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The Spatial Econometric Analysis on Democracy and Economic Determinants of Official Development Assistance: Evidence from Korea*

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Abstract This study analyzes the determinants affecting Korea's official development assistance (ODA) to recipient countries using spatial econometric models, unlike most studies. We tested whether the recipient country's democracy level or political stability, the distance between Korea and the recipient country, trade, GDP, world ODA, and world FDI have an impact on the determinants of Korea's ODA to recipient countries. The empirical results revealed that Korea's ODA is impacted by spatial dependence effects. The spatial empirical models showed that while the democracy level of recipient countries, distance, recipient country's GDP, and world ODA seem to positively influence Korea's ODA, Korea's trade does not affect its ODA to recipient countries. The distance between countries is not inversely related to ODA, unlike the trade gravity models. The spatial error-correction estimation with combined spatial effects also shows both spatial effects in the short run. Thus, the country needs to consider the spatial effects of the determinants of ODA to create more effective ODA policies.

Keywords Official development assistance, spatial dependence, development, gravity model.

JEL Classification F63, F35.

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1. INTRODUCTION

The Korean government enacted the Framework Act on International Development Cooperation to enhance the official development assistance (ODA) aid for the economic development of recipient countries after Korea's accession to the Organization for Economic Co-operation and Development Assistance Committee (OECD DAC) in 2010. The country has also continuously increased its ODA to contribute to the advancement of developing countries.

Korea began providing earnest assistance to developing countries in the late 1980s with the launch of the Economic Development Cooperation Fund (EDCF) in 1987 and Korea International Cooperation Agency (KOICA) in 1991. In 2010, Korea officially established itself as a donor country. Based on its successful development experience, Korea is attempting to build a new paradigm for development cooperation by bridging developed and developing countries. Thus, Korea has been making proactive efforts to integrate development into the agenda of key global fora. In 2021, the share of grants and loans stood at 64% (USD 1,365.6 million) and 36% (USD 779.6 million), respectively. In 2021, the total of Korea's bilateral ODA to recipient countries was USD 2,145.17 million.

While considerable studies have analyzed ODA in several topics and academic fields, only a few studies have demonstrated how Korea's ODA was allocated to recipient countries. ODA is the most widely accepted measure of foreign aid and financial support from the donors to improve recipient countries that are poor. However, there is still an ongoing debate regarding the determinants of ODA allocations. Furthermore, there are different motivations for ODA allocation, divided into two main categories such as aid recipients' need and donors' interest.

However, most previous studies have not realized the importance of the effect of the spatial dependence in the ODA analysis. As the first law of geography, Tobler (1970, p. 236) suggests "everything is related to everything else, but near things are more related than distant things." Many researchers started analyzing the spatial dependence. Hall and Petroulas (2008) revealed the importance of considering spatial dependence in several academic fields. Despite that, most previous ODA studies have not considered the spatial effects of ODA to analyze the important factors of ODA model to recipient countries. The spatial dependence effects of aid flows are very important to analyze the allocation of the aid, because the international aid flows are inherently spatial interactions.

When there is a spatial autocorrelation in the ODA analysis, if we ignore these spatial effects of the determinants of international aids, the ordinary least squares (OLS) estimation cannot induce the unbiased and efficient parameter estimates as Anselin (1988), LeSage and Pace (2008), and Anselin and Rey (2014) argued. Therefore, the theoretical misalignment leads to wrong lessons not only from the theoretical but also empirical perspectives as Metulini (2013) argued. Thus, Davies and Klasen (2019) began to analyze the spatial effects in aid allocation focused on spatial lag model. Furthermore, we have to use the spatial econometric estimation methods which are totally different from the standard non-spatial econometric estimation methods to get the consistent estimators of allocating factors of ODAs.

In recent years, several models and estimation methods in the spatial econometric field have considered spatial dependence and examined its effects in other academic fields. Certainly, the proximity of one country's ODAs to recipient countries can affect its ODA to recipient countries. Even though, a lot of studies on recent Korea's ODA analyses are distributed among academic fields such as sociology, public administration, and education, economic studies on ODA are relatively very scarce. Moreover, Korea's ODA recipient countries are very diverse in recent years. Nonetheless, why does the topic matter? While there have been only few ODA analyses including the spatial effects, there have been no studies yet to consider the spatial dependence effects in Korea's ODA allocation analysis. If there is a spatial dependence effect, we cannot obtain the consistent estimators of the coefficients of the ODAs using the standard non-spatial OLS estimation. Thus, to properly account for spatial dependence in regression analysis, we need to investigate what spatial estimation methods were used to get the consistent estimators.

In addition, since the missing or zero values in ODA data involving very low income recipient countries are important issues, this paper inserted the Poisson Pseudo-Maximum Likelihood (PPML) estimation issues following Silva and Tenreyro (2006) and Chen and Roth (2024). And even though the focus of this paper is not the fixed and random effect models of the panel analysis. There are so many unobservable factors such as political, historical, and specific factors. These unobservables could include factors like cultural ties, historical relationships, or persistent policy preferences. This omission can lead to biased estimates if these unobserved factors are correlated with the explanatory variables in the model. To do this, this paper is also going to examine the fixed and random effect models using Housman test in ODA analysis.

Therefore, this study differs not only from non-spatial previous ODA studies completely but also from the spatial ODA study of Davies and Klasen (2019). While this study uses the spatial lag and spatial error models with the spatial weights, this study additionally utilizes the newest combined the spatial lag and spatial error model with cointegration estimation methodology. Moreover, to deal with endogeneity and spatial dependences, this paper uses the spatial two stages least squares (S2SLS) estimation, spatial maximum likelihood estimation (SMLE), spatial weighted estimation (SWLS), and the spatial generalized method of moments (SGMM) to obtaining more robust and consistent estimators unlike most previous standard non-spatial OLS analyses.

Furthermore, this study will apply the newest spatial dependence models in the determinants of ODA to answer the following research questions to get the consistent estimators in spatial ODA analyses. First, what determinants can be different in non-spatial ODA and spatial ODA analyses? Second, the economic and trade factors can affect the Korea's ODA flows using spatial models? Third, which political factor, such as the level of democracy of the recipient country, is significant in the allocation of Korea's ODA in the spatial models? Fourth, is the geographical distance between Korea and recipient countries inversely related to Korea's ODA as the trade gravity models argued? Fifth, any previous ODA studies have not analyzed the spatial cointegration model yet. This study proves whether a spatial cointegrated model with error correction holds for the spatial estimation of Korea's ODA to recipients?

Accordingly, this study will be the first study to analyze the determinants of political, economic, geographic, and spatial effects of Korea's ODA allocation policies using the spatial estimation methodology. This study investigates the spatial effects of Korea's ODA allocation to available 55 recipient countries during 2010s by spatial econometrics and several consistent spatial estimation methods unlike the previous standard non-spatial estimation methods. Thus, this study can contribute to the ODA literature with regard to the spatial dependence effects of ODA allocation and then provide the correct effective ODA policies.

The rest of this paper is structured as follows. Section 2 reviews the relevant literature on ODA including spatial effects. Section 3 describes the brief theoretical framework. Section 4 introduces the econometric specification of measuring the spatial effects of the ODA flows and in-depth spatial econometric methods. Section 5 describes the data and the empirical results. Section 6 provides the main findings from the study and suggests policy implications.

2. LITERATURE REVIEW OF ODA STUDIES

While there are several studies on ODA, most of them do not consider the spatial effects on the determinants of ODA policies. There are different motivations for ODA allocation which are divided into mainly two main perspectives: the recipient country's need and the donor country's interest. First, the determinant models of ODA distribution have been classified according to donor country's interests and recipient country's needs as Maizels and Nissanke (1984) and Berthélemy (2006) argued. The donor country's interest models, created by Berthélemy and Tichit (2004) and Tuman and Strand (2006), assume that ODA is distributed as means of military, political, and economic and trade interests. Berthélemy and Tichit (2004) argued that donors pay great attention to political governance to increase the effectiveness of ODA.

Hansen and Tarp (2001) analyzed data from 64 countries to determine the relationship between aid and economic growth. Wagner (2003) investigated the relationship between ODA and donor countries' export expansion using the gravity model. Alesina and Dollar (2000) emphasized aid allocation policies with donor interest. Younas (2008) argued that political and strategic considerations of donors are the major determinants of aid allocation. Bermeo (2017) viewed aid allocation as a targeted development in an increasingly connected world. Lin *et al.* (2020) studied the model for enhancing aid effectiveness for donors to raise the level of effort recipients.

