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Spatial regional spillover of economic growth: Evidence from Vietnamese provinces

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Abstract

This study examines the spatial spillover of economic growth among provinces in seven Vietnamese socio-economic regions. Using the spatial autoregressive (SAR) model, the empirical results show regional, solid economic linkages among provinces within the same region. However, the spillover of growth in economic size (GDP) seems stronger than the transmission of growth in living standards (GDP per capita). The economic growth linkages are stronger in regions with a higher level of economic

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development. Our results also indicate that geographical location and regional culture can drive the differences in economic connections among areas.

Keywords: Spatial spillover, economic growth, spatial autoregressive model, economic linkages

1. Introduction

The problem of development strategy for domestic and regional economic linkages has attracted attention in many studies (Hirschman, 1958; Scott, 1983; Vulevic, 2018). According to LeSage and Fischer (2008), long-run regional economic growth depends on the own region as well as neighboring region characteristics, the spatial connectivity structure of the areas, and the strength of spatial dependence. The spatial effect has been recognized as essential in the regional convergence process (Rey & Montouri, 1999). Ignoring the spatial estimation would result in serious misspecification (Abreu et al., 2005). Recently, a large body of empirical research on the convergence of regions and countries has shown spatial dependence and spatial heterogeneity. For example, Ertur et al. (2006) find strong spatial spillover effects in the convergence process of 138 European regions over the 1980 to 1995 period. Fingleton and Lopez-Bazo (2006) thoroughly review the spatial impact on growth. The common conclusion is that the growth rate in a region depends not only on its own initial income level and saving rate of physical and human capital but also on those of its neighbors.

Much research focuses on finding factors that impact the spillover of economic growth within (or among) countries. Shao and Zheng (2010) employ C-D production functions to develop a spatial econometric model and determine a strong spatial correlation between regional economic development and logistics in China. Raza and Hina (2016) explore the regional dependency and direct and indirect effects of fiscal decentralization on the economic growth of Pakistan's provinces. The empirical analysis is based on the provincial panel data from 1990 to 2011. The spatial Durbin model (SDM) results indicate that revenue decentralization has a positive effect on province economic growth, whereas expenditure decentralization has a negative impact. Hoang and Dao (2021) analyze the connection between market integration and regional economic growth in Vietnam using data from 30 Vietnamese provinces from 2005 to 2018. The results indicate a strong positive correlation between market integration and regional economic development. This study also shows

that regional income growth in a particular province of Vietnam is favorably correlated with the income of its adjacent provinces. Amidi et al. (2020) use the spatial dynamic panel model to examine the spatial effects of geographical distance on economic growth in selected Asian nations from 1992 to 2016. The results indicate that spatial dependence is one of the principal causes of economic growth spillovers. We could find similar findings in Wang et al. (2021) and Karahasan and Pinar (2022).

Although many studies investigate the spatial transmission of economic growth, not many studies evaluate and compare these spillover effects across regions within a country. This issue deserves attention because each region in a country can have different characteristics, leading to different linkages between provinces in each region. Understanding this relationship will help policymakers make appropriate decisions in regional economic development. Therefore, in this study, we focus on the economic development spillovers of provinces in different regions of Vietnam. With a fast development speed, Vietnam is considering regional economic development as the focus of the national economic development strategy.

In Vietnam, the government has long determined that the division of socio-economic regions is essential for each region's specific planning, thereby exploiting each province's potential and advantages. This is due to provinces and regions in Vietnam having many geographical, cultural, social, and economic differences. Therefore, grouping provinces by region will help these localities easily cooperate in infrastructure, value chain, socio-economic development, etc. Vietnam is composed of 63 provinces and centrally-governed cities (five centrally-governed cities stand on the same administrative level as provinces). Based on the proposal by the Vietnam Ministry of Planning and Investment in 2020 for a new division of social-economic regions, the whole country is divided into seven social-economic regions, including the Northern Mountains (10 provinces), Red River Delta (15 provinces), North Central (6 provinces), South Central (8 provinces), Central Highlands (5 provinces), Southeastern (6 provinces), and Mekong River Delta (13 provinces). Figure 1 below illustrates the locations of these seven socio-economic regions.

Figure 1. The seven socio-economic regions of Vietnam

Source: https://tienphong.vn/ca-nuoc-chia-thanh-7-vung-kinh-te-uu-diem-ra-sao-han-che-the-nao-post1246157.tpo

This study examines the question if there are any spatial spillover effects of economic growth among provinces in Vietnam. To answer this question, we analyze the panel data of 63 Vietnamese provinces during the period from 2016 to 2020 using the spatial autoregression (SAR) model. The results confirm strong regional economic linkages and the spillover effects of

economic growth among Vietnamese provinces. The magnitudes of spatial parameters show that the spillover of growth in economic size seems to be easier than the transmission of growth in living standards. When looking at each socio-economic region, the empirical results find that economic growth spillovers depend on each region's economic development level; geographical location and regional culture can also drive the differences in economic linkages among regions.

Our study contributions to the literature are threefold. First, by using the SAR model, this paper confirms the causal spillover effects of economic growth among neighboring provinces. It proves that economic growth in one area could motivate nearby regions for growth. Second, this study provides empirical evidence of economic linkages and inter-regional spillover of economic growth among provinces in Vietnam. This result supports the view of the necessity of regional economic development. Finally, by separately examining each socio-economic region, this study provides a comparison of the closeness of economic linkages among regions. It brings insight into the current regional division of Vietnam and gives some suggestions to policymakers in finding areas with weak regional economic linkages to promote the regional economy in these areas.

