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A modified generalized estimating equation approach for simultaneous spatial durbin panel model: Case study of economic growth in ASEAN countries

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A B S T R A C T

This article briefly explains the simultaneous spatial durbin panel (SSDP) model. The study of the SSDP model is substantial because it can explain the interaction between geographic units, is more informative, diverse, efficient, exhaustive, and accurate in reaching conclusions that influence the policy determination. This article's intention is to derive a parameter estimation method from the SSDP model using a modified generalized estimating equation approach, which is then used to model economic growth in ASEAN nations. This article compares the SSDP model with rook contiguity, 2-nearest neighbors, and a customized spatial weighted matrix in relation to an independent, first-order autoregressive, exchangeable working correlation structure. To model economic growth in ASEAN countries, a customized weighted matrix with first-order autoregressive and exchangeable working correlations is chosen based on the CIC value. The parameter analysis outcomes indicate: 1) it is a significant spatial dependence among ASEAN countries; 2) it is a significant simultaneous interaction among the gross domestic product (GDP) and foreign direct investment (FDI); 3) GDP has a greater influence on FDI than FDI does on GDP; 4) The economic growth is directly affected by the labor force total; and 5) trade openness has a direct effect on FDI.

1. Introduction

Observations in econometric models can be constructed at the same time (cross-section) or over multiple time intervals (time series). Frequently, the number of observations (sample size) imposes limitations on cross-sectional observations, making it difficult to determine the degree of freedom. Combining cross-sectional and time series data, which is identified as panel data, is one method for overcoming these obstacles. Panel data is more insightful, diverse, efficient, and able to assess impacts that are not recognized with true cross-section data and true time series (Baltagi, 2005). According to Hsiao (2003), panel data has numerous advantages, including the ability to control heterogeneity between individuals, greater degrees of freedom, and the ability to construct and test more complex models. Panel effects that are typically employed can be either fixed or random. Individual or time-fixed effects make up fixed panel effects (Baltagi, 2005; Greene, 2012; Gujarati & Porter, 2009). The study of econometrics continues to evolve periodically. One of them involves location (spatial) effects. If the model accounts for connections between locations, it is referred to as a spatial econometric design. The presence of a weighting matrix (**W**) in a model indicates that it has a spatial effect. The spatial model has the advantage of providing information on the direct, indirect, and total effects of exogenous variables (Jaya & Andriyana, 2020; LeSage

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& Pace, 2009). According to Elhorst (2014), there are three types of location interaction effects in spatial econometric models: (1) spatial interactions on endogenous variables are called spatial autoregressive models (SAR) or spatial lag models; (2) spatial interactions on errors are called spatial errors model (SEM); and (3) The spatial durbin model (SDM) characterizes the spatial interaction among endogenous and exogenous variables.

Maximum likelihood estimation (MLE) is used to estimate a regression model with spatial effects for both cross-section and panel data, while nonlinear optimization and spatial parameter constraints impose restrictions on the estimation process. (Anselin, 1988). Anselin (1988) recommended instrumental variable estimation techniques, Bayesian techniques, and robust estimation method. For both cross-section and panel data, the SDM is the spatial model that receives the most attention from scholars. Mur & Angulo (2006) examined the common factor test utilizing the likelihood ratio test on SDM. Bekti et al. (2013) estimated the parameters of SDM using the MLE method based on the eigenvalues. Atikah et al. (2020) investigated the SDM utilizing the moment method. Mur & Angulo (2006), Bekti et al. (2013), and Atikah et al. (2020) utilized a single equation and simulated cross-section data. The empirical study of SDM using a single equation was investigated by Bekti & Sutikno (2012), Seya et al. (2012), Kusrini & Mukhtasor (2015), Tientao et al. (2016), Xu & Wang (2017), Hakim et al. (2019), Li et al. (2019), Liu & Geng (2019), Li & Li (2020), Long et al. (2020), Xie et al. (2020), and Xiao & Mao (2021). If the used data are panel data, the model is known as the spatial durbin panel model. Debarsy (2012) examined the spatial durbin panel model using the Mundlak method, where the panel effect was a random effect. Lee & Yu (2015) discussed the spatial dynamic panel model for individual and time-fixed effects using two-stage least squares (2SLS) and MLE method. Wei et al. (2021) developed a panel threshold spatial durbin (PTSD) model on fixed effects using the within-group spatial 2SLS estimation method and threshold test. Feng et al. (2018), Zhou et al. (2018), Liu & Song (2020), Wu & Pu (2020), and Song (2020) have conducted an analysis for the application of the spatial durbin panel model. The model examined by previous researchers still employs a single equation and has not been modified to incorporate simultaneous equations.

A simultaneous equation model is an equation model that includes multiple endogenous variables and multiple equations. The benefit of simultaneous equations is that they display more comprehensive information about related problems (Astuti et al., 2020; Gujarati & Porter, 2009). The type of the interaction is denoted by the appearance of variables as endogenous variables in some equations, exogenous variables in others, and vice versa. The simultaneous spatial durbin panel (SSDP) model is the outcome of applying the spatial durbin panel model to a simultaneous equation. This model's advantages are that it can explain how geographical units interact with one another, that it is more informative, diverse, efficient, comprehensive, and accurate when it comes to drawing conclusions that influence policy decisions. There are two approaches to estimating parameters in simultaneous equations: the limited information approach or single equation and the complete information approach or system equation (Gujarati & Porter, 2009; Maddala & Lahiri, 2009). The single equation approach is a method that only uses information derived from the equation being estimated, as opposed to utilizing all the information contained in the simultaneous equation system. While in the systems approach, all parameters in the equation are estimated concurrently and all information constraints in the structural equation (simultaneous equation system) are considered (Koutsoyiannis, 1977; Maddala & Lahiri, 2009). Kelejian & Prucha (2004) studied a simultaneous spatial model without including the panel effect using the Generalized spatial three-stage least squares (GS3SLS) approach. Jeanty et al. (2010) developed a study conducted by Kelejian & Prucha (2004) for the case of population migration and house price dynamics for panel data using the SAR model. Yang & Lee (2019) investigated the simultaneous equation model of spatial dynamic panels using the full information maximum likelihood estimate (FIMLE) technique. The spatial durbin model is not addressed in Jeanty et al. (2010) and Yang & Lee (2019).

The SSDP model is complex in terms of parameter estimation. This is because of the autocorrelation issue caused by repeated observations over time with panel data (Hedeker & Gibbons, 2006) and simultaneous relationship variables (Greene, 2012; Gujarati & Porter, 2009). This influences the precise covariance structure, which is difficult to calculate. To address the autocorrelation issue, Liang and Zeger (1986) initiated the Generalized Estimating Equation (GEE) technique. The GEE method is utilized to model repeatedly measured data, handles correlated data, and permits the requirement of a working covariance matrix which reduces the use of covariance structures (Liang & Zeger, 1986). Using the iteratively reweighted least squares (IRLS) technique, GEE completion is performed iteratively (Hardin & Hilbe, 2013; Hedeker & Gibbons, 2006). The benefit of the GEE procedure would be that it generates asymptotically reliable and robust estimators although the true covariance specification is not perfectly determined (Liang & Zeger, 1986; McCullagh & Nelder, 1989). According to Hedeker & Gibbons (2006), GEE approach does not require complex numerical evaluations. The GEE theory has been looked at in terms of a single equation and how it can be used in different fields by Pan (2001), Hanley et al. (2003), Touloumis et al. (2004), Balan & Schiopu-Kratina (2005), Natarajan et al. (2007), Goetgeluk & Vansteelandt (2008), Koper & Manseau (2009), Chen et al. (2010), Warton (2011), Shen & Chen (2012), Stoklosa et al. (2014), Chen et al. (2015), Jaman et al. (2016), Mardyanti & Fajriyah (2017), Purnomo (2018), Nikoloulopoulos (2020), Huang & Pan (2021), and Liya et al. (2021). The objective of this study is to invent a way for GEE approach upon the simultaneous spatial durbin panel model known as a modified GEE method. This method is a combination of the limited information approach proposed by Koutsoyiannis (1977), Gujarati & Porter (2009), Maddala & Lahiri (2009), and Greene (2012) and GEE method by Liang & Zeger (1986). There are three key distinctions between this study and previous research. First, the parameter estimation process is completed using the Gauss-Newton iteration method. This technique was chosen because it will not demand the second function's derivative to be calculated per parameter. This method was selected since it does not require the second derivative of the function for each parameter. The second derivative has the possibility of producing matrices which are not positive-definite (Mardalena et al., 2022). In addition, the Gauss-Newton optimization method is one of the strategies proposed by Anselin (1988) for overcoming computational issues in the presence of spatial effects. Second, the MLE method is still applicable when determining the initial value of the spatial effect parameter as described in (Anselin, 1988). Third, the estimation process is carried out as many as the number of equations. With a modified GEE method, spatial effects and autocorrelation caused by panel data and simultaneous effects should be able to be computed without causing computational difficulties.

The SSDP model and the modified GEE estimation method are applied to model economic growth in ASEAN countries. Economic growth is fascinating to study because it is a key indicator for evaluating three factors: 1) community welfare, 2) economic development success, and 3) the success of implementing local government policies. Furthermore, growth of the economy is the eighth Sustainable Development Goal or SDG. (Biermann et al., 2022). The gross domestic product (GDP) is one indicator of economic expansion. (Hussin & Saidin, 2012). Foreign direct investment (FDI) is another factor thought to affect growth in the economy (Khaliq, 2006; Ngo, 2019; Wakyereza, 2017). According to Ruxanda and Muraru (2010), Anwar and Nguyen (2010), and Cahyono (2013), GDP and FDI have a two-way relationship (simultaneous effect), GDP influencing FDI and vice versa. They have not mentioned spatial effects. The presence of ASEAN and the ASEAN Economic Community (AEC) have a significant effect on the economies of ASEAN member states. Therefore, the study of spatial effects must be added to the study of economic growth in ASEAN countries to add to what has already been learned.

In this investigation, we employed three spatial weight matrices and three working correlation matrices. This research aims to evaluate the effectiveness of each spatial weighting matrix and working correlation matrix in modeling the economic growth of ASEAN member nations and to identify the variables that affect it based on the most effective model. It is anticipated that the outcomes of this analysis will aid local governments in formulating economic growth-related policies. The flow of discussion begins with an explanation of the reasons for studying the SSDP model using the LISGEE approach, then defines the SSDP model, the modified GEE approach, and economic variables in Section 2, describes the real-world implementation of the SSDP model in Section 3, discusses the variables that affect the growth in economy of ASEAN countries during 2010 to 2019 based on the model selected in Section 4, and concludes with recommendations for future studies through Section 5.