Second, the recipient country's need models have been analyzed by Ranis *et al.* (2000), Neumayer (2003), Gates and Hoeffler (2004), Tuman and Ayoub (2004), Hoeffler and Outram (2011). They examined the affecting factors of ODA distributions by using population, gross domestic product (GDP), infant mortality, political freedom, and human rights. Svensson (2003) explained that aid to developing countries with a well-established system contributes to economic growth. Collier and Dollar (2001, 2002) analyzed the effects of ODA to reduce poverty. Easterly (2003) analyzed the foreign aid to economic growth. Golder *et al.* (2021) investigated Bangladesh foreign aid's influence on the country's economic growth with annual data covering the 1989–2018. They found that the aid has a positive effect on the recipient country's economic growth in the long run.

However, it is not easy to separate the recipient country's need and donor country's interest as motivations of ODA allocation as the overlap. Furthermore, the aid coordination between countries can increase the aid effectiveness, as Bigsten and Tengstam (2015) found that the dyadic ODA interests could improve the effects of ODA. In particular, Davies and Klasen (2019) assessed to examine whether donor coordination, free-riding, selectivity, specialization, and common donor motivations drive bilateral aid allocation as determinants using spatial econometrics. They found that recipients will be favored by most donors "darlings" while others are largely deserted by the international community and are aid “orphans”. Without effective coordination, such fragmentation thereby can have the negative effects on receiving the international aid.

There have been a few studies on the distribution of Korea’s ODA. Lumsdaine and Schopf (2007) found that Korea’s foreign assistance levels remained quite low throughout the 1980s and 1990s, but have risen significantly in the beginning of 2000’s. They argued that while, historically, strong support for aid has been linked primarily to humanitarian motives, Korea did not emphasize these rationales for aid very strongly together with the weak development of Korean civil society, thereby resulted in low levels of support for aid and low aid levels through the 1990s. Dreher, Nunnenkamp and Thiele (2011) analyzed the determinants of Korea’s aid using Tobit model. The population, share of recipient export, mineral and energy depletion, and fragile state dummy variables had the negative effects on Korea’s aid, while the distance, per capita GDP, corruption, and people affected by disasters did not affect Korea’s aid to recipient countries.

Koo and Kim (2011) analyzed the explaining determinants of Korea’s ODA during 1989–2007 using logit and generalized least squares regression from the sociological perspective. Sohn *et al.* (2011) analyzed Korea’s ODA allocation using Tobit and logit models using trade amount, FDI, energy production, per capita income, and political rights. Chung and Hwang (2022) investigated the economic and social impacts of international aid at the national level on African countries. Moon (2022) studied the determinants of green ODA distribution on OECD Development Assistance during 2002–2015 from politics and environment. Jung *et al.* (2022) examined the determinants of ODA from donors’ political and economic interests and recipients’ socio-economic needs using the simple regression model with a neo-realist and structural approach. However, they analyzed the political aspects of determinants of ODA using the simple regression model and did not consider the spatial effects of ODA at all.

Thus, most previous ODA studies above did not consider the spatial effects on the determinants of ODA policies. However, the spatial dependence of aid flows are very important to examine the allocation of international aid because the aid flows are inherently spatial interactions. If we ignore these spatial effects of the determinants of aids, the estimators will be the inconsistent and inefficient estimators as seen in Yi (2023, 2024). As the dependent variable is likely to be correlated with its spatial lag, Davies and Klasen (2019) considered the spatial lag effects of foreign aid and used the generalized method of moments (GMM) with instrument variables instead of OLS estimation method.

3. THEORETICAL BACKGROUND OF THE MOTIVES FOR INTERNATIONAL AID

In this study we focus on the dependence effects of international aid flows such as ODAs. This does not cover the entire motives of donor's aid flows into recipient countries. When the aid allocation literature has analyzed aid flows, the previous studies have the tendency to distinguish motivations and interests of donors and recipients. Moreover, a process of mutual interaction between donors and recipients also affect the aid flows. International aid flows would prefer to have a positive effects of donor's gross national incomes that satisfy their needs. The larger donor's gross national incomes, trade, and FDI, the more likely they will be able to provide the international aids. Donors may pursue donor-specific motivations of aid flows which may affect the priorities of aid allocation to particular recipients.

On the other hand, the recipient countries are interested in maximizing the aid flows on economic development. Davies and Klasen (2019) pointed out as the recipient's aid needs might be important determinants for international aid flows, the selectivity might also be driven by the positive developments in recipient countries. Countries with successful economic policies might attract more aid to associate that success with these aid flows. This could strengthen a crowding-in in 'donor darlings', and a collective flight from 'donor orphans' that it makes 'donor orphans' more difficult to attract foreign aid. The recipient country's income trade, and FDI also may influence the amount of donor's aid which may be depend on different motivations.

Finally, the level of corrupt recipient's autocracy will also lead the negative effects on receiving the foreign aid because donor's aid will be uncertain and unpredictable. Aid is often provided to those countries on which the donor countries have political and strategic interest so that they can influence the internal politics of the recipient countries through political regime. Thus, donor countries in capitalism and market economy want the recipient countries to establish democratic governments.

Thus, the foreign aid will greatly depend on the overall motivation of the donor and recipient as well as the effectiveness of fulfilling their different motivations. International aid would also prefer more coordination between the donors and recipients. This coordination would imply a positive effects on the donor's aid flows into recipient countries as it coordinates their aid motivations and make aid flows more predictable.

However, the motivations of donors and recipient are not well captured since their motivations and effectiveness are mixed and complementary each other to fulfill their strategic, political, and economic objectives. The relative importance of these objectives might also vary over specific country and time so that it becomes largely an empirical question to inquire which effects dominate for different country and time periods. Thus, it is impossible to distinguish between common motives of aid allocation. Thus, this paper will select the motivations of ODA allocation as combining recipient country's need, donor country's interest, and their coordination based on the existing literature as follows.

First, recipients need foreign aids for economic growth. Donor countries also allocate the aid to promote economic development in the recipient countries. Second, they require FDI from donor countries. Third, donor and recipient often used ODA as a tool for expanding trade to achieve national development. This trade relationship increases bilateral aid from donor countries. Fourth, aid has been used as an effective tool for establishing the democracy level of recipient with political relationship between donor and recipient countries.

In addition to motives of aid flows, this study will consider whether Korea's aid flows have the spatial dependence effects to obtain the consistent and efficient consistent estimators of determinants of Korea's ODA in recent years.

4. EMPIRICAL SPECIFICATION OF SPATIAL AID ALLOCATION

This study will consider whether Korea's aid flows have the spatial dependence effects to obtain the consistent and efficient estimators of determinants of Korea's ODA in recent years. Davies and Klasen (2019) used the endogenous spatial lag model and cluster error terms. However, this paper uses not only the spatial lag and spatial error models but also and the combined spatial lag and spatial error model with the cointegration methodology. In this section, we describe our empirical methodology as follows.

4.1. NON-SPATIAL ODA ALLOCATION MODEL

The traditional model of ODA does not consider spatial effects. In this study, we synthesized the donor's interest model and the recipient's need models. The determinants of the ODA allocation are based on the applied gravity model after synthesizing the donor country's interest model and the recipient country's need.

Thus, the ODA will be positively influenced by the democracy level (LDEMO) and GDP of the ODA recipient country (LMGDP), world ODA (LTODA), and world FDI (WFDI). However, it will be negatively influenced by the distance (LDIST) between the donor country and recipient country, the donor country's export (LEX) and import (LIM). Therefore, we have the following determinants model of non-spatial ODA model:

$$LKODA_{ij,t} = \alpha_i + \beta_1 LDEMO_{jt} + \beta_2 LDIST_{ij} + \beta_3 LEX_{ij,t} + \beta_4 LIM_{ij,t} + \beta_5 LMGDP_{ij,t} + \beta_6 LTWODA_{jt} + \beta_7 LWFDI_{jt} + u_{ijt},$$

where t represents the year, i represents donor country, j represents recipient country, and temporal disturbances, respectively, and uijt represents the disturbance term. The model describes that the main determinants of donor country's ODA are affected by the non-spatial model.

However, we can think of the panel model with the fixed effect and the random effect if the error term consists of the three components since the other explainable factors can be included in the error term. Suppose we have a two-way error component model as follows:

$$LKODA_{ij,t} = \alpha_i + \beta_1 LDEMO_{jt} + \beta_2 LDIST_{ij} + \beta_3 LEX_{ij,t} + \beta_4 LIM_{ij,t} + \beta_5 LMGDP_{ij,t} + \beta_6 LTWODA_{jt} + \beta_7 LWFDI_{jt} + u_i + \mu_t + \varepsilon_{ijt},$$

Where $u_{ijt} = u_i + \mu_t + \varepsilon_{ijt},$. u_i is the unobservable characteristic of the specific group, μ_t is the unobservable characteristic of the specific time, and ε_{ijt}, is the iid disturbance term. While the fixed effect model regards both u_i and μ_t as the parameters to estimate, the random effect model regards both u_i and μ_t as the disturbance terms in this study.

