-regime spatial durbin model with fixed effects. *Journal of Regional Science*, *49*(5), 931-951.

Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. Springer, 53-57.

Elhorst, J. P. (2010). Spatial panel data models. In Fischer, M. M., & Getis, A. (eds.). *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications*, Springer, 377- 407.

Lee, L., & Yu, J. (2010a). Estimation of spatial autoregressive panel data models with fixed effects. *Journal of Econometrics*, *154*(2), 165-185.

Lee, L., & Yu, J. (2010b). Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, *40*(5), 255-271.

Lee, L., & Yu, J. (2012). Spatial panels: Random components versus fixed effects. *International Economic Review*, *53*(4), 1369-1412.

Lee, L. (2004). Asymptotic distribution of quasi-maximum likelihood estimators for spatial autoregressive models. *Econometrica*, *72*(6), 1899-1925.

LeSage, J. P., & Pace, R. K. (2010). *Introduction to Spatial Econometrics*. CRC Press, 24-53.

LeSage, J. P., & Pace, R. K. (2008). Spatial econometric modeling of origin-destination flows. *Journal of Regional Science*, *48*(5), 941-967.

Li, X. (2010). *Smallholder-based agricultural development: A comparative analysis of Chinese and African experiences.* Social Sciences Academic Press (China).

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies*, *60*(3), 531-542.

Qian, J., & Cai, G. (2010). Theoretical basis and empirical evidence of multilateral gravity equation. *The Journal of World Economy (Shijie Jingji),* 5.

State Council Information Office. (2013). China-Africa economic and trade cooperation.

Wang, R., & Chen, W. (2014). Analysis of the current conditions and main problems of China's foodstuff import and export. *Agricultural Economy (Nongye Jingji)*, 3.

Yan, H., & Sha, B. (2011). Agricultural capitalism or Neo-Colonialism? — China's agricultural investment in Zambia. *Beijing Cultural Review (Wenhua Zongheng)*, 4.

Yang, Y. (2007). *China-Africa outward direct investment*. China Dongbei University of Finance & Economics, Master's Thesis.

Zhang, Y. (2011). What is US doing in Africa? *World Affairs (Shijie Zhishi)*, 14.

Zhu, S. (2008). Food safety and national food trade policy. *Journal of Nanjing Party Institute of CPC (Zhonggong Nanjing Shiwei Dangxiao Xuebao)*, 6.