2. Materials and Methods

2.1. Simultaneous Spatial Durbin Panel Model

This section explains the simultaneous spatial durbin panel model. Fixed effect panels used are individual specific effects. Simultaneous spatial durbin panel model with fixed effects is written in Equation (1). The model represented by equation (1) is an extension of the model investigated by Deng (2013).

$$\begin{aligned}
\mathbf{y}_1 &= \delta_1(\mathbf{I}_J \otimes \mathbf{W})\mathbf{y}_1 + \mathbf{Y}_{-1}\boldsymbol{\gamma}_{-1} + \mathbf{X}_1\boldsymbol{\beta}_1 + (\mathbf{I}_J \otimes \mathbf{W})\mathbf{X}_1\boldsymbol{\theta}_1 + (\boldsymbol{\iota}_J \otimes \mathbf{I}_N)\boldsymbol{\upsilon}_1 + \mathbf{u}_1 \\
\mathbf{y}_2 &= \delta_2(\mathbf{I}_J \otimes \mathbf{W})\mathbf{y}_2 + \mathbf{Y}_{-2}\boldsymbol{\gamma}_{-2} + \mathbf{X}_2\boldsymbol{\beta}_2 + (\mathbf{I}_J \otimes \mathbf{W})\mathbf{X}_2\boldsymbol{\theta}_2 + (\boldsymbol{\iota}_J \otimes \mathbf{I}_N)\boldsymbol{\upsilon}_2 + \mathbf{u}_2 \\
&\vdots \qquad\qquad \vdots \qquad\qquad \vdots \\
\mathbf{y}_M &= \delta_M(\mathbf{I}_J \otimes \mathbf{W})\mathbf{y}_M + \mathbf{Y}_{-M}\boldsymbol{\gamma}_{-M} + \mathbf{X}_M\boldsymbol{\beta}_M + (\mathbf{I}_J \otimes \mathbf{W})\mathbf{X}_M\boldsymbol{\theta}_M + (\boldsymbol{\iota}_J \otimes \mathbf{I}_N)\boldsymbol{\upsilon}_M + \mathbf{u}_M .
\end{aligned} \tag{1}$$

Eq. (1) can be rewritten in the form of an Eq. (2).

$$\mathbf{y}_m = \delta_m(\mathbf{I}_J \otimes \mathbf{W})\mathbf{y}_m + \mathbf{Y}_{-m}\boldsymbol{\gamma}_{-m} + \mathbf{X}_m\boldsymbol{\beta}_m + (\mathbf{I}_J \otimes \mathbf{W})\mathbf{X}_m\boldsymbol{\theta}_m + (\boldsymbol{\iota}_J \otimes \mathbf{I}_N)\boldsymbol{\upsilon}_m + \mathbf{u}_m \tag{2}$$

where $n = 1,2,\ldots,N$ as index of location, $j = 1,2,\ldots,J$ as index of the time, $m = 1,2,\ldots,M$ as the endogenous variables index, $k = 1,2,\ldots,K$ as the exogenous variables index, $\mathbf{y}_m$ is the *m*-th endogenous vector of size $NJ \times 1$, $\mathbf{W}$ is a spatial weighted matrix with $N \times N$ size, $\mathbf{I}_J$ and $\mathbf{I}_N$ are identity matrices with dimensions $J \times J$ and $N \times N$, respectively, $\mathbf{Y}_{-m}$ is a matrix of endogenous variables except for the *m*-th endogenous variable of size $NJ \times (M-1)$, $\mathbf{X}_m$ is the *m*-th exogenous variable matrix with size $NJ \times MK_m$, $\boldsymbol{\upsilon}_m$ is the *m*-th individual specific effect parameter of size $N \times 1$, δ_m is the *m*-th spatial effect parameter of the endogenous variable, $\boldsymbol{\gamma}_{-m}$ is the (-*m*) simultaneous effect parameter vector of the endogenous explanatory variables with size $(M-1) \times 1$, $\boldsymbol{\beta}_m$ is the *m*-th parameter vector of the exogenous variable with size $MK_m \times 1$, $\boldsymbol{\theta}_m$ is the *m*-th spatial effect parameter vector of the exogenous variable with size $MK_m \times 1$, $\boldsymbol{\iota}$ is a vector of one with size $J \times 1$, and $\mathbf{u}_m$ is the *m*-th error vector with size $NJ \times 1$ assuming the average vector is $\mathbf{0}$ and the covariance variance matrix $\sigma_m^2 \mathbf{I}_{NJ}$, σ_m^2 is the unknown *m*-th error variance parameter, $\mathbf{I}_{NJ}$ is $NJ \times NJ$ dimensioned identity matrix, and the constraint is $\sum_{n=1}^{N} \upsilon_{nm} = 0$.

If equation (1) is rewritten in matrix form as according Kelejian & Prucha (2004) and Yang & Lee (2019), the results can be found in Eq. (3).

$$\mathbf{Y}_{mt}\boldsymbol{\Gamma}_m = \mathbf{W}\mathbf{Y}_{mt}\boldsymbol{\Lambda}_m + \mathbf{X}_t\mathbf{B}_m + \mathbf{W}\mathbf{X}_t\boldsymbol{\Theta}_m + \mathbf{M}_m + \mathbf{U}_{mt} \tag{3}$$

where $\mathbf{Y}_{mt} = \left[\mathbf{y}_{1t}, \mathbf{y}_{2t}, \ldots, \mathbf{y}_{Mt}\right]$ is an endogenous variable matrix with $N \times M$ size for the *j*-th time, $\boldsymbol{\Gamma}_m$ is a simultaneous effect matrix with $M \times M$ size, $\mathbf{W}$ is $N \times N$ spatial weighted matrix, that be equal for all variables, $\boldsymbol{\Lambda}_m$ is a $M \times M$ size matrix for spatial effect coefficients on endogenous variables, $\mathbf{X}_t = \left[\mathbf{X}_{1t}, \mathbf{X}_{2t}, \ldots, \mathbf{X}_{Kt}\right]$ is $N \times K$ exogenous variable matrix for the *j*-th time and the *m*-th equation, $\mathbf{B}_{km}$ is exogenous variables coefficient matrix with $K \times M$ size, $\boldsymbol{\Theta}_m$ is $K \times M$ spatial coefficient matrix of exogenous variables, $\mathbf{M}_m$ is an individual effect matrix with $K \times M$ size, and $\mathbf{U}_{mt} = \left[\mathbf{u}_{1t}, \mathbf{u}_{2t}, \ldots, \mathbf{u}_{Mt}\right]$ is error matrix for the *j*-th time and the *m*-th equation which assumed to be $N\left(\mathbf{0}, \boldsymbol{\Sigma}_{um}\right)$. The spatial weighted matrix $\mathbf{W}$ used is equal for all equations. Stationary conditions for the spatial parameters in Eq. (1) and Eq. (2) are fulfilled if they meet the conditions $\frac{1}{\omega_{\min}} < \delta < 1$ where ω as the eigenvalue of the weighted matrix $\mathbf{W}$ (Elhorst, 2014).

According to Stakhovych & Bijmolt (2008), the spatial weighted matrix can be arranged based on the proximity of geographical relationships between observations, namely: the relationship of contiguity and distance. In addition, the spatial weighted can be obtained from close social and economic relationships, which is called customized (Anselin, 1988). The parameter estimation process in the SSDP model begins by eliminating the individual fixed effect on the model to measure individual observations as deviations from individual means over time. This method uses a transformation matrix of size $NJ \times NJ$ and idempotent. This transformation procedure adopts the steps performed by Baltagi (2005, 2021), Hsiao (2014), and Mutl & Pfaffermayr (2008). The transformation matrix is written in Eq. (4).

$$\mathbf{Q} = \left(\mathbf{I}_J - \left(\frac{1}{J}\right)\boldsymbol{\iota}_J\boldsymbol{\iota}_J^T\right) \otimes \mathbf{I}_N \tag{4}$$

When Eq. (4) is applied to Eq. (2), it yields Eq. (5) .

$$\mathbf{Q}\mathbf{y}_m = \delta_m\left(\mathbf{I}_J \otimes \mathbf{W}\right)\mathbf{Q}\mathbf{y}_m + \mathbf{Q}\mathbf{Y}_{-m}\boldsymbol{\gamma}_{-m} + \mathbf{Q}\mathbf{X}_m\boldsymbol{\beta}_m + \left(\mathbf{I}_J \otimes \mathbf{W}\right)\mathbf{Q}\mathbf{X}_m\boldsymbol{\theta}_m + \mathbf{Q}\left(\boldsymbol{\iota}_J \otimes \mathbf{I}_N\right)\boldsymbol{\upsilon}_m + \mathbf{Q}\mathbf{u}_m \tag{5}$$

since $\mathbf{Q}\left(\boldsymbol{\iota}_J \otimes \mathbf{I}_N\right) = \left(\mathbf{I}_J - \left(\frac{1}{J}\right)\boldsymbol{\iota}_J\boldsymbol{\iota}_J^T\right)\boldsymbol{\iota}_J \otimes \mathbf{I}_N\mathbf{I}_N = \left(\boldsymbol{\iota}_J - \frac{1}{J}\boldsymbol{\iota}_J J\right) \otimes \mathbf{I}_N = \underbrace{\mathbf{0}}_{J\times 1} \otimes \underbrace{\mathbf{I}}_{N\times N} = \underbrace{\mathbf{0}}_{NJ\times N}$ consequently, Eq. (5) becomes Eq. (6) .

$$\mathbf{Q}\mathbf{y}_m = \delta_m\left(\mathbf{I}_J \otimes \mathbf{W}\right)\mathbf{Q}\mathbf{y}_m + \mathbf{Q}\mathbf{Y}_{-m}\boldsymbol{\gamma}_{-m} + \mathbf{Q}\mathbf{X}_m\boldsymbol{\beta}_m + \left(\mathbf{I}_J \otimes \mathbf{W}\right)\mathbf{Q}\mathbf{X}_m\boldsymbol{\theta}_m + \mathbf{Q}\mathbf{u}_m \tag{6}$$

or

$$\mathbf{y}_m^{\#} = \delta_m\left(\mathbf{I}_J \otimes \mathbf{W}\right)\mathbf{y}_m^{\#} + \mathbf{Y}_{-m}^{\#}\boldsymbol{\gamma}_{-} + \mathbf{X}_m^{\#}\boldsymbol{\beta}_m + \left(\mathbf{I}_J \otimes \mathbf{W}\right)\mathbf{X}_m^{\#}\boldsymbol{\theta}_m + \mathbf{u}_m^{\#}$$

where $\mathbf{y}_m^{\#} = \mathbf{Q}\mathbf{y}_m$, $\mathbf{X}_m^{\#} = \mathbf{Q}\mathbf{X}_m$, and $\mathbf{u}_m^{\#} = \mathbf{Q}\mathbf{u}_m$.