4.2. SPATIAL ESTIMATION MODEL AND SPECIFICATION

We now analyze the influencing factors of Korea's ODA including its spatial effects. This model adopts the spatial lag model to analyze the existence of the spatial effect on the ODAs based on Anselin and Rey (2014). Here, we adopt the Spatial Autoregressive Models following Yi (2023, 2024). Spatial Autoregressive Models can be classified as the spatial lag model, spatial error model, and the combined spatial lag and spatial error model or spatial autocorrelation model.

However, if there exist any spatial effects on the ODA, we cannot use the standard econometric estimation methods in the spatial dependence models such as the spatial lag model and spatial error model. Therefore, we have to check whether the ODAs have spatial effects or not. In spatial model, the spatial weight (or connectivity) matrix is at the heart of spatial econometrics. If the data are observed on a regular square lattice grid as Arbia (2014) argued, closeness can be used rook or queen criterion. However, in spatial econometrics, this paper utilizes the irregular spaced regions or countries. Thus, the $n \times n$ spatial weight matrix (W) can be defined as follows.

Thus, we cannot use the conventional standard econometrics to obtain the consistent estimators when the entry $w_{ij} \neq 0$ if $i \neq j$. W can be the functions of geographical, economic or social distances between areas. In this study, W can be the spatial dependence from the distances. Thus, this study utilizes the inverse distance criterion between donor and recipient countries. The conventional W matrix for the irregular spaced countries is standardized to sum unity in each row. Furthermore, the conventional W matrix is standardized to sum unity in each row as follows. Thus we can have the spatially lagged dependent variable vector (Wy) for the spatial weight matrix W as follows:

$$W_{IJ} = \frac{W_{IJ}}{\sum_{J=1}^{N} W_{IJ}}.$$

4.2.1. Spatial Lag Model

The main function of the spatial lag model is to verify the spatial spillover effect caused by the dependent variable. The influence factors of the dependent variable can be used in other regions, and the spatial lag model is expressed with the following formula:

$$y = \rho Wy + X\beta + u, u \sim N(0, \Sigma_n),$$

where y is a $n \times 1$ vector of observations on the dependent variable such as Korea's ODA, W is a $n \times n$ spatial weight matrix. Wy is a spatially lagged dependent variable vector for the spatial weight matrix W with spatial autoregressive parameter ρ. Thus we can have the spatially lagged dependent variable vector(Wy) for the spatial weight matrix W as follows:

$$Wy = \sum_{j=1}^{n} \frac{w_{ij}}{\sum_{j=1}^{n} w_{ij}}.$$

X is an $n \times k$ matrix of k exogenous explanatory variables such as determinants of ODA with β, and the $n \times 1$ vector of errors u. Therefore, ρ denotes a spatial regression coefficient, and β reflects the influence of the independent variable X on dependent variable Y, and the role of Wy lies in the spatial distance.

The influence of the spatial distance is reflected, and ε is the $n \times 1$ error vector. The variance-covariance matrix for error terms is $E(uu') = \Sigma_n$ which covers the heteroscedasticity, spatial autocorrelation, or both. In the absence of heteroscedasticity and spatial autocorrelation, the variance–covariance matrix for error terms is $E(uu') = \sigma^2 I_n$. However, the presence of the spatially lagged dependent variable induces endogeneity or simultaneous equation bias. Therefore, the spatial lag term is as follows:

$$Wy = W(I–\rho W)^{-1}X\beta + W(I–\rho W)^{-1}u.$$

As this term violates the classical assumptions of OLS estimation that this Wy variable should be uncorrelated with the error terms as below, an OLS estimator of β is inappropriate to obtain the consistent estimators of β.

Therefore, we use the two stage least squares (S2SLS) after adopting a set of instruments $Q = [X, WX, W^2X]$ to correct the endogeneity of Wy. The spatial lag model specification can be further generalized by including additional endogenous variable; Y is an $n \times s$ observation on endogenous variables other than the spatially lagged dependent variable with the coefficient γ.

$$y = \rho Wy + X\beta + Y\gamma + u = Z\delta + u,$$

where $Z = [X, Y, Wy]$ and the $(k+s+1) \times 1$ coefficient column vector $\delta = [\beta', \gamma', \rho']'$. Then we have

$$E[Wy|Z] = W(I–\rho W)^{-1}X\beta + W(I–\rho W)^{-1}Y\gamma.$$

Thus, as Y can be endogenous, Y and $W(I–\rho W)^{-1}$should be replaced by its instruments such as spatial lagged variables. Then the estimator becomes

$$\delta_{S2SLS} = (H'Z)^{-1}H'y, \text{ where } H = (Q'Q)^{-1}Q'Z.$$

We can also use the full maximum likelihood method (ML) in a spatial lag regression analysis. ML estimation (MLE) can effectively overcome the estimation bias caused by endogenous problems and also scientifically reflect the spatial dependence of countries and accurately measure the spatial effect. Therefore, we can estimate the following determinants of the Spatial Lag Model of ODA by S2SLS or MLE.

$$\begin{aligned} LKODA_{ij,t} = \alpha_i &+ \rho WLKODA_{ij,t} \\ &+ \beta_1 LDEMO_{jt} + \beta_2 LDIST_{ij} + \beta_3 LEX_{ij,t} + \beta_4 LIM_{ij,t} \\ &+ \beta_5 LMGDP_{ij,t} + \beta_6 LTWODA_{jt} + \beta_7 LWFDI_{jt} \\ &+ u_{ijt} \end{aligned}$$

4.2.2. Spatial Error Model

As Anselin and Bera (1998) argued, a spatial error model uses a spatial weights matrix which is applied to the error terms instead of the dependent variable like the spatial lag model. The resulting error variance will be such that while unbiased, OLS estimates will be inefficient; thus, other estimation techniques are required.

Now, we have a spatial error autocorrelation model as follows. Where y is a $n \times 1$ vector of observations on the dependent variable, X is an $n \times k$ matrix of observations on exogenous explanatory variables with β. W is a $n \times n$ spatial weight matrix operator vector of observations as defined before, and a $n \times k$ vector of errors u.

$$y = X\beta + u, u = \lambda W u + \varepsilon,$$

where λ is the spatial autoregressive parameter. ε is a vector of idiosyncratic error. These errors can be heteroscedastic with $E[\varepsilon_i^2]$, but uncorrelated $E[\varepsilon_i \varepsilon_j] = 0$ for $i \neq j$. In heteroscedastic case, $E[\varepsilon_i^2] = \sigma^2$. Thus, we have the following equation:

$$u = (I – \lambda W)^{-1}\varepsilon \text{ and } y = X\beta + (I – \lambda W)^{-1}\varepsilon.$$

Now, the reduced form of the SAR error process is derived as following equation:

$$(I – \lambda W)y = (I – \lambda W)X\beta + \varepsilon.$$

Thus, the spatial filter $(I – \lambda W)$ removes the spatial error autocorrelation from the error terms but not heteroscedasticity as a spatial Cochrane-Orcutt transformation. Now let $y_s = (I – \lambda W)y$ and $X_s = (I – \lambda W)X$. Then, we have $y_s = X_s\beta + \varepsilon$.

Thus, we can estimate this equation by the spatially weighted least squares (SWLS) estimation method or spatial Cochrane-Orcutt estimation using spatially filtered variables using the consistent estimator of λ for the autoregressive parameter.

$$\beta_{SWLS} = (X_s' X_s)^{-1} X_s' y_s, \text{ where } X_s = (I – \lambda W)X, y_s = (I – \lambda W)y$$

The SAR error model can be specified as below where exogenous and endogenous variables are present on the right hand side.

$$y = Z\delta + u, u = \lambda W u + \varepsilon,$$

where the matrix Z includes both exogeneous and endogenous variables. Then, spatially filtered form or spatial Cochrane-Orcutt transformation removes the spatial autoregression from error term as below:

$$(I – \lambda W)y = (I – \lambda W)Z\delta + \varepsilon, y_s = Z_s\delta + \varepsilon,$$

where these errors can be heteroscedastic with $E[\varepsilon_i^2]$, but uncorrelated $E[\varepsilon_i \varepsilon_j] = 0$ for $i \neq j$. Therefore, we can estimate this equation by the spatially weighted two stage least squares (SW2SLS) estimation method as below:

$$\delta_{SW2SLS} = (H'Z_s)^{-1}H'y, \text{ where } H = (Q'Q)^{-1}Q'Z.$$

However, when we have homoscedastic errors, we have a consistent estimator of λ, if we have heteroscedastic errors, we cannot get a consistent estimator of λ. Therefore, in this case, we must use the GMM estimation. The GMM estimator is robust to the heteroscedastic errors and an asymptotic variance matrix is obtained for the parameter λ. Therefore, we can estimate the following determinants of the spatial error model (SEM) of ODA by the SW2SLS estimation or GMM estimation.

$$\begin{aligned} LKODA_{ij,t} = \alpha_i + \rho WLKODA_{ij,t} \\ + \beta_1 LDEMO_{jt} + \beta_2 LDIST_{ij} + \beta_3 LEX_{ij,t} + \beta_4 LIM_{ij,t} \\ + \beta_5 LMGDP_{ij,t} + \beta_6 LTWODA_{jt} + \beta_7 LWFDI_{jt} \\ + (I\text{–}\lambda W)^{-1}\varepsilon_{ij,t} \end{aligned}$$

4.2.3. Cointegrated Spatial Autoregressive Combined Model

We consider a model that combines the features of the spatial lag model and the spatial autoregressive model as follows:

$$y = \rho Wy + X\beta + u, u = \lambda Wu + \varepsilon.$$

In the regression model, the notations are the same as before. y is a $n \times 1$ vector of observations on the dependent variable, W is a $n \times n$ spatial weight matrix operator vector of observations, Wy is a spatial lag term with spatial autoregressive parameter ρ, X is an $n \times k$ matrix of observations on exogenous explanatory variables. The error (u) follows a spatial autoregressive specification. W is a $n \times n$ spatial weight matrix operator vector of observations, and a $n \times 1$ vector of errors u. λ is the spatial autoregressive parameter. ε is a vector of idiosyncratic error. Now, if we substitute $u = (I\text{–}\lambda W)^{-1}\varepsilon$ into the spatial lag model, we have the reduced form can be easily derived as follows:

$$y = (I\text{–}\rho W)^{-1}X\beta + (I\text{–}\rho W)^{-1}(I\text{–}\lambda W)^{-1}\varepsilon.$$

Therefore, the combo model will be a special case of a spatial autoregressive error term that contains endogenous explanatory variables like below:

$$y = Z\delta + (I\text{–}\lambda W)^{-1}\varepsilon.$$

where $Z = [Wy, X, Y]$, and $\delta = [\beta', \gamma', \rho']'$. That includes the spatially lagged dependent variable (Wy), exogeneous (X), and endogenous (Y) explanatory variables. Thus, we can use a GMM estimation as the generalized SW2SLS (GS2SLS) of the combo model of ODA using a spatial error correction term (ECM) in long-run cointegration equation as seen in Yi (2023). Then, we can estimate the cointegrated spatial autoregressive combined model (CSAC) by generalized SW2SLS of SGMM estimation as follows:

$$\begin{aligned}\Delta LKODA_{ij,t} = \alpha_i &+ \beta_1 (I–\rho W)^{-1} \Delta LDEMO_{jt} + \beta_2 (I–\rho W)^{-1} \Delta LDIST_{ij} \\ &+ \beta_3 (I–\rho W)^{-1} \Delta LEX_{ij,t} + \beta_4 (I–\rho W)^{-1} \Delta LIM_{ij,t} \\ &+ \beta_5 (I–\rho W)^{-1} \Delta LMGDP_{ij,t} + \beta_6 (I–\rho W)^{-1} \Delta LTWODA_{jt} \\ &+ \beta_7 (I–\rho W)^{-1} \Delta LWFDI_{jt} + \beta_8 (I–\rho W)^{-1} \Delta ECM_{ij,t} \\ &+ (I–\lambda W)^{-1} (I–\lambda W)^{-1} \varepsilon_{ij,t}\end{aligned}$$

4.2.4. Spatial Autocorrelation and Spatial Dependence Test

In the study of regional economic phenomena, we test the corresponding spatial autocorrelation or spatial dependence in the spatial models. To test the spatial autocorrelation or spatial dependence, we use Moran's I test in the classic OLS estimation; however, we use Anselin-Kelejian's (1997) test of the extended version of Moran's I test in a 2SLS estimation where only non-spatial endogenous variables are in the model.

$$\text{Moran's I} = \frac{n \sum_i \sum_j W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_i \sum_j W_{ij} (X_i - \bar{X})^2} = \frac{e'We/S_0}{e'e/n}.$$

Where $S_0 = \sum_i \sum_j W_{ij}$, e is a vector of OLS residuals.

$$\text{Anselin-Kelejian's Test} = \frac{\left(e'We/(\frac{e'e}{n})\right)^2}{\text{tr}(WW + W'W)} \sim \chi^2(1)$$

5. EMPIRICAL RESULTS

The data collected for this study were from 2010 to 2019 using all available countries without missing aid and other economic statistics, mainly from the Bank of Korea, World Foreign Direct Investment Statistics, World Bank Database, and the Global Governance Indicators Database. The available 55 recipient countries were selected based on core partner country of Korea as in Table 1.

Region (number of countries)	Countries
Asia (22)	Cambodia, Indonesia, Laos, Mongolia, Philippines, Thailand, Vietnam, Afghanistan, Azerbaijan, Bangladesh, India, Kazakhstan, Myanmar, Nepal, Pakistan, Sri Lanka, Uzbekistan, Iran, Iraq, Jordan, Lebanon, Yemen
Africa (18)	Algeria, Egypt, Libya, Morocco, Tunisia, Ethiopia, Kenya, Mozambique, Rwanda, Uganda, Tanzania, Cameroon, DR Congo, Côte d'Ivoire, Ghana, Mali, Nigeria, Senegal
Europe (3)	Belarus, Moldova, Ukraine
Pacific (4), Central America (8)	Fiji, Papua New Guinea, Solomon Islands, Vanuatu Mexico, Honduras, Guatemala, Bolivia, Colombia, Ecuador, Paraguay, Peru

Table 1: SELECTED 55 RECIPIENT COUNTRIES LIST OF ODA FROM KOREA. Table 1 represents the available selected 55 countries list of ODA from Korea.

The GDPs were extracted from the World Bank. Korea's trade values with recipient countries were extracted from IMF statistics. The democracy index was obtained from Economist Intelligence from each year's Democracy Index based on surveys of political system for 55 countries.[1] All ODAs, import values, and export values are measured as thousand US dollars; recipient country's GDP and world foreign direct investment are measured as million US dollars.

Table 2 shows the basic statistics of the democracy index (DEMINDEX), distance from Korea (DISTANCE), Korea's export (EX) to recipients, Korea's import (IM) from recipients, Korea's ODA(KODA), recipient country's GDP (MGDP), total ODA to recipient countries (TWODA), world foreign direct investment (WFDI), respectively. Some minimum values are zeros in Korea's exports, Korea's ODAs, the world ODA and world foreign direct investment to recipient countries.

This study introduces the spatial weight of distance between countries GeoDa, STATA, R, and Python softwares to estimate the spatial effects in several spatial econometric models. Thus, the determinants of Korea's ODA was based on

[1]Economist Intelligence (EIU), Democracy Index each year, https://www.eiu.com/n/

Variable	Mean	Maximum	Standard Deviation
DEMINDEX	4.5224	7.92	1.7599
DISTANCE	8735.8	18504	4018
EX	32631	$3.2194 \cdot 10^5$	56853
IM	40850	$5.1675 \cdot 10^5$	73502
KODA	19752	$2.3811 \cdot 10^5$	29370
MGDP	$1.6897 \cdot 10^5$	$2.9402 \cdot 10^6$	$3.6403 \cdot 10^5$
TWODA	$1.202 \cdot 10^6$	$8.0569 \cdot 10^6$	$1.2434 \cdot 10^6$
WFDI	$3.7085 \cdot 10^6$	$5.0791 \cdot 10^7$	$7.5016 \cdot 10^6$

Table 2: BASIC STATISTICS OF ODA DETERMINANTS. Table 2 shows the basic statistics of the democracy index (DEMINDEX), distance from Korea (DISTANCE), Korea's export (EX) to recipients, Korea's import (IM) from recipients, Korea's ODA(KODA), recipient country's GDP (MGDP), total ODA to recipient countries (TWODA), world foreign direct investment (WFDI), respectively.

donor interest and recipient need, as well as the applied trade gravity model. All values are transformed as log values. Based on the different characteristics of Korea's ODA, along with 55 countries, this study selected the recipient country's GDP (LGDP), Korea's export to recipient countries (LEX), Korea's import from recipient countries (LIM), total FDI to recipient countries (LWFDI), total ODA to recipient countries (LWFDI), distance between Korea and the recipient country (LDIST), and democracy index of the recipient country (LDEMO).