The equation for the elimination of individual effects is written in Eq. (7).

$$\mathbf{y}_m^{\#} = \left[\mathbf{I}_J \otimes \left(\mathbf{I}_N - \delta_m\mathbf{W}\right)\right]^{-1}\left[\mathbf{Y}_{-m}^{\#}\boldsymbol{\gamma}_{-} + \mathbf{X}_m^{\#}\boldsymbol{\beta}_m + \left(\mathbf{I}_J \otimes \mathbf{W}\right)\mathbf{X}_m^{\#}\boldsymbol{\theta}_m + \mathbf{u}_m^{\#}\right] \tag{7}$$

2.2. A Modified Generalized Estimating Equation Method

The limited information approach is a method of parameter estimation in structural equations that is carried out individually or in each equation (Greene, 2012; Gujarati & Porter, 2009; Koutsoyiannis, 1977). Parameters in the SSDP model were estimated using a modified GEE approach. This means that each equation in the simultaneous equation is estimated by the GEE technique. The earliest step of the GEE technique is to determine the link function, variance function, and working correlation structure. The determination of the link function and the variance function depends on the distribution approach of the endogenous variables (Hedeker & Gibbons, 2006). In the SSDP model, the assumption of the distribution of endogenous variables is Gaussian (normal), so the link function used is the identity, namely $g\left(\boldsymbol{\mu}_m\right) = \boldsymbol{\mu}_m$ and the variance function is $v\left(\boldsymbol{\mu}_m\right) = 1$. The general form of GEE for each equation in the SSDP model is written in Eq. (8).

$$\mathbf{Z}\left(\boldsymbol{\pi}_m\right) = \sum_{n=1}^{N}\left(\frac{\partial\boldsymbol{\mu}_m}{\partial\boldsymbol{\pi}_m}\right)^T \mathbf{V}_n^{-1}\left(\boldsymbol{\pi}_m, \alpha, \phi\right)\left(\mathbf{y}_m^{\#} - \boldsymbol{\mu}_m\right) = \mathbf{0}_{(M+2K+1)\times 1}, \tag{8}$$

where $\boldsymbol{\mu}_m = E\left[\mathbf{y}_m^{\#}\right] = \left(\mathbf{I}_J \otimes \left(\mathbf{I}_N - \delta_m \mathbf{W}\right)\right)^{-1}\left[\mathbf{Y}_{-m}^{\#}\boldsymbol{\gamma}_{-} + \mathbf{X}_m^{\#}\boldsymbol{\beta}_m + \left(\mathbf{I}_J \otimes \mathbf{W}\right)\mathbf{X}_m^{\#}\boldsymbol{\theta}_m\right]$, if $\boldsymbol{\pi}_m = \left[\delta_m^T \quad \boldsymbol{\gamma}_{-m}^T \quad \boldsymbol{\beta}_m^T \quad \boldsymbol{\theta}_m^T\right]^T$ then $\dfrac{\partial \boldsymbol{\mu}_m}{\partial \boldsymbol{\pi}_m}$ is the first partial derivative of $\boldsymbol{\mu}_m$ to $\boldsymbol{\pi}_m$ for the m-th endogenous vector, $\mathbf{V}_{nm} = \mathbf{A}_{nm}^{\frac{1}{2}}\mathbf{R}_{nm}(\alpha)\mathbf{A}_{nm}^{\frac{1}{2}}\phi_m$ is the working variance-covariance matrix for the n-th observation for the m-th endogenous vector with size $J \times J$, $\mathbf{A}_{nm}$ is a diagonal matrix of $J \times J$ size for the m-th endogenous vector where $v\left(\mu_{njm}\right)$ as the j-th diagonal element for the n-th observation for the m-th endogenous vector, $\mathbf{R}_{nm}$ is a working correlation matrix of size $J \times J$ for the n-th observation for the m-th endogenous vector, ϕ_m is the constant for the m-th endogenous vector which is estimated using the Eq. (9) and Eq. (10) for a known estimator $\boldsymbol{\pi}_m$.

$$e_{njm} = \frac{y_{njm} - \hat{\mu}_{njm}}{\sqrt{v\left(\hat{\mu}_{njm}\right)}}, \tag{9}$$

$$\phi_m = \frac{1}{NJ - K}\sum_{n=1}^{N}\sum_{j=1}^{J} e_{njm}^2, \tag{10}$$

where e_{njm} is the Pearson residual for the m-th endogenous vector, N is the total observations of individuals (subjects) for the m-th endogenous vector, J is the total time observations for the m-th endogenous vector, K is the dimensions of the exogenous variables for the m-th endogenous vector, $\boldsymbol{\pi}_m$ and α_m are constants for the m-th endogenous vector which are estimated based on the work correlation structure used, namely: independent, exchangeable, and first-order autoregressive (Dobson & Barnett, 2008; Hardin & Hilbe, 2013; Hedeker & Gibbons, 2006; Purnomo, 2018). The working correlation matrix basic form is adopted from Astuti et al. (2021), Hin & Wang (2009), and Purnomo (2018) and provided in Table 1.

Table 1
The working correlation matrix structure.

Correlation Structure	Corr (Y_{ij}, Y_{jjT})	Matrix	Estimator
Independent	$Corr\left(Y_{nj}, Y_{nj^T}\right) = \begin{cases} 1 & j = j^T \\ 0 & j \neq j^T \end{cases}$	$\begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}_{J \times J}$	Not Available
Exchangeable	$Corr\left(Y_{nj}; Y_{n,j+c}\right) = \begin{cases} 1 & j = j^T \\ \alpha & j \neq j^T \end{cases}$	$\begin{bmatrix} 1 & \alpha_m & \alpha_m & \cdots & \alpha_m \\ \alpha_m & 1 & \alpha_m & \cdots & \alpha_m \\ \alpha_m & \alpha_m & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \alpha_m \\ \alpha_m & \alpha_m & \cdots & \alpha_m & 1 \end{bmatrix}_{J \times J}$	$\hat{\alpha}_m = \frac{1}{(P-K)\hat{\phi}_m}\sum_{n=1}^{N}\sum_{j>j^T} e_{njm}e_{njm^T}$ $P = \frac{1}{2}NJ(J-1)$
First-order Autoregressive (AR1)	$Corr\left(Y_{nj}, Y_{n,j+c}\right) = \alpha^c,$ $c = 0, 1, \ldots, J - j$	$\begin{bmatrix} 1 & \alpha_m^1 & \alpha_m^2 & \cdots & \alpha_m^{j-1} \\ \alpha_m^1 & 1 & \alpha_m^1 & \ddots & \vdots \\ \alpha_m^2 & \alpha_m^1 & 1 & \ddots & \alpha_m^2 \\ \vdots & \ddots & \ddots & \ddots & \alpha_m^1 \\ \alpha_m^{j-1} & \cdots & \alpha_m^2 & \alpha_m^1 & 1 \end{bmatrix}_{J \times J}$	$\hat{\alpha}_m = \frac{1}{(p-K)\hat{\phi}_m}\sum_{n=1}^{N}\sum_{j \leq J-1} e_{njm}e_{n,j+1,m}$ $p = \sum_{n=1}^{N}(J-1)$

Eq. (8) is not a closed form. In other words, the estimator obtained is still dependent on other parameters that must be estimated. This causes the estimation process to continue using numerical iteration. The iteration method used is the Fisher Scoring Typed method, which is a modification of the Gauss-Newton iteration. The algorithm for estimating parameter $\boldsymbol{\pi}_m$ is described as follows.

Step-1 Establish the starting value of $\boldsymbol{\pi}_m^{(0)}$ in Eq. (7). Utilizing the MLE method by Anselin (1988), the initial values for the spatial effect parameters were determined. The OLS method is used to determine additional parameters (Hedeker & Gibbons, 2006).

Step-2 Apply the Eq. (11) to the estimation procedure.

$$\boldsymbol{\pi}_m^{(a+1)} = \boldsymbol{\pi}_m^{(a)} + \left\{ \sum_{n=1}^{N} \left(\frac{\partial \boldsymbol{\mu}_{nm}^{(a)}}{\partial \boldsymbol{\pi}_{nm}^{(a)}} \right)^T \mathbf{V}_n^{-1}\left(\boldsymbol{\pi}_m^{(a)}, \alpha_m, \phi_m \right) \left(\frac{\partial \boldsymbol{\mu}_{nm}^{(a)}}{\partial \boldsymbol{\pi}_{nm}^{(a)}} \right) \right\}^{-1} \times \left\{ \sum_{n=1}^{N} \left(\frac{\partial \boldsymbol{\mu}_{nm}^{(a)}}{\partial \boldsymbol{\pi}_{nm}^{(a)}} \right)^T \mathbf{V}_n^{-1}\left(\boldsymbol{\pi}_m^{(a)}, \alpha_m, \phi_m \right) \left(\mathbf{y}_{nm}^{\#(a)} - \boldsymbol{\mu}_{nm}^{(a)} \right) \right\} \tag{11}$$

where $a = 0,1,2,\ldots$.