5.1. NON-SPATIAL ECONOMETRIC ESTIMATION

5.1.1. Heteroskedastic and Autocorrelation Consistent Estimation

The spatial effect is not included in the classical OLS econometric model. In Table 3, the heteroskedastic and autocorrelation consistent (HAC) standard errors estimates and the associated p-values. The HAC standard errors estimate suggests that the democracy level of ODA recipient countries can have a significantly positive impact on Korea's ODA to recipient countries at the 5% significance level. The distance can have a significantly negative impact on Korea's ODA to recipient countries as the trade gravity model implies.

Korea's export to and its import from the recipient country will not affect Korea's ODA to recipients at the 5% significance level. This implies that Korea's ODA to recipient countries is not related with its trade. The economic impact of the recipient GDP (LMGDP) on Korea's ODA seems to have a positive impact

ODA Variables	HAC Estimation		
Variable	Coefficient	Std. Error	P-value
LDEMO	1.0813	0.2281	0.0000
LDIST	-0.9070	0.1161	0.0000
LEX	-0.0763	0.0922	0.4081
LIM	-0.1677	0.1745	0.3370
LMGDP	0.1386	0.1511	0.3593
LTWODA	0.1503	0.0359	0.0000
LWFDI	0.0359	0.0230	0.1191

Table 3: HAC ECONOMETRIC ESTIMATION OF ODA DETERMINANTS. In Table 3, the heteroskedastic and autocorrelation consistent (HAC) standard errors estimates and the associated p-values. The HAC estimation shows that the democracy level of ODA recipient countries and world ODA (LTWODA) positively influence but the distance can have a negative impact on Korea's ODA.

and its elasticity coefficient is 0.14. However, it is not significant at the 5% level because the p-value is larger than 0.05.

The world ODA (LTWODA) to recipient countries positively influences Korea's ODA to recipients at the 5% significance level. It implies that recipients need ODAs not only from Korea but also from other countries. However, the world FDI (LWFDI) does not positively affect Korea's ODA to the recipients at the 5% significance level. This implies that Korea's ODA to the recipients does not consider the economic environment such as international trade, FDI, and the economic sources relatively.

5.1.2. Poisson Pseudo-Maximum Likelihood Estimation

Missing observations in bilateral data can occur due to various reasons, such as lack of reporting, differences in data collection standards, or unavailability of data for certain periods or countries. Ignoring missing data or using simple imputation methods can lead to biased estimates if the missingness is not completely random. Zeros in bilateral data, particularly in trade or ODA flows, are common when no trade or aid is recorded between pairs of countries. Simply dropping these observations or replacing them with small positive numbers can introduce bias or distort the true relationships.

Silva and Tenreyro (2006) propose the Poisson Pseudo-Maximum Likelihood (PPML) estimator as a robust method to handle zero trade flows and heteroscedasticity in economic gravity models. The PPML estimator can be used in situations where the dependent variable includes zeros, as it does not require log-transformation of the dependent variable. This approach can be extended to other contexts, such as ODA flows, where zeros are prevalent.[2]

Chen and Roth (2024) also argue that the missing data and zeros might relate to a recent development in econometric methodologies addressing similar issues. Hypothetically, this work could involve advanced methods like machine learning based imputation or model based approaches to deal with missing data and zeros, potentially building on earlier methodologies like PPML or extending them to more complex settings. Thus, PPML is particularly useful when the dependent variable has zeros, which is common in bilateral ODA model. PPML is consistent even in the presence of heteroscedasticity and can handle different types of distributional assumptions for the errors.

Table 4 shows the results of PPML estimations using distance cluster(LDIST) and country cluster(id1). Korea's exports, Korea's imports, the recipient GDP, and the world FDI (LWFDI) to the recipients seem to be not significant in Korea's ODA determination. This means that there are unobservable factors such as political, historical, social, cultural factors as well as spatial dependence effects.

ODA Variables		Cluster(LDIST)		Cluster(id1)	
Variables	Coefficient	Std. Error	P-value	Std. Error	$P > \|z\|$
LDEMO	0.1244	0.0276	0.000	0.0725	0.086
LDIST	-0.1006	0.0126	0.000	0.0329	0.002
LEX	-0.0091	0.0106	0.394	0.0228	0.692
LIM	0.0180	0.0197	0.361	0.0500	0.719
LMGDP	0.0154	0.0169	0.363	0.0483	0.750
LTWODA	0.0180	0.0047	0.000	0.0098	0.066
LWFDI	0.0043	0.0028	0.128	0.0047	0.363
Pseudo log-likelihood		-1218.9686		-1218.9686	
Pseudo R^2		0.1300		0.0125	

Table 4: POISSON PSEUDO-MAXIMUM LIKELIHOOD (PPML) ESTIMATION OF ODA DETERMINANTS. Table 4 shows the results of PPML estimations using distance cluster(LDIST) and country cluster(id1). The Korea's exports, Korea's imports, the recipient GDP, and the world FDI (LWFDI) to the recipients seem to be not significant in Korea's ODA determination.

[2]The anonymous reviewer pointed out this PPML issues with the missing data and zero values in the ODAs.

However, even though the missing data and zeros are important in ODA model, only a few observations below 2% of economic variables have the zeros and missing values as seen in Table 4. Thus, this study does not focus on the missing data and zero value issues. Also we have several PPML estimations using the distance and year clusters, the results are almost the same.

5.1.3. Panel Estimation with Fixed and Random Effect

In panel regression, there are two types of models: fixed-effects models, which include all explainable factors in addition to the independent variables as error terms, and random-effects models. However, while the fixed effect models consider the variations from specific group and specific time as the parameters of the error terms to estimate, the random effect models consider the random errors in the disturbance error terms. These unobservable factors could include cultural ties, historical relationships, or persistent policy preferences in ODAs. The standard OLS estimation approaches applied to panel data, without considering fixed effects, might fail to account for these unobserved factors. This omission can lead to biased estimates if these unobserved factors are correlated with the explanatory variables in the model.

Thus, Table 5 shows that the panel estimation with the fixed and random effects by each recipient country using OLS, GLS, and MLE methods. First, Table

ODA Variables	FE(id1) : OLS			RE(id1): GLS			RE (id1): MLE		
Variable	Coeff	Std. Error	$P>\|z\|$	Coeff	Std. Error	$P>\|z\|$	Coeff	Std. Error	$P>\|z\|$
LDEMO	0.359	0.458	0.436	0.485	0.452	0.283	0.469	0.321	0.143
LEX	-0.051	0.096	0.595	-0.048	0.081	0.549	-0.048	0.082	0.555
LIM	-0.378	0.236	0.115	-0.323	0.220	0.143	-0.329	9.220	0.041
LMGDP	2.079	0.389	0.000	0.691	0.280	0.013	0.728	0.200	0.000
LTWODA	0.034	0.013	0.010	0.038	0.013	0.005	0.037	0.021	0.080
LWFDI	-0.041	0.021	0.064	-0.030	0.014	0.029	-0.031	0.020	0.117
sigma_u	3.138			1.634			1.752		
sigma_e	0.908			0.908			0.923		
rho	0.922			0.793			0.782		
FE test: F test that all $u_i = 0$: $F(54, 489) = 32.19$, $Prob > F = 0.000$									
RE test: LR test of sigma_u=0: $chibar2 = 552.68$, $Prob >= chibar2 = 0.000$ in RE(id1,theta):MLE									

Table 5: PANEL FIXED EFFECT AND RANDOM EFFECT ESTIMATION (BY COUNTRY). The rho represents the fraction of variance due to sigma_u. Coeff and Std. Error represent the coefficient and the standard error, respectively. Table 5 shows that the panel estimation with the fixed and random effects by each recipient country using OLS, GLS, and MLE methods.