Eq. (12) to Eq. (15) are partial derivatives of $\boldsymbol{\mu}_m^{(a)}$ with respect to $\boldsymbol{\pi}_m^{(a)}$.

$$\frac{\partial \boldsymbol{\mu}_m}{\partial \delta_m} = \left(\mathbf{I}_J \otimes \left(\mathbf{I}_N - \delta_m \mathbf{W} \right) \right)^{-1} \left(\mathbf{I}_J \otimes \mathbf{W} \right) \left(\mathbf{I}_J \otimes \left(\mathbf{I}_N - \delta_m \mathbf{W} \right) \right)^{-1} \left[\mathbf{Y}_{-m}^{\#} \boldsymbol{\gamma}_{-} + \mathbf{X}_m^{\#} \boldsymbol{\beta}_m + \left(\mathbf{I}_J \otimes \mathbf{W} \right) \mathbf{X}_m^{\#} \boldsymbol{\theta}_m \right] \tag{12}$$

$$\frac{\partial \boldsymbol{\mu}_m}{\partial \boldsymbol{\gamma}_{-}} = \left(\mathbf{I}_J \otimes \left(\mathbf{I}_N - \delta_m \mathbf{W} \right) \right)^{-1} \mathbf{Y}_{-m}^{\#} \tag{13}$$

$$\frac{\partial \boldsymbol{\mu}_m}{\partial \boldsymbol{\beta}_m} = \left(\mathbf{I}_J \otimes \left(\mathbf{I}_N - \delta_m \mathbf{W} \right) \right)^{-1} \mathbf{X}_m^{\#} \tag{14}$$

$$\frac{\partial \boldsymbol{\mu}_m}{\partial \boldsymbol{\theta}_m} = \left(\mathbf{I}_J \otimes \left(\mathbf{I}_N - \delta_m \mathbf{W} \right) \right)^{-1} \left(\mathbf{I}_J \otimes \mathbf{W} \right) \mathbf{X}_m^{\#} \tag{15}$$

The working variance-covariance matrix structure used in the iteration process is $\mathbf{V}_{nm} = \mathbf{R}_{nm}(\alpha)\phi_m$ because $\mathbf{A}$ is an identity matrix caused by the value of $v(\boldsymbol{\mu}_m) = 1$. The arrangement of the matrix $\mathbf{V}_{nm}$ adjusts to the working correlation matrix in Table 1.

Step-3 If the convergence criteria in Eq. (16) are reached, the iteration will stop at $\boldsymbol{\pi}_m^{(a+1)}$ (Purnomo, 2018).

$$\left| \log L\left(\boldsymbol{\pi}_m^{(a+1)} \right) - \log L\left(\boldsymbol{\pi}_m^{(a)} \right) \right| < \varepsilon \text{ for } \varepsilon > 0, \tag{16}$$

where $\log L$ is a log-likelihood function, which can be seen in Equation (17).

$$L_m = \left(2\pi\sigma_m^2 \right)^{\frac{NT}{2}} \exp\left(-\frac{\mathbf{u}_m^2}{2\sigma_m^2} \right) \left| \frac{\partial \mathbf{u}_m}{\partial \mathbf{y}_m} \right| = \left(2\pi\sigma_m^2 \right)^{\frac{NT}{2}} \exp\left(-\frac{\mathbf{u}_m^2}{2\sigma_m^2} \right) \left| \mathbf{I}_J \otimes \left(\mathbf{I}_N - \delta_m \mathbf{W} \right) \right|$$

$$\log L_m = -\frac{NT}{2} \log\left(2\pi\sigma_m^2 \right) + J \log\left| \left(\mathbf{I}_N - \delta_m \mathbf{W} \right) \right| - \frac{1}{2\left(\sigma_m^2 \right)} \mathbf{u}_m^{\#T} \mathbf{u}_m^{\#}. \tag{17}$$

Step-4 Obtain parameter estimates in a state of convergence, $\hat{\boldsymbol{\pi}}_m = \boldsymbol{\pi}_m^{(a+1)}$

Step-5 Calculate the sandwich covariance matrix $Cov(\hat{\boldsymbol{\pi}}_m)$ using the formula below:

$$Cov(\hat{\boldsymbol{\pi}}_m) = \mathbf{V}_m(\hat{\boldsymbol{\pi}}) = \mathbf{B}_m^{-1} \mathbf{M}_m \mathbf{B}_m^{-1} \tag{18}$$

where $\mathbf{B}_m = \sum_{n=1}^{N} \mathbf{D}_{nm}^T \hat{\mathbf{V}}_{nm}^{-1} \mathbf{D}_{nm}$ is the "bread" matrix size $(M+2K+1)\times(M+2K+1)$ for the *m*-th endogenous vector, $\mathbf{M}_m = \sum_{n=1}^{N} \mathbf{D}_{nm}^T \hat{\mathbf{V}}_{nm}^{-1} Cov\left(\mathbf{y}_m^{\#} \right) \hat{\mathbf{V}}_{nm}^{-1} \mathbf{D}_{nm}$ is the "meat" matrix of the *m*-th endogenous vector with size $(M+2K+1)\times(M+2K+1)$ where $Cov\left(\mathbf{y}_m^{\#} \right) = \left[\mathbf{y}_m^{\#} - E\left[\mathbf{y}_m^{\#} \right] \right] \left[\mathbf{y}_m^{\#} - E\left[\mathbf{y}_m^{\#} \right] \right]^T$, $\mathbf{D}_{nm} = \left(\frac{\partial \boldsymbol{\mu}_m}{\partial \boldsymbol{\pi}_m} \right)$ is the first partial derivative of $\boldsymbol{\mu}_m$ with respect to $\boldsymbol{\pi}_m$ for the *m*-th endogenous vector.

A property of the estimator of $\boldsymbol{\pi}_m$ is asymptotic normality, which means that for large sample sizes, the estimator of $\boldsymbol{\pi}_m$ will converge to the normal distribution. In other words, the sample distribution of estimator $\boldsymbol{\pi}_m$ approaches the normal distribution with increasing sample size. Eq. (19) is a statistical test utilized to determine the significance of the parameters.

$$t_{ratio} = \frac{\hat{\boldsymbol{\pi}}_m}{SE\left(\hat{\boldsymbol{\pi}}_m\right)} \tag{19}$$

where $SE\left(\hat{\boldsymbol{\pi}}_m\right)$ is the standard error of each parameter. SE is determined by calculating the square root of the diagonal elements of the variance-covariance matrix Eq. (18). The statistical test asymptotically followed the t distribution for $NT-(M+2K+1)$ degrees of freedom. Decision of null hypothesis is refused if $t_{\text{statistics}}$'s absolute value exceeds the critical value $t_{\left(\frac{\alpha}{2}, NT-(M+2K+1)\right)}$. This article evaluates the SSDP model in comparison to the queen contiguity weighted matrix, distance, and the customized for independent, first-order autoregressive, and exchangeable working correlations. The customized weighted matrix is formulated based on the import-export relationships between ASEAN nations. Based on the smallest CIC value, the best model is chosen. According to Purnomo (2018) and Hin & Wang (2009), the CIC formula is presented in the Eq. (20).

$$CIC\left(R\right) = tr\left(\boldsymbol{\Phi}\mathbf{V}_m\left(\hat{\boldsymbol{\pi}}\right)\right) \tag{20}$$

where $\boldsymbol{\Phi}$ is the model-based variance estimator of the independent working correlation and $\mathbf{V}_m\left(\hat{\boldsymbol{\pi}}\right)$ is the sandwich covariance of the observed working correlation structure.

2.3. Economics Variables

Economic growth is an essential indicator for ensuring the continuity of economic development and boosting the prosperity of a region. According to Kuznets (1973), economic growth is the capacity of a nation to increase its output as a result of technological progress and ideological changes. According to Todaro & Smith (2014), the growth of economic is a process of increasing the productive capacity of an economic system in a manner that is sustainable over time in order to produce an increase in national GDP and output. According to Denison in Boldeanu & Constantinescu (2015), economic growth is measured by a rise in real GDP or GDP per capita. Economic growth can be influenced by direct and indirect factors. Boldeanu & Constantinescu (2015) asserted that indirect factors include institutions, aggregate demand, savings, and investment such as foreign direct investment (FDI), and labor. Direct factors include country's natural resources, finances, and technological advancement. Numerous studies on the factors that affect economic growth have been conducted by researchers and are presented in Table 2. For several variables, the research results continue to yield contradictory results.

Table 2
Previous research of the connection between economic growth and FDI

Author	Objective	Discovering	Approach	Shortcoming
Iyke & Ho (2017)	Examine the connection between wage inequality and economic expansion in Italy. Human capital, labor, capital, income inequality, and inflation are all factors that contribute to the income gap.	On both the short-term and long-term, income inequality has a significant and negative effect on economy's growth. When capital per capita decreases, the labor factor has a negative impact on the economy's growth.	Autoregressive Distributed Lag (ARDL) approach	Still utilizing a single-equations and failing to investigate spatial effects
Ngo (2019)	Inspects the extent to which FDI induced growth in the economy from 2007 to 2017.	The complementary implications of schooling and FDI recommend that a lowest educational level must be achieved for FDI to actually affect growth in the economy. In addition, the level of education in this sample group is below what is deemed adequate to stimulate economic growth, which has an impact on the absorbent capacity.	Fixed effect panel regression	Still utilizing a single-equations and failing to investigate spatial effects
Hossain et al. (2022)	Examined the impact of trade openness and FDI on economic expansion in 30 Asian economies that were experiencing crises.	FDI and trade openness make a significant contribution to boosting the economy in Asian economies, and their effects are also durable over time. In addition, the Asian and worldwide economic collapse of 1997 to 1998 and 2008 to 2009, in both, had a negative effect on economic growth in the region. Furthermore, the economic expansion among many Asian countries is lower than the SDG-8 target.	Panel corrected standard errors (PCSE) and generalized method of moments (GMM) technique.	Still utilizing a single-equations and failing to investigate spatial effects
Ruxanda & Muraru (2010)	Discusses whether FDI influence Romania's growth in the economy.	Established the two-way relationship among FDI and GDP, indicating that FDI encourages economic expansion, and a higher GDP appeals FDI.	Panel simultaneous model and 2SLS estimation method	Not yet investigated spatial effects
Cahyono (2013)	Analyzing the FDI and GDP Determinants in Indonesia. As determinants of FDI, variables such as GDP, real labor wages, infrastructure development, economic flexibility, rate of the real exchange rate, and rate of real interest are considered. In the meantime, the effects of FDI on GDP will be predicted using various GDP-influencing variables such as government funding, government expenditure, economic flexibility, and the inflation rate.	The factors affecting the entry of FDI into Indonesia are the country's gross domestic product, labor salaries, facilities, and economic flexibility. The most important factor for attracting FDI to Indonesia is the increase in GDP, that indicates a larger market. FDI has a positive impact on the GDP of Indonesia.	Panel simultaneous model and 2SLS estimation method	Not yet investigated spatial effects
Wakyereza (2017)	Determine the FDI impact on economic growth, poverty reduction, and employment in Uganda.	Local resources in Uganda, such as labor force employment and human capital, contribute significantly to economic growth and poverty reduction. This is due to the fact that innovations	Vector Error Correction Mechanism (VECM) Granger causality approach	Not yet investigated spatial effects

	in variance decomposition indicate that employment will cause the most fluctuations in economic growth and poverty reduction in Uganda.

2.3. Compositional Structure

This study employs a modified version of Anwar & Nguyen (2010), Ruxanda & Muraru (2010), Cahyono (2013), and Wakyereza (2017) to model economic growth with a simultaneous equation. The innovative aspect of this study is the spatial effects addition into the modeling of the economic growth of ASEAN nations, on both endogenous and exogenous variables, and a modified GEE method for parameter estimation. Two endogenous variables, GDP and FDI, and two exogenous variables, labor force total (LFT) and trade openness (TO), are utilized. Fig. 1 depicts the relationship between variables used in this study in a system of simultaneous equations.

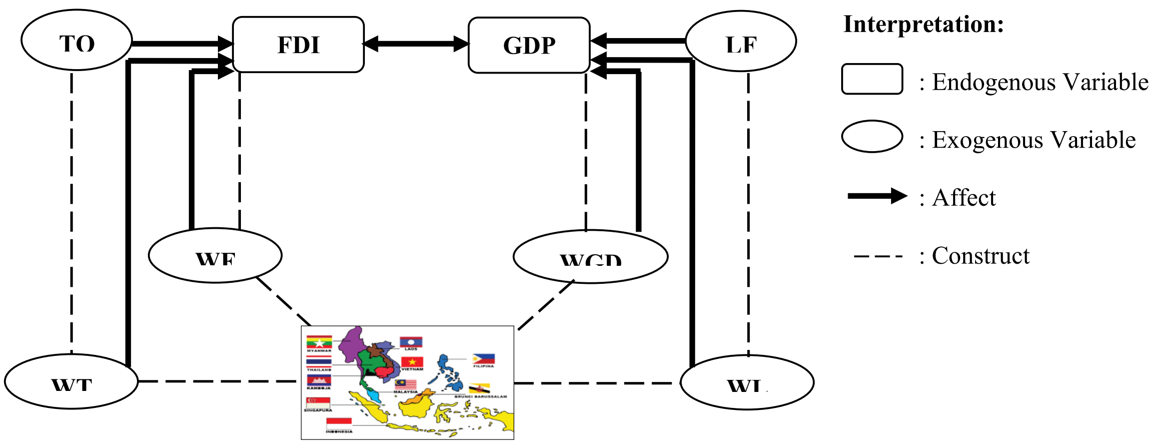


Fig. 1. Research Variable Relationships Representation

The data of variables in this article is transformed into the natural logarithm (ln). The purpose of the transformation is to reduce the original data skewness (Feng et al., 2014). In addition, this transformation can facilitate the model's interpretation. Eq. (21) describes the simultaneous spatial durbin panel model design of the growth in economy of ASEAN nations. This model incorporates two equations: lnGDP and lnFDI.

$$\begin{aligned} \ln GDP_{nj} &= \beta_{10} + \beta_{11} \ln LFT_{nj} + \delta_{11} \left(\mathbf{I}_J \otimes \mathbf{W}\right) \ln GDP_{nj} + \theta_{11} \left(\mathbf{I}_J \otimes \mathbf{W}\right) \ln LFT_{nj} + \gamma_{11} \ln FDI_{nj} + \upsilon_{n1} + u_{nj1} \\ \ln FDI_{nj} &= \beta_{20} + \beta_{21} \ln TO_{nj} + \delta_{21} \left(\mathbf{I}_J \otimes \mathbf{W}\right) \ln FDI_{nj} + \theta_{21} \left(\mathbf{I}_J \otimes \mathbf{W}\right) \ln TO_{nj} + \gamma_{21} \ln GDP_{nj} + \upsilon_{n2} + u_{nj2} \end{aligned} \quad (21)$$

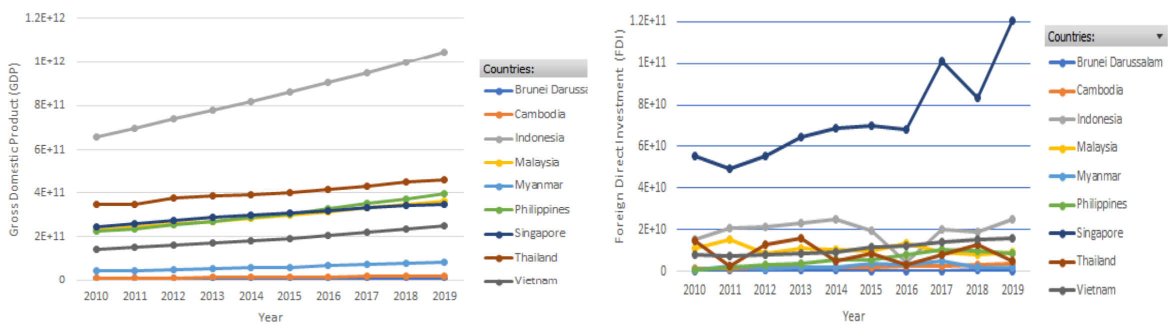
3. Results

This article employs panel data for its data structure. The study unit consists of ASEAN members, excluding Laos, with an observation period from 2010 to 2019. There are a total of ninety observations. Data sourced from The World Bank (2020). The data summary is provided in
Table **3**.

Table 3
The summary of data

Variables	Mean	Standard Deviation	Minimum	Maximum	Unit
GDP (y_1)	270,464.12	249,557.68	12,609.99	1,049,318.97	Million US $
lnGDP	11.86	1.38	9.44	13.86	
FDI (y_2)	14,990. 13	22,848.65	150.55	120,439.47	Million US $
lnFDI	8.71	1.45	5.01	11.70	
LFT (x_1)	34,625.14	36,720.67	191.152	135,802.88	Thousand people
lnLFT	16.47	1.82	12.16	18.73	
TO (x_2)	128.56	89.45	11.86	379.10	%
lnTO	4.63	0.71	2.47	5.94	

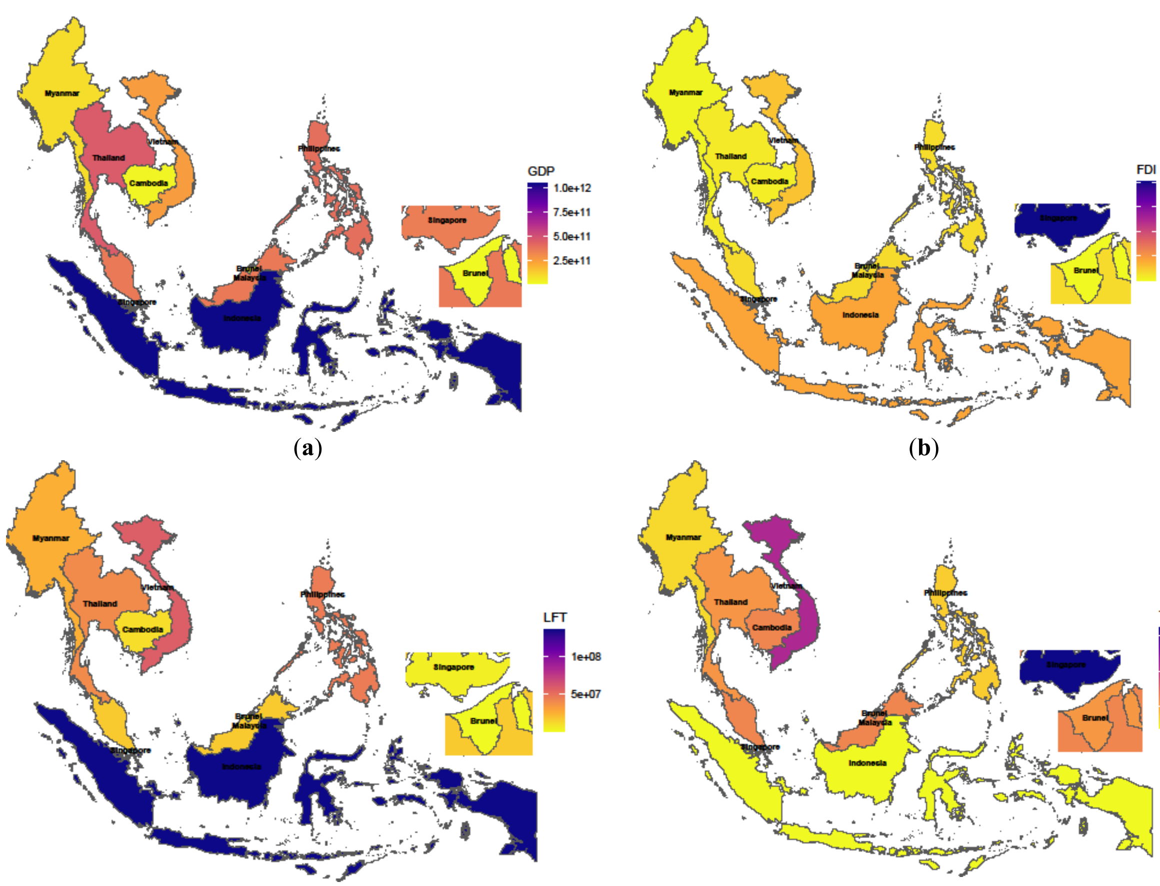
Fig. 2 shows the trend of GDP and FDI in ASEAN countries from 2010 to 2019. The GDP of each ASEAN nation is likely to increase, from 2010 to 2019. The yearly upward trend reflects the improvement in the quality of people's well-being and economic development. The country with the highest GDP in each year of observation is Indonesia, while Brunei Darussalam has the lowest. The FDI achievements of ASEAN nations fluctuated during the observation period, except for Cambodia and Vietnam. Each year of observation, the value of FDI in Cambodia and Vietnam tends to grow. Brunei Darussalam received the least amount of FDI during the observable year, whereas Singapore received the most. The GDP and FDI between ASEAN nations tend to have distinct characteristics, allowing them to generate distinct models between nations, which are reflected by the intercept value.



(**a**) (**b**)

Fig. 2. Evolution of ASEAN economic growth indicators from 2010 to 2019: **(a)** GDP; **(b)** FDI.
Source: primary data processed with the Microsoft Excel.

Fig. 3 presents a map of the distribution of GDP, FDI, LFT, and TO for 2019. It shows that Indonesia is a member of the ASEAN countries with the highest GDP and LFT in 2019. The highest FDI and TO in 2019 were achieved by Singapore. There are indications that there are spatial dependencies between ASEAN countries for all observation variables. This is indicated by the relatively similar colors between adjacent countries on the variable distribution map. Countries with relatively similar values are close to each other.