ODA Variables	FE(Year) : OLS Method			RE(Year): MLE Method		
Variable	Coefficient	Std. Error	$P > \|z\|$	Coefficient	Std. Error	$P > \|z\|$
LDEMO	0.8075	0.1909	0.0000	0.7986	0.1898	0.0000
LEX	-0.0625	0.1083	0.5640	-0.0732	0.1072	0.4940
LIM	0.1021	0.1575	0.5170	0.0975	0.1561	0.5320
LMGDP	-0.0547	0.1074	0.6110	-0.0308	0.1060	0.7710
LTWODA	0.1318	0.0317	0.0000	0.1321	0.0316	0.0000
LWFDI	0.0558	0.0236	0.0180	0.0525	0.0234	0.0250
sigma_u	0.3674			0.2449		
sigma_e	1.8225			1.8125		
rho	0.0390			0.0179		
Test	F test that all $u_i = 0$: $F(9,534) = 2.20$, $Prob > F = 0.0206$			LR test vs. linear model: $chibar2(01) = 2.93$, $Prob >= chibar2 = 0.0436$		

Table 6: PANEL FIXED EFFECT AND RANDOM EFFECT ESTIMATION (BY YEAR). Table 6 shows the panel estimation with the fixed and random effects by time (YEAR) across of Korea's ODA determinants using the OLS and MLE method, respectively.

5 shows the fixed and random effects by individual country (id1) of Korea's ODA determinants. The fixed effect model within regression shows that the recipient GDP (LMGDP) and the recipient's world ODA (LTWODA) and using within-group transformation are positively related with Korea's ODA at 5% significant levels.

Accordingly, the fixed effects models allow for the control of unobservable, time-invariant factors that differ across countries but are constant within a country over time. In the context of ODA, factors such as historical relationships such as colonial ties, long-standing diplomatic relations, or initial levels of ODA received can be crucial determinants of ongoing aid flows. By including country-specific fixed effects, the model would control for these unobservable factors, and obtain more accurate and reliable estimates of the effects of other explanatory variables. This is particularly important in ODA studies of bilateral relationships, where these unobservable factors often play a significant role.

Second, Table 6 shows the panel estimation with the fixed and random effects by time (YEAR) across of Korea's ODA determinants using the OLS and MLE method, respectively. The fixed effect and random effect models within regression shows that the recipient‘s democracy level (DEMO), the recipient's

Variable	(b)	(B)	(b-B)	$\sqrt{\text{diag}(V\_b - V\_B)}$
Coefficient	Group_FE	Group_RE	Difference	Std. Err.
LDEMO	0.3591532	0.4851222	-0.1259690	0.2166956
LEX	-0.0517543	-0.0487919	-0.0029624	0.0198074
LIM	-0.3782886	-0.3232716	-0.0550170	0.0648004
LMGDP	2.079559	0.6917035	1.3878550	0.2557864
LTWODA	0.0345772	0.0380196	-0.0034424	0.0039442
LWFDI	-0.0409602	-0.0309496	-0.0100106	0.0053266
Test of H_0: Difference in coefficients not systematic.				
$chi2(6) = (b-B)'(V_b - V_B)^{-1}(b-B) = 35.32$, $Prob > chi2 = 0.000$				

Table 7: HAUSMAN TEST AND MODEL SELECTION. b = Consistent under H_0 and H_a; B = Inconsistent under H_a, efficient under H_0; obtained from the one-way error component model.

world ODA (LTWODA) are positively related with Korea's ODA at 5% significant levels. But, the world FDI to recipients are positively related with Korea's ODA at 5% significant levels.

Table 7 shows the very low P-values represents the both fixed (FE) and random effects (RE) exist by the F test and the likelihood (LR) test. Since the Table 5 and Table 6 show that the fixed and random effects exist, we have to examine which effect model is more appropriate by Hausman test by the one-way error component regression model with the specific YEAR and Country. The null hypothesis of Hausman test using equation (2) is as follows: $H_0 = \text{Cov}(x_{ijt}, u_i) = 0$ and $\text{Cov}(x_{ijt}, \mu_t) = 0$. The null hypothesis ($H_0$) is accepted, we choose the random effect (RE) model. Otherwise, since the random effect (RE) model can be efficient but inconsistent, we choose the fixed effect (FE) model which is efficient and consistent.

If the null hypothesis, that is, the covariance between the explanatory variables and the error component (U_i) is zero, then the estimators in both effect models are consistent so that we can choose the random effect model. Otherwise, the random effect model estimator cannot be a consistent estimator. In Table 7, since the p-value is smaller than 0.05, the null hypothesis (H_0) is rejected and we choose the fixed effect model is better.

5.2. SPATIAL DEPENDENCE TEST AND SPATIAL ECONOMETRIC ESTIMATION

However, Table 8 shows that adjusted R-squared = 0.123, Akaike information criterion (AIC), Schwarz criterion (SC), and somewhat high multicollinearity. According to the diagnostics of heteroscedasticity, the Breusch-Pagan and Koenker-Bassett tests show that there exist heteroscedasticity in errors at the 5% significance level.

In addition, according to the spatial dependence, the value of Moran's I is shown to be 0.078 with an associated Z-value of 10.859. Moran's I is significant at $p < 0.05$. In other words, Moran's I value rejects the null hypothesis of no spatial autocorrelation. However, Moran's I does not indicate whether the spatial error model or the spatial lag model is the proper alternative spatial regression model.

	Value	p-value
Fitness of Model		
Adjusted R-squared	0.1228	
AIC	2210.363	
SC	2244.843	
Multicollinearity	86.632	
Jarque-Bera	280.521	0
Heteroscedasticity Test		
Breusch-Pagan test	40.601	0
Koenker-Bassett test	18.109	0.0115
Spatial Dependence Test		
Moran's I (error)	Moran's I=0.078 10.859 (Z-value)	0
Lagrange Multiplier (lag)	245.882	0
Robust LM (lag)	205.335	0
Lagrange Multiplier (error)	93.107	0
Robust LM (error)	52.56	0
Lagrange Multiplier (SARMA)	298.442	0

Table 8: DIAGNOSTICS OF FITNESS AND SPATIAL DEPENDENCE FOR NON-SPATIAL OLS. In Table 8, the statistics of Moran's I and Lagrange Multipliers suggest that there are the spatial dependence and the spatial effects in Korea's ODA.

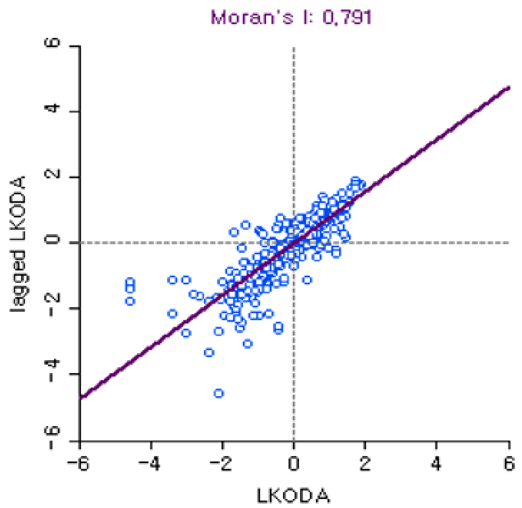

Figure 1: POSITIVE SPATIAL DEPENDENCE OF KOREA'S ODA. Figure 1 represents the positive dependency between Korea's ODA and Korea's lagged ODA.

Thus, we need a more appropriate search strategy which is based on Lagrange Multipliers statistics. Further, the spatial dependence of Korea's ODA to the lagged ODA to recipients is positively related as shown in Figure 1. Robust LM in lags and errors, and Lagrange Multipliers in SARMA are rejected at $p < 0.05$. Therefore, the statistics of Moran's I and Lagrange Multipliers in lags and errors suggest that there are the spatial dependence models to consider the spatial effects such as spatial lag and spatial error autocorrelation models as well as even heteroscedasticity.

5.3. SPATIAL LAG MODEL ESTIMATION

As the dependent variable is likely to be correlated with its spatial lag, an endogeneity problem emerges, and the OLS estimator is not unbiased anymore. Therefore, we must use GMM estimators with spatial lag two stage least squares (S2SLS) or spatial lag maximum likelihood (SLML) estimator to have consistent and robust estimators.

5.3.1. Spatial Lag Two Stage Least Squares and GMM

Even if we use the GMM with White (GMM White) or GMM with HAC (GMM HAC), the standard errors and P-values are very similar, and the qualitative results are the same as GMM in standard case as shown in Table 9. First, when we used the GMM estimation with S2SLS in standard errors, the coefficient (ρ) of first order spatially lagged dependent variable of Korea's ODA (W_LKODA) to the ODA recipient appeared to be 0.829, which represents the spatial lagged effect; further, the pseudo R-squared is 0.22 and the spatial pseudo R-squared is 0.0563. The democracy level of ODA recipients seems to positively influence Korea's ODA to recipient countries, and it is significant at the 5% level. In other words, the political stability of the ODA recipients has a significant impact on the Korea's ODA to the recipients. The political stability of the recipients is an important positive factor affecting Korea's ODA which is related to the donor country's interest. However, the distance between Korea and the recipients cannot have a significantly negative impact on Korea's ODA to recipients at the 5% significance level unlike the conventional trade gravity model. The coefficient is negative, but not significant. We can infer that while the distance seems to be inversely related with ODA, the distance is not important as in international trade because trade is closely related with mutual interest.