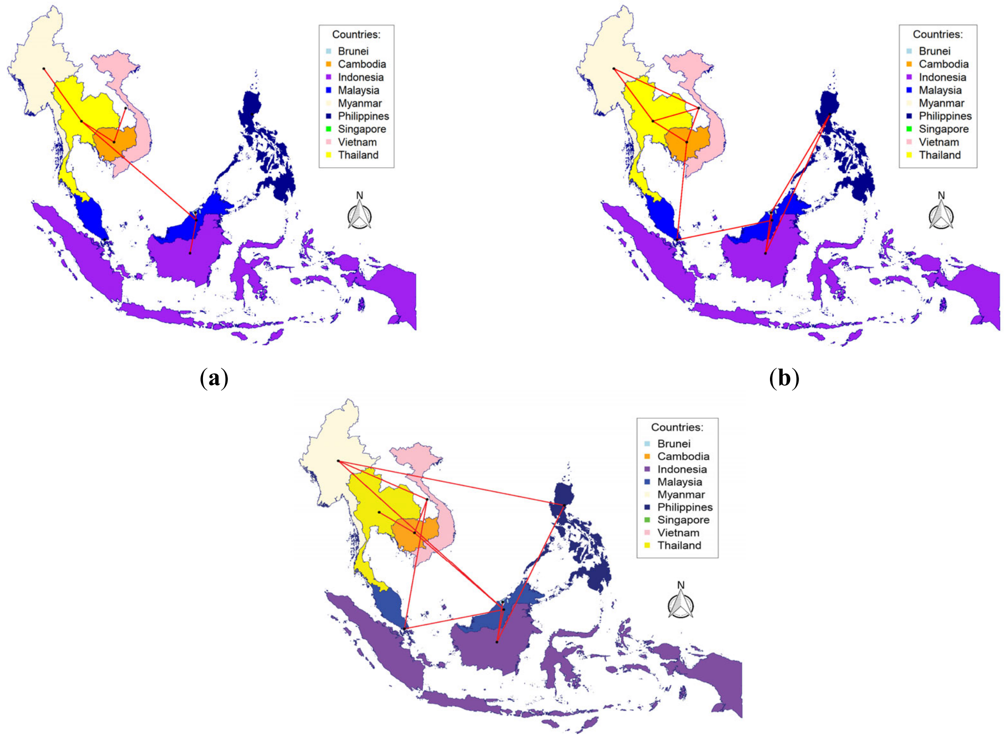


(**a**) (**b**)

(**c**) (**d**)

Fig. 3. Distribution map of variables in 2019: **(a)** GDP; **(b)** FDI; (**c**) LFT; (**d**) TO.
Source: primary data processed with the R Software.

Further checking of spatial dependencies was carried out using the Moran index test (Anselin, 1988) and the Lagrange multiplier or LM test (Anselin et al., 2008). The test of Moran index serves to measure global spatial effects for residual, endogenous, and exogenous variables. According to Elhorst (Elhorst, 2014) and Anselin (Anselin, 1988), the LM test results can recognize the type of spatial regression model to be modeled, whether it be the SAR model or the spatial error model (SEM). The SAR model if the LM lag or robust LM lag value is substantial and the SEM if the LM error or robust LM error is significant. The weighted matrix used for the spatial dependency test is the queen contiguity matrix; the *k*-nearest neighbors (*k-NN*) type distance approach with k = 2 nearest neighbor locations; and the socio-economic relationship approach (customized). The queen contiguity matrix was chosen to represent the interrelationships according to the intersection of the area sides between locations. For example, areas that intersect by region are considered to have close characteristics, for example, Indonesia and Malaysia. The two countries are considered to have a spatial relationship because they are territorially intersected or directly adjacent to each other. The *k*-nearest neighbors' matrix with k = 2 or 2-*NN* was chosen to represent the regional linkages according to distance. The customized matrix was chosen to represent the interrelationships of social and economic relationships between locations. Areas that do not contain side intersections may be related to other areas because of economic relations or proximity to social characteristics. The customized weighting matrix is based on the import-export relations between ASEAN countries. The visualization of the path of the queen contiguous, the 2-NN distance approach, and the import-export relationship of ASEAN countries can be seen in Fig. 4. The three weighted matrices used are row-standardized (Anselin, 1988). The elements of the weighted matrix **W** that have been standardized by row provided in Appendix A.



(**a**) (**b**) (**c**)

Fig. 4. Spatial weighted matrix map: **(a)** queen contiguity; **(b)** 2-NN; (**c**) customized.
Source: primary data processed with the R software.

The spatial dependence test result for each model residual is provided in Table 4.

Table 4

Residual spatial dependency test results

Spatial Weighted	Structural Equations	Moran's I	LM lag	LM error	Robust LM lag	Robust LM error
Queen Contiguity	lnGDP	-0.033	0.298	0.098	0.244	0.044
	lnFDI	-0.039	11.537**	0.143	12.169**	0.776
2-Nearest Neighbors	lnGDP	-0.044	7.918**	0.212	15.206**	7.499**
	lnFDI	-0.377**	11.092**	15.352**	5.301**	20.653**
Customized	lnGDP	-0.097*	1.619*	0.886	8.371**	7.638**
	lnFDI	-0.356**	5.051**	11.888**	12.741**	19.579**

** Significant at α = 5% and * Significant at α = 20%

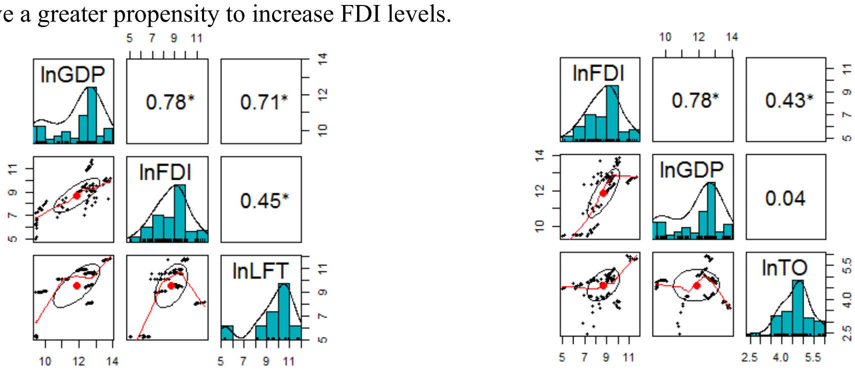
There is no spatial dependence on the lnGDP structural equation for the queen contiguity weighted matrix, but the spatial dependence of lnFDI shows significant results in the LM test only for the SAR model with a significance level of $\alpha = 5\%$. For the 2-NN weighted matrix, the Moran index and LM values show significant results in the lnFDI structural equation, but in lnGDP the results are significant only in the LM value, both the SAR model and SEM at a significance level of $\alpha = 5\%$. For the customized weighted matrix, the Moran index and LM values are significant in the structural equations of lnGDP and lnFDI. Thus, the customized weighting matrix is a weighted matrix that will be used for further modeling with the SAR model. The spatial dependence test result for each variable is provided in Table 5. There is a spatial dependence on endogenous variables (lnGDP and lnFDI) and exogenous variables (lnLFT and lnTO) using a customized weighted matrix. A positive Moran index value indicates the existence of a significant clustering pattern. In other words, the value of the GDP corresponds to the region where export-import activities are conducted. The same holds true for the TO value. Negative FDI and LFT values indicate significant spatial autocorrelation with nonsystematic adjacent patterns. Since there is a spatial interaction between endogenous and exogenous variables, the economic growth of ASEAN countries is investigated using the SDM.

Table 5
The spatial dependency test results for each variable.

Variable	Spatial Weighted		
	Queen Contiguity	2-Nearest Neighbors	Customized
lnGDP	0.190	0.085	0.137*
lnFDI	-0.137	-0.250**	-0.160*
lnLFT	-0.023	-0.311**	-0.422**
lnTO	-0.102	0.103	0.270**

** Significant at $\alpha = 5\%$ and * Significant at $\alpha = 20\%$

The relationship between endogenous and exogenous variables for each equation in the structural equation is depicted in Fig. 5. The scatterplot matrix on Fig. 5 reveals that the data in the lnFDI structural equation has a substantial positive correlation to lnGDP at significance level, $\alpha = 5\%$. This indicates that ASEAN countries with higher GDP value characteristics have a tendency for their economic growth rates to increase, and vice versa. The relationship between LFT and GDP is significant. This indicates that ASEAN nations with a large labor force have a greater propensity to increase their GDP. The relationship between TO data and FDI is statistically significant. This indicates that ASEAN nations with a high TO level have a greater propensity to increase FDI levels.



(a) (b)

Fig. 5. Scatterplot matrix of variable relationships in structural equations: (**a**) lnGDP; (**b**) lnFDI.
Source: primary data processed with the R software.

This article employs two equations that have a mutually influential relationship, and a simultaneous relationship is suspected. A simultaneous equations system is a collection of equations in which the outcome variable in one or more equations is the response variable in several other equations. Consequently, a variable can simultaneously serve as both an independent and a dependent variable. Prior to estimating the simultaneous equation system parameters, it is necessary to conduct tests series, including the identification of the simultaneous equation and the simultaneity test. Identification will reveal whether structural parameters (original equation coefficients) are being derived from parameters of reduced form. The equation is identified if the structural form parameter estimation (original equation) can be derived from the reduced form. Alternatively, if the estimation is unsuccessful, the equation cannot be determined (Gujarati & Porter, 2009; Koutsoyiannis, 1977; Setiawan & Kusrini, 2010). To identify a simultaneous equations system, there are two conditions that must be satisfied: the order and rank conditions (Koutsoyiannis, 1977).

Table **6** displays the simultaneous equation system identification results.

Table 6
Identification of simultaneous equations for order conditions

Equations	$(K - k)$	$(m - 1)$	Decision	Results
lnGDP	$10 - 5 = 5$	$1 - 1 = 0$	$(K - k) > (m - 1)$	*Overidentified*

lnFDI	10 – 5 = 5	1 – 1 = 0	**(*K* – *k*) > (*m* – 1)**	*Overidentified*

Table **6** proves that the lnGDP and lnFDI equations satisfy the order condition in which $(K - k) > (m - 1)$. For instance, the results of checking the order conditions for the lnGDP equation can be derived from the predetermined variables number in the model ($K = 10$), the predetermined variables number in the equation of lnGDP ($k = 5$), and the number of endogenous variables in the lnGDP equation ($m = 1$), so we obtain ($K - k = 5$) and ($m - 1 = 2$), respectively. Since $(K - k) > (m - 1)$, the structural equation of lnGDP satisfies the order condition and is classified as overidentified. Likewise, structural equality of lnFDI holds true. After verifying the order conditions for both equations, it can be concluded that the equations in the model satisfy the order conditions and are classified as overidentified equations. Therefore, all equations in this article satisfy the conditions of order and overidentification.

Another rule for finding simultaneous equations is the rank requirement (Koutsoyiannis, 1977). Rank pertains to the concept of a matrix with a determinant equal to 0 (zero) or the maximum number of rows or columns that are linearly independent. The rank condition is necessary because, even though the order requirements test for an equation shows that it has been identified, it is possible that the rank requirements have not been satisfied through testing. This makes it impossible to estimate the parameters of simultaneous equations. Consequently, the determination of simultaneous equations for rank conditions is required. After the elimination process, it is possible to identify simultaneous equations if the order matrix contains at least one non-zero determinant. The results of identifying rank conditions are presented in Table 7. Since the lnGDP and lnFDI equations satisfy the rank conditions, they are classified as overidentified.

Table 7
Identification of simultaneous equations for rank conditions

Equations	Rank	Results
lnGDP	$Rank\left(\Delta_{\ln GDP}\right) \neq 0$	Eligible rank condition
lnFDI	$Rank\left(\Delta_{\ln FDI}\right) \neq 0$	Eligible rank condition

Source: Appendix B

The purpose of simultaneous testing is to empirically demonstrate that a system of equations has a simultaneous relationship between its structural equations (Greene, 2012; Gujarati & Porter, 2009; Koutsoyiannis, 1977). The F-statistic of the equation of the endogenous variable and the t-statistic of the residual endogenous variable, which is a significant explanatory variable, indicate the existence of a simultaneous equation. Simultaneous testing was carried out with the Hausman test and are provided in Table 8. The Hausman test results show that the F-Statistics and t-Statistics values were significant at $\alpha = 1\%$.

Table 8
Simultaneous test results

Equations	F-Statistics	Variables	t-Statistics	Results
lnGDP	59.667***	Res_FDI	8.612***	Simultaneous
lnFDI	59.551***	Res_GDP	8.612***	Simultaneous

*** Significant at α = 1%

With the satisfaction of order and rank conditions, elements of simultaneity, and spatial durbin effects, the simultaneous spatial durbin panel model can proceed to the estimation phase. A modified GEE approach was utilized to estimate the simultaneous spatial durbin panel model parameters in the case of economic growth in ASEAN countries. Customized weighted matrix is chosen for use in the estimation of parameters. Individual fixed effects are employed for each panel. Table 9 displays the results of parameter estimation.

Table 9
Parameter estimation results on simultaneous spatial durbin panel model

Parameters	Independent			First-order Autoregressive (AR1)			Exchangeable		
	Estimate	Standard Error	t-Stat	Estimate	Standard Error	t-Stat	Estimate	Standard Error	t-Stat
lnGDP									
β_{10}	8.19×10^{-8}	4.77×10^{-9}	1.72×10^{1} ***	7.17×10^{-3}	3.79×10^{-7}	1.89×10^{4} ***	-8.62×10^{-8}	7.10×10^{-10}	1.21×10^{2} ***
β_{11}	0.536	4.29×10^{-5}	1.25×10^{4} ***	0.452	3.65×10^{-5}	1.24×10^{4} ***	0.541	4.36×10^{-5}	1.24×10^{4} ***
δ_{11}	0.173	4.93×10^{-5}	3.51×10^{3} ***	0.273	4.17×10^{-5}	6.55×10^{3} ***	0.167	5.21×10^{-5}	3.21×10^{3} ***
θ_{11}	1.800	1.37×10^{-4}	1.31×10^{4} ***	1.492	9.74×10^{-5}	1.53×10^{4} ***	1.815	1.38×10^{-4}	1.32×10^{4} ***
γ_{21}	0.075	1.38×10^{-6}	5.44×10^{4} ***	0.019	4.81×10^{-7}	4.12×10^{4} ***	0.075	1.35×10^{-6}	5.56×10^{4} ***
lnFDI									
β_{20}	7.07×10^{-3}	5.05×10^{-5}	1.40×10^{2} ***	5.44×10^{-3}	1.75×10^{-4}	3.11×10^{1} ***	7.42×10^{-4}	1.58×10^{-6}	7.05×10^{1} ***
β_{22}	0.437	5.85×10^{-4}	7.48×10^{2} ***	0.434	1.72×10^{-3}	2.53×10^{2} ***	0.424	3.90×10^{-4}	2.10×10^{3} ***
δ_{22}	0.027	2.78×10^{-1}	9.86×10^{-2}	0.002	3.05×10^{-1}	6.78×10^{-3}	0.006	5.07×10^{-5}	1.42×10^{-1}

θ_{22}	0.871	4.09×10^{-4}	2.13×10^{3} ***	0.878	2.41×10^{-3}	3.63×10^{2} ***	0.780	2.69×10^{-4}	1.67×10^{3} ***
γ_{12}	0.876	1.04×10^{-3}	8.41×10^{2} ***	0.906	3.18×10^{-4}	2.85×10^{3} ***	0.928	7.20×10^{-4}	1.07×10^{3} ***

*** Significant at α = 1%

Consideration was given to the statistical significance of the variables and the compatibility of the sign of the equation coefficient with the correlation coefficient during the analysis of

Table **9**. In the lnGDP equation, the parameter coefficient value of the lnLFT (β_{11}) has a significant and favorable impact on lnGDP at a significance level α = 1% for the three working correlations. The value of the parameter coefficient of the simultaneous effect of lnFDI (γ_{21}) has a significant and favorable impact on lnGDP at a significance level α = 1% for all three working correlations. The coefficients for the lnLFT and lnFDI have the same sign as the correlation coefficient. For the three working correlations, the coefficient value of the spatial effect parameter of the lnGDP (δ_{11}) has a significant and favorable impact at α = 1%. For all three working correlations, the coefficient value of the spatial effect parameter of the lnLFT (θ_{11}) has a significant and favorable impact on lnGDP at a significance level α = 1%. At statistical significance α = 1%, the parameter coefficient value of the lnTO (β_{22}) has a significant and favorable impact on the lnFDI variable. At α = 1%, the simultaneous effect coefficient value of the lnGDP (γ_{12}) has a positive and statistically significant effect on lnFDI. The coefficients for lnTO and lnGDP have the same sign as the correlation coefficient. The spatial effect parameter coefficient value of lnFDI (δ_{22}) has no significant impact on the three working correlations. For the three working correlations, the coefficient value of the spatial effect parameter of the lnTO variable (θ_{22}) has a significant and favorable impact on lnFDI at a significance level α = 1%. In the structural equations of lnGDP and lnFDI, the estimator characteristics for the three working correlations are typically the same. This demonstrates that the estimator obtained through the LISGEE method is a consistent estimator. The best model among the three working correlations is chosen by using the smallest CIC value. Table 10 indicates that the smallest CIC value for the lnGDP structural equation is first-order autoregressive (AR1), while for the lnFDI structural equation it is exchangeable work correlation. Thus, Eq. (21) can be rewritten in the form of Eq. (22).

Table 10
CIC value

Working Correlation	lnGDP	lnFDI
Independent	8.27×10^{-10}	6.22×10^{-3}
First Order Autoregressive (AR1)@@	4.02×10^{-10}	7.78×10^{-4}
Exchangeable@@	8.36×10^{-10}	1.57×10^{-5}

@@: The best model.

$$\begin{aligned} \ln GDP_{nj} &= 7.17\times10^{-3} + 0.452\ln LFT_{nj} + 0.273(\mathbf{I}_J\otimes\mathbf{W})\ln GDP_{nj} + 1.492(\mathbf{I}_J\otimes\mathbf{W})\ln LFT_{nj} + 0.019\ln FDI_{nj} + \upsilon_{n1} \\ \ln FDI_{nj} &= 7.42\times10^{-4} + 0.424\ln TO_{nj} + 0.006(\mathbf{I}_J\otimes\mathbf{W})\ln FDI_{nj} + 0.780(\mathbf{I}_J\otimes\mathbf{W})\ln TO_{nj} + 0.928\ln GDP_{nj} + \upsilon_{n2} \end{aligned} \tag{22}$$

where $n=1,2,\ldots,9$; $j=2010,2011,\ldots,2019$; υ_n is the individual effect (country) as a fixed panel effect, and Table 11 displays its value.

Table 11
Country value (individual fixed effect)

id	Countries Code	Countries	Effect	
			lnGDP	lnFDI
1	BRN	Brunei Darusalam	-14.282	-7.659
2	KHM	Cambodia	-13.352	-7.365
3	IDN	Indonesia	-7.717	-8.069
4	MYS	Malaysia	-8.740	-8.232
5	MMR	Myanmar	-12.462	-7.714
6	PHL	Philiphine	-12.035	-7.900
7	SGP	Singapore	-9.779	-6.883
8	THA	Thailand	-7.932	-9.307
9	VNM	Vietnam	-9.160	-7.993

4. Discussion

The simultaneous spatial durbin panel model's parameter estimation results using a modified GEE method have demonstrated a match between econometric theory concepts and empirical results. The significance of each variable's parameters is largely met. The modified GEE method yields estimators with nearly identical characteristics for independent, first-order autoregressive, and exchangeable working correlations. Consequently, the modified GEE methodology is robust. Eq. (22) reveals that the value of the simultaneous effect parameter coefficients for GDP and FDI between ASEAN countries proves a positive relationship. If the value of FDI is increased by 1 percent, then GDP also increases by 0.019 percent at the time of ceteris paribus in the GDP equation. This aligns with the studies of Anwar & Nguyen (2010), Hamoudi & Aimer (2017), Ruxanda & Muraru (2010). Investment's contribution to economic growth might be viewed by the demand and supply perspectives. From a demand perspective, increased investment will stimulate economic growth by fostering effective expansion. In the meantime, on the supply side, investment growth will stimulate economic growth by increasing capital reserves, which will lead to an expansion of production capacity.

If the value of GDP rises by 1 percent, then the value of FDI rises by 0.928 percent, all other factors being equal. GDP has a greater influence on FDI than FDI does on GDP. This means that a member of ASEAN with a higher GDP will attract foreign investors. This influences the value of foreign direct investment (FDI) entering ASEAN countries, which is also rising. This study's results concur with those of Cahyono (2013) and Türkcan et al. (2008). Countries with a high GDP level typically attract investors. A country's high GDP indicates good economic performance. GDP is used to calculate the level of a country's national income. It is indicated that a country's market potential will be strong if its income is high. It's because nations with massive businesses can encourage product sales. The increase in national income indicates that the community's income is also rising, which influences the rising demand for goods and services. The enhancement in product and service demand will have a positive impact on company profitability, thereby attracting investors to the country.