Spatial Lag Econometric Regression (GMM with Spatial 2SLS)							
		1. GMM		2. GMM (White)		3. GMM (HAC)	
Variable	Coeff	Std. Error	P-value	Std. Error	P-value	Std. Error	P-value
LDEMO	1.0309	0.1853	0.0000	0.2243	0.0000	0.2207	0.0000
LDIST	-0.1058	0.1801	0.5571	0.1392	0.4475	0.1372	0.4407
LEX	-0.1149	0.1004	0.2527	0.0950	0.2267	0.0941	0.2220
LIM	-0.1896	0.1529	0.2148	0.1741	0.2760	0.1716	0.2691
LMGDP	0.2071	0.1023	0.0430	0.1530	0.1758	0.1510	0.1702
LTWODA	0.0949	0.0305	0.0018	0.0327	0.0037	0.0318	0.0029
LWFDI	0.0007	0.0224	0.9744	0.0264	0.9783	0.0261	0.9780
$W\_LKODA(\rho)$	0.8290	0.0947	0.0000	0.0726	0.0000	0.0719	0.0000
Fitness of Model							
Pseudo R-squared		0.2200				0.2215	
Spatial Pseudo R-squared		0.0563				0.1522	
Spatial Dependence Test (Anselin-Kelejian Test)							
Value		33.052					
p-value		0.0000					

Table 9: SPATIAL LAG REGRESSION WITH SPATIAL 2SLS GMM. Table 9 shows that Korea's ODA will increases as the democracy level and the world ODA to recipients rise. The spatial autoregressive coefficient (ρ) is positive and significant. In Table 9, Anselin-Kelejian test shows the spatial dependence and the inclusion of the spatial lag term has not corrected the spatial correlation.

Second, Korea's export to the recipients and Korea's import from the recipients do not negatively affect Korea's ODA to the recipients. Thus, Korea's ODA is not related to the interest of increasing trade with recipients. However, the economic impact of the recipient's GDP on Korea's ODA is positive 0.207, and it is significant at the 5% level according to the GMM estimation. This means that the motivation of ODA is consistent with recipient countries' needs for economic growth or development. While the world FDI to the recipients does not positively influence Korea's ODA to the recipients at the 5% significance level, the world ODA to the recipients positively influences Korea's ODA to recipients at the significance level. Thus, the more ODA a donor country provides to the recipients, the more the ODA Korea also provides to the same recipients as the recipients needs more ODAs.

Then we use the OLS estimation, the Moran's I test is used. However, we use Anselin-Kelejian (1997) test in a 2SLS estimation as shown in Table 9. According to the diagnostics Anselin-Kelejian test for spatial dependence, the inclusion of the spatial lag term has not corrected the spatial correlation at the 5% significance level. It means that there seems not to have a presence of residual spatial autocorrelation in this S2SLS model.

5.3.2. SLML Model

We estimate the coefficients of explanatory variables by a spatial lag model with spatially maximum likelihood (SLML) estimation when we assume that error terms are homogeneous. The results of spatially maximum likelihood estimation are very similar to the results of spatially weighted least squares estimation except the significance of the spatial autoregressive coefficient (ρ).

As shown in Table 10, the output for spatially full MLE shows that the pseudo R-squared is 0.2215 and the spatial pseudo R-squared is 0.1522. The spatial autoregressive coefficient (ρ) of MLE is 0.618 which is significant at the 5% level. The democracy level of the ODA recipients as the donor interest can positively affect Korea's ODA to the recipients at the 5% significance level.

However, unlike GMM estimators, the distance between Korea and recipients can have a significantly negative impact on Korea's ODA allocation as argued by the trade gravity model.

Both Korea's export to the recipients and Korea's import from the recipients reassure the previous results of GMM estimators that trade will not significantly affect Korea's ODA to the recipients at the 5% significance level. That is, the motivation of Korea's ODA is not consistent with the donor interest of increasing Korea's trade. The economic impact of the recipients' GDP on Korea's ODA

Full Maximum Likelihood Estimation				
Variable	Coeff	Std. Error	z-Statistic	P-value
LDEMO	1.0437	0.1836	5.6852	0.0000
LDIST	-0.3102	0.1547	-2.0056	0.0449
LEX	-0.1050	0.0993	-1.0577	0.2902
LIM	-0.1840	0.1514	-1.2155	0.2242
LMGDP	0.1896	0.1010	1.8770	0.0605
LTWODA	0.1090	0.0295	3.6940	0.0002
LWFDI	0.0097	0.0218	0.4449	0.6564
W_LKODA(ρ)	0.6175	0.1182	5.2264	0.0000
Fitness of Model				
Pseudo R-squared	0.2215			
Spatial Pseudo R-squared	0.1522			
Akaike info criterion	2158.377			
Schwarz criterion	2197.167			

Table 10: SPATIAL LAG FULL MAXIMUM LIKELIHOOD ESTIMATION. Table 10 also shows that Korea's ODA will increases as the democracy level and the world ODA to recipients rise. It also represents the positive dependency between Korea's ODA and Korea's lagged ODA.

seems to have a positively significant effect at the 10% significance level. However, it is not significant at the 5% level.

Therefore, the motivation of ODA is consistent with recipient countries' need for economic growth at 10% significance level. While the world FDI to the recipients does not positively influence Korea's ODA to the recipients at the 5% significance level, the world ODA (LTWODA) to the recipient's ODA positively influences Korea's ODA to the recipients at the 5% significance level. This confirms that Korea is willing to allocate more ODA to the same recipients that other donor countries have provided as such countries require more ODA.

5.4. SPATIAL ERROR MODEL ESTIMATION

The Spatial Error Model emerges when omitted variables exhibit spatial dependence. As the dependent variable is likely to be correlated with its errors, OLS estimator will thus not be unbiased anymore. In a model with only exogenous explanatory variables and spatial error terms, the SWLS (Spatially Weighted Least Squares) estimation in heteroscedasticity would be satisfactory

Variable	Coefficient	Std. Error	z-value	P-value
LDEMO	0.6181	0.1879	3.2890	0.0010
LDIST	0.0445	0.1353	0.3289	0.7422
LEX	-0.1613	0.1479	-1.0907	0.2754
LIM	0.1279	0.0599	2.1347	0.0328
LMGDP	0.2847	0.0729	3.9041	0.0001
LTWODA	-0.6833	0.4776	-1.4307	0.1525
LWFDI	0.4691	0.2789	1.6822	0.0925
Lambda (λ)	0.8633	0.0140	61.7670	0.0000
Fitness of the Regression Model				
Pseudo R-squared	0.1457			

Table 11: SPATIAL ERROR MODEL ESTIMATION IN HETEROSCEDASTICITY (GMM; SWLS). Table 11 shows spatial error coefficient (λ) is positive at the 5% significant level. It also shows that Korea's ODA will increases as the democracy level, Korea;s import, and the world ODA to recipients rise.

to have the consistent estimators. As shown in Table 11, when error terms are heterogeneous, the output for spatially weighted least squares shows that the pseudo R-squared is 0.1457 and spatial error coefficient (λ) is 0.863 which is significant at the 5% level.

The democracy level of ODA recipients can positively affect Korea's ODA at the 5% significance level which reassures the motivation of donor country's interest.

When error terms are heterogeneous, the distance does not have a significant impact on Korea's ODA to recipients at the 5% significance level unlike in the trade gravity model. This confirms that the motivation of the donor country's ODA to very poor recipients is not different from the motivation of mutual interest in international trade. While Korea's export does not significantly affect its ODA, Korea's import from the recipient affects it at the 5% significance level. This indicates that the motivation of a donor country's ODA to poor recipients is not the donor country's interest, which is different from the motivation of the mutual economic interest in trade theory.

The economic impact of the recipient's GDP on Korea's ODA also positively affects Korea's ODA to the recipients at the 5% significance level. This means that the motivation of ODA is the recipient's need for economic growth or development. However, the world ODA and world FDI do not affect Korea's ODA to recipients at the 5% significance level.

5.5. COINTEGRATED SPATIAL AUTOREGRESSIVE COMBINED MODEL ESTIMATION

Now, if we have both the spatial lag and error models, then the OLS estimators cannot be unbiased estimators. In this case, if it is not easy to get both spatial effects owing to the unit root problem of the economic series in the long-run, that is, if the economic series have unit roots but they are cointegrated, we can apply the spatial error correction models to analyze the spatial effects. We can use the difference model to analyze the short-run effects of the determinants of ODA or the spatial error correction model, if we also analyze the long-run spatial error correction process.