The spatial effect parameter coefficients for the GDP and FDI equations indicate a spatial dependence among ASEAN nations. According to LeSage & Pace (2009) and LeSage & Fischer (2008), the parameter coefficients in spatial durbin regression cannot be interpreted as in ordinary regression, both for single and simultaneous equations. Measurement of the impact of exogenous variable changes on endogenous variables is based on marginal effects, namely direct, indirect, and total effects. The exogenous variables marginal effects are established in Table 12.

Table 12
Exogenous variables marginal effects

Equations	Variable	Direct	Indirect	Total
lnGDP	lnLFT	0.307	-1,738	-1.431
lnFDI	lnTO	0.423	-0.781	-0.358

Table 12 demonstrates that the entire labor force possesses a direct effect on a nation's Gross Domestic Product. If the labor force in a country grows by one percent, the country's GDP would rise by 0.307 percent. This indicates that a person's income will be affected by their employment status. Increased income will influence the purchasing power of individuals, which will also increase. Thus, an increase in the number of workers will increase people's purchasing power, which will boost economic growth in ASEAN nations. This is in accordance with the findings by Atikah et al. (2021), Soava et al. (2020), and Utami et al. (2021). The indirect and total effects indicate that even an addition to the number of employees within one of the ASEAN countries has no positive effect on the economy of countries that engage in import-export activities in the vicinity of the reference country. Investment in ASEAN countries is directly and positively impacted by trade openness. If the value of an ASEAN country's trade openness increases by 1 percent, then foreign investment in that country will increase by 0.293 percent. This aligns with the findings by Djulius (2017), Lien (2021), Tahmad & Adow (2018), and Zaman et al. (2018). High trade openness in a country indicates that the performance of international trade in that country has improved, which impacts the ease with which foreign investors can invest. Foreign investors will invest substantial sums if investment procedures are simplified. The total and indirect effect for trade openness in ASEAN countries on foreign direct investment in neighboring countries is not favorable. This is owed to the fact that the commodities traded by the majority of ASEAN nations are nearly equivalent.

5. Conclusions

The modified GEE method was applied to the analysis of the SSDP model. The true covariance matrix structure in the SSDP model can be relaxed when the parameter estimation process is carried out using the LISGEE approach. The estimator generated by the LISGEE approach is robust. There are three working correlations used in the estimation process, namely: independent, first-order autoregressive, and exchangeable with three spatial weighting matrices, namely: queen, 2-*NN*, and customized. To model the economic growth in ASEAN countries during 2010 to 2019, the first-order autoregressive and exchangeable working correlation with a customized weighted matrix were selected based on the CIC value. The parameter analysis results indicate: 1) it is a significant spatial dependence among ASEAN countries; 2) it is a significant simultaneous interaction among the GDP and FDI; 3) GDP has a greater influence on FDI than FDI does on GDP; 4) The economic growth is directly affected by the labor force total; and 5) trade openness has a direct effect on FDI.

6. Implication

The analysis results indicate that the GDP is the most important factor in attracting FDI to ASEAN countries. Therefore, policymakers in each ASEAN nation should maintain and expand their respective economic growth. The economic security and stability of a country is among the factors that attract investors. In formulating its policies, the government should consider the economic conditions of its neighbors and other countries in which it has established cooperative ties. Additionally, the local government must play an active role in providing citizens with diverse training opportunities and talent development. The government must also conduct periodic monitoring to preserve the productivity and labor force quality, which has a bearing on enhancing the number of workers to stimulate economic growth. Moreover, to improve trade relations, the governments of each ASEAN nation must implement a policy of diversification of trade products. The implications of this study may hopefully assist ASEAN governments in achieving the eighth Sustainable Development Goal. Future researchers should be able to extend the findings of this study by examining economic variables other than those used in this study that are believed to influence GDP and FDI and incorporating dynamic effects to assess the short-term and long-term effects of an economic variable. Within the discipline of statistics, future researchers can also supplement the use of working correlations such as Toeplitz, m-dependent, and unstructured by developing criteria for selecting the best model, employing a full information approach (system equations), and conducting data simulations.

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Appendix A

Table A1
Queen contiguity weighted matrix.

	BRN	KHM	IDN	MYS	MMR	PHL	SGP	THA	VNM
BRN	0	0	0	1	0	0	0	0	0
KHM	0	0	0	0	0	0	0	0.5	0.5
IDN	0	0	0	1	0	0	0	0	0
MYS	0.3	0	0.3	0	0	0	0	0.3	0
MMR	0	0	0	0	0	0	0	1	0
PHL	0	0	0	0	0	0	0	0	0
SGP	0	0	0	0	0	0	0	0	0
THA	0	0.3	0	0.3	0.3	0	0	0	0
VNM	0	1	0	0	0	0	0	0	0

Table A2
2-NN weighted matrix

	BRN	KHM	IDN	MYS	MMR	PHL	SGP	THA	VNM
BRN	0	0	0.5	0.5	0	0	0	0	0
KHM	0	0	0	0	0	0	0	0.5	0.5
IDN	0.5	0	0	0.5	0	0	0	0	0
MYS	0.5	0	0	0	0	0	0.5	0	0
MMR	0	0	0	0	0	0	0	0.5	0.5
PHL	0.5	0	0.5	0	0	0	0	0	0
SGP	0	0.5	0	0.5	0	0	0	0	0
THA	0	0.5	0	0.3	0.3	0	0	0	0.5
VNM	0	0.5	0	0	0	0	0	0.5	0

Table A3
Customized weighted matrix

	BRN	KHM	IDN	MYS	MMR	PHL	SGP	THA	VNM
BRN	0	0	1	0	0	0	0	0	0
KHM	0	0	0	0.3	0	0	0	0.3	0.3
IDN	0.3	0	0	0.3	0	0.3	0	0	0
MYS	0	0	0	0	0.5	0	0.5	0	0
MMR	0	0	0	0.3	0	0.3	0	0.3	0
PHL	0	0	0.5	0	0.5	0	0	0	0
SGP	0	0	0	0.5	0	0	0	0.5	0
THA	0	0.5	0	0	0	0	0.5	0	0
VNM	0	1	0	0	0	0	0	0	0

Appendix B

Simultaneous equation identification steps with rank conditions.

Step-1 Change the Equation (21) to Equation (B.1) and (B.2).

$$\ln GDP - \beta_{10} - \beta_{11} \ln LFT - \delta_{11}\left(\mathbf{I}_J \otimes \mathbf{W}\right)\ln GDP - \theta_{11}\left(\mathbf{I}_J \otimes \mathbf{W}\right)\ln LFT - \gamma_{21}\ln FDI - \mathbf{υ}_1 = \mathbf{u}_1 \quad \text{(B.1)}$$

$$\ln FDI - \beta_{20} - \beta_{22} \ln TO - \delta_{21}\left(\mathbf{I}_J \otimes \mathbf{W}\right)\ln FDI - \theta_{22}\left(\mathbf{I}_J \otimes \mathbf{W}\right)\ln TO - \gamma_{12}\ln GDP - \mathbf{υ}_2 = \mathbf{u}_2 \quad \text{(B.2)}$$

Step-2 Rewrite Eq. (B.1) and Eq. (B.2) in the following table form with the coefficients of each equation.

Equation	Intercept	lnGDP	lnFDI	lnLFT	lnTO	$(\mathbf{I}_J \otimes \mathbf{W})$ lnGDP	$(\mathbf{I}_J \otimes \mathbf{W})$ lnFDI	$(\mathbf{I}_J \otimes \mathbf{W})$ lnLFT	$(\mathbf{I}_J \otimes \mathbf{W})$ lnTO
lnGDP	$-\beta_{10}$	1	$-\gamma_{12}$	$-\beta_{11}$	0	$-\delta_{11}$	0	$-\theta_{11}$	0
lnFDI	$-\beta_{20}$	$-\gamma_{21}$	1	0	$-\beta_{22}$	0	$-\delta_{22}$	0	$-\theta_{22}$

Step-3 Cross out the coefficients from the identified equation row and cross out the coefficients from the column corresponding to the identified equation coefficient and not equal to zero.

Equation	Intercept	lnGDP	lnFDI	lnLFT	lnTO	$(\mathbf{I}_J \otimes \mathbf{W})$ lnGDP	$(\mathbf{I}_J \otimes \mathbf{W})$ lnFDI	$(\mathbf{I}_J \otimes \mathbf{W})$ lnLFT	$(\mathbf{I}_J \otimes \mathbf{W})$ lnTO
~~lnGDP~~	~~$-\beta_{10}$~~	~~1~~	~~$-\gamma_{12}$~~	~~$-\beta_{11}$~~	~~0~~	~~$-\delta_{11}$~~	~~0~~	~~$-\theta_{11}$~~	~~0~~
lnFDI	$-\beta_{20}$	$-\gamma_{21}$	1	~~0~~	$-\beta_{22}$	~~0~~	$-\delta_{22}$	~~0~~	$-\theta_{22}$

Equation	Intercept	lnGDP	lnFDI	lnLFT	lnTO	$(\mathbf{I}_J \otimes \mathbf{W})$ lnGDP	$(\mathbf{I}_J \otimes \mathbf{W})$ lnFDI	$(\mathbf{I}_J \otimes \mathbf{W})$ lnLFT	$(\mathbf{I}_J \otimes \mathbf{W})$ lnTO
lnGDP	$-\beta_{10}$	1	$-\gamma_{12}$	$-\beta_{11}$	~~0~~	$-\delta_{11}$	~~0~~	$-\theta_{11}$	~~0~~
~~lnFDI~~	~~$-\beta_{20}$~~	~~$-\gamma_{21}$~~	~~1~~	~~0~~	~~$-\beta_{22}$~~	~~0~~	~~$-\delta_{22}$~~	~~0~~	~~$-\theta_{22}$~~

Step-4 Arrange in matrix form.

$$\Delta \ln GDP = \left[-\beta_{22} \quad -\delta_{22} \quad -\theta_{22}\right]$$

$$\Delta \ln FDI = \left[-\beta_{11} \quad -\delta_{11} \quad -\theta_{11}\right]$$

Step-5 Determine the rank of the matrix at step 4.

$$rank\left(\Delta \ln GDP\right) = 1$$

$$rank\left(\Delta \ln FDI\right) = 1$$