According to Johansen (1991) cointegration test, even though we omit the test results here, the variables are cointegrated so that we can apply the spatial error correction models to the spatially combined regression models. As variables have unit roots, we must take differences or use the error correction models when economic variables are cointegrated. Thus, we estimate the coefficients of explanatory variables by combining the spatial lag and the spatial error with generalized SW2SLS of GMM estimation when error terms are heteroscedastic. In other words, the spatially weighted least squares estimation would be satisfactory to have consistent estimators.

When error terms are heteroscedastic, as shown in Table 12, the short-run output for generalized SW2SLS of the cointegrated spatial autoregressive combined (CSAC) model estimation shows that the pseudo R-squared is 0.1307 and the spatial pseudo R-squared is 0.1401. The spatial autoregressive coefficient (ρ) is 0.6791 and spatial error coefficient (λ) is -0.8989. Both the spatial coefficients are significant in this combined spatial lag and spatial error estimation with generalized SW2SLS of GMM estimation at the 5% significance level. The error correction term also seems to be insignificant at the 5% level. The error correction term (ECM) does not have a tendency to recover the long-run level of Korea's ODA to recipient countries.

In the short run, the democracy level of ODA recipients can positively affect Korea's ODA (DLKODA) to the recipients at the 5% significance level. However, the distance between Korea and recipients cannot affect Korea's ODA to recipients at the 5% significance level unlike trade gravity model. It means that distance is not an important factor that affects Korea's ODA in the short run unlike the trade gravity model.

When error terms are heteroscedastic, both Korea's export (DLEX) to the

Variable	Coefficient	Std. Error	P-value
W_DLKODA (ρ)	0.6791	0.1106	0.0000
LDEMO	1.3453	0.2056	0.0000
LDIST	0.1020	0.1356	0.4521
DLEX	0.0176	0.0575	0.7601
DLIM	0.3158	0.1962	0.1075
DLMGDP	-0.2170	0.1841	0.2385
DLTWODA	0.0212	0.0443	0.6318
DLWFDI	0.0072	0.0255	0.7778
ECM	0.0393	0.0379	0.3005
Lambda (λ)	-0.8989	0.4177	0.0314
Fitness of the Regression Model			
Pseudo R-squared	0.1307		
Spatial Pseudo R-squared	0.1401		

Table 12: SPATIAL COINTEGRATION AND COMBINED SPATIAL HETEROSCEDASTIC MODEL ESTIMATION. Table 12 shows that while the spatial autoregressive coefficient (ρ) is positive, the spatial error coefficient (λ) are negative. Korea's ODA will increases as the democracy level rises. However, Korea's ODA does not have a tendency to recover the long-run level of Korea's ODA.

recipients and Korea's import (DLIM) from the recipients will not significantly affect Korea's ODA at the 5% level in the short run. The economic impact of recipient's GDP (DLMGDP) on Korea's ODA is not significant at the 5% level. Both the world ODA (DLTWODA) and the world FDI (DLWFDI) to the recipients do not positively influence Korea's ODA to the recipients at the 5% significance level in the short run. Finally, the negative sign for the spatial error coefficient (λ) suggests spatial heterogeneity, which is compatible with the evidence for heteroscedasticity found earlier. Interestingly, the negative sign for the spatial error coefficient (λ) is quite common when the spatial autoregressive coefficient (ρ) is positive and highly significant as Anselin and Ray (2014) argued. When we assume the heteroscedastic errors, both spatial autoregressive coefficient (ρ) and the spatial error coefficient (λ) are significant at the 5% level. Therefore, the short-run spatial effects in the determinants of Korea's ODA to recipients are estimated by the combined spatial autoregressive and spatial error model.

6. CONCLUSION: MAIN FINDING AND IMPLICATION

This study used a spatial dependence model to analyze the factors affecting Korea's ODA to the data available 55 recipients in 2010s. The ODA is significantly affected by spatial effects with spatial econometrics. Despite that, if we do not include spatial dependence effects of the ODAs, the coefficients of the determinants of ODAs will be biased or inconsistent estimators. However, most previous studies on ODA do not consider its spatial dependence effects. In particular, there has been no studies yet on the spatial effect models of Korea's ODA.

Therefore, we have to test whether the factors of allocating ODAs have the spatial dependence effects or not. This study adopted the spatial econometric models of the ODAs and then tested whether a recipient's democracy level or political stability, the distance between Korea and recipients, trade, GDP, world ODA, and world FDI have an important impact on the determinants of Korea's ODA to the recipients. The main findings of this study are as follows.

First, in the non-spatial conventional models, the democracy level of ODA recipients and the world ODA can positively influence Korea's ODA to from the perspective of the recipients' needs. However, the recipient's GDP with recipient's need and Korea's trade with donor interest do not significantly affect Korea's ODA to recipient countries. The distance can have a significant negative impact on Korea's ODA to recipients as the trade gravity model implies.

Second, to consider the missing data and zeros in the ODA data, this paper study introduced the PPML estimation. And then, by including country specific and time fixed effects, this study examined the panel analysis with fixed and random effect models to control the unobservable factors. The fixed effect model in panel analysis appears to be more appropriate in Korea's ODA determinant model.

Third, Breusch-Pagan test and Koenker-Bassett test show that there exist heteroscedasticity in errors. However, Moran's I value, Robust LM in lags and errors, and Lagrange Multipliers reject the null hypothesis of no spatial dependence effect of Korea's ODA. Therefore, we need to consider the spatial dependence models such as spatial lag or spatial error correlation models to analyze the spatial effects of ODA.

Fourth, furthermore, if there is a spatial dependence effect, we cannot use the OLS estimations like most previous studies to get the robust and consistent estimators of the ODA allocation models. We have to use the spatial two stage least squares or the spatial maximum likelihood estimators in the spatial lag models and the spatial maximum likelihood estimators in the spatial error models.

Fifth, the spatial lag models with the spatial two stage least squares estimators and the spatial maximum likelihood estimators show the first order spatially lagged dependent effect of Korea's ODA to the recipient countries. Korea's trade does not affect its ODA. However, the democracy level of recipient countries, recipient's GDP, and world ODA to recipients positively influence Korea's ODA as per the recipients' needs by 5% or 10%.

Sixth, the spatial error correction models with spatially weighted least squares or SW2SLS using GMM estimation that there are positive spatial error coefficients when error terms are homogeneous and heterogeneous. When error terms are heterogeneous, the democracy level of a recipients and its GDP level positively influence Korea's ODA as the recipients' needs perspective. However, the trade and the distance cannot give a significantly negative impact on Korea's ODA to recipient countries.

Finally, the spatial error correction models with combined the spatial lag and the spatial errors show that both spatial effects of two coefficients are both significant even in the short-run. However, the error-correction term appeared not to be significant so that there was no long run effect to correct the short run disequilibrium.

Therefore, when we analyze the factors affecting Korea's ODA, the spatial dependence model needs to be considered. Otherwise, if we use the standard non-special econometric estimations, it will be inconsistent. Thus, if we have to test whether the spatial effects exist or not in ODAs, then we have to use the spatial econometric estimations to get the consistent estimators of ODAs.

Simultaneously, even if we select the spatial ODA models, as the empirical results seem to be somewhat different, we need to select the more appropriate spatial econometric model to analyze more realistic Korea's ODA. Then, we should obtain the consistent and more efficient estimators of Korea's determinants of ODA allocation. Hence, we should consider the spatial effects to create more effective ODA policies unlike the most previous studies.

It is also worthwhile to analyze the important determinants behind Korea's ODA to recipients using the spatial econometric models unlike most previous non-spatial ODA studies. In this regard, this study is the first to analyze Korea's ODA using spatial models such as spatial lag, spatial error and cointegrated spatial autoregressive combined models. Furthermore, the novelty of the study is that it is a first newly attempt of a cointegrated spatial autoregressive combined model (CSAC) estimation using the error correction term in a cointegration model to get the long-run effects as well as short-run effects in ODA models. It will contribute to the analysis of ODA determinants of other countries worldwide.

Nevertheless, this study does not consider more dynamic factors and heterogeneity of regimes of economic, social, cultural, and institutional differences using longer and more data in spatial econometric models and these factors could be considered to establish more effective ODA policies. It will be worthwhile to consider the spatial panel effect models with fixed and random effects after obtaining more recipient countries' data. Thus, it will be also to examine more accurate and reliable spatial panel weighting matrix and panel spatial estimates including more unobservable ODA factors. However, this is beyond the scope of the current study and is left for future studies.

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