The rest of this paper is organized as follows: Section 2 illustrates the SAR model used for our analysis; Section 3 presents the data description and the creation of the spatial weights matrix; Section 4 provides empirical results and discussions; the conclusion of this paper is presented in Section 5.

2. Methodology

In this study, we use the spatial autoregression (SAR) model that captures spatial interactions across spatial units and overtime for panel data. We assume that our panel data covers $i = 1, ..., N$ spatial units for $t = 1, ..., T$ periods. The general SAR model is:

$$
\mathbf{Y} = \lambda \left(\mathbf{I}_T \otimes \mathbf{W}_N \right) \mathbf{Y} + \beta \mathbf{X} + \mathbf{u},\tag{1}
$$

where **Y** is a $NT \times 1$ vector of the dependent variable, **X** is a $NT \times k$ matrix of exogenous predictors, \mathbf{I}_T is an identity matrix of dimension T, \mathbf{W}_N is the $N \times N$ spatial weights matrix whose diagonal elements are set to zero, and λ is the spatial autoregressive parameter which measures the strength of spatial interrelation. We express the disturbance vector as:

$$
\mathbf{u} = (\mathbf{u}_T \otimes \mathbf{I}_N) \mathbf{\mu} + \mathbf{\varepsilon},
$$
 (2)

where $\mathbf{\dot{e}}_r$ is a $T \times 1$ vector of one, \mathbf{I}_N is an identity matrix of dimension $N \times N$, **i** is a vector of time-invariant individual-specific effect (with elements μ_i , and $\hat{\mathbf{a}}$ is a vector of spatially autocorrelated innovations that follow a spatial autoregressive process of the form:

$$
\mathbf{\varepsilon} = \rho \left(\mathbf{I}_T \otimes \mathbf{W}_N \right) \mathbf{\varepsilon} + \mathbf{v},\tag{3}
$$

where ρ is the spatial error parameter; all elements of $\ddot{\textbf{a}}$ follow

 $\varepsilon_{it} \sim (0, \sigma_{\varepsilon}^2)$, and all elements of **í** follow $v_{it} \sim (0, \sigma_{\nu}^2)$ $v_{it} \sim (0, \sigma_v^2)$. Since our focus is the inter-regional spillover of the dependent variable, the specification in Equation (3) helps to control for the spatial spillover of all unobserved variables that affect Y .

Similar to ordinal panel regression, we could also account for the SAR model's random and fixed effects. For the random-effects model, the unobserved individual effects are uncorrelated with the other explanatory variables in the model. Therefore, we can express our model as:

$$
\mathbf{Y} = \lambda \left(\mathbf{I}_T \otimes \mathbf{W}_N \right) \mathbf{Y} + \beta \mathbf{X} + \left(\mathbf{t}_T \otimes \mathbf{I}_N \right) \boldsymbol{\mu} + \left(\mathbf{I}_T \otimes \left(\mathbf{I}_N - \rho \mathbf{W}_N \right)^{-1} \right) \mathbf{v}, \qquad (4)
$$

For the fixed-effects model, we follow Elhorst (2003) to set up a fixed-effects spatial lag model as

$$
\mathbf{Y} = \lambda \left(\mathbf{I}_T \otimes \mathbf{W}_N \right) \mathbf{Y} + \beta \mathbf{X} + \left(\mathbf{I}_T \otimes \mathbf{I}_N \right) \mathbf{\mu} + \varepsilon. \tag{5}
$$

 To estimate the parameters of the above Equation, Millo and Piras (2012) provide two ways of implementation, including the maximum likelihood (ML) approach and the generalized moments (GM) approach. For the ML approach, the estimation can be operationalized by a two-step iterative procedure that alternates between generalized least squares (GLS) for **â** and σ_{v}^{2} and concentrated likelihood for the remaining parameters (λ , ρ , and σ_{v}^{2}) until convergence. For the GM approach, ρ and the variance components σ_{ε}^2 and σ_v^2 are estimated by GM, while the coefficients λ and $\hat{\mathbf{a}}$ are estimated by a Feasible GLS method.

To compare the fixed effects and random effects models, we employ the spatial Hausmann test proposed by Mutl and Pfaffermayr (2011). The test static of the spatial Hausmann test takes the following form:

$$
H = NT \left(\hat{\theta}_{FGLS} - \hat{\theta}_W\right)' \left(\hat{\Sigma}_W - \hat{\Sigma}_{FGLS}\right)^{-1} \left(\hat{\theta}_{FGLS} - \hat{\theta}_W\right),
$$

where $\hat{\theta}_{FGLS}$ and $\hat{\theta}_w$ are the spatial GLS and within estimators, respectively; $\hat{\Sigma}_{_{W}}$ and $\hat{\Sigma}_{_{FGLS}}$ are the corresponding estimates of the coefficients' variance-covariance matrices. *H* is asymptotically distributed χ^2 with *k* degrees of freedom where *k* is the number of regressors in the model. We implement the estimation process and spatial Hausmann test in R 4.1.2.

3. Data descriptions

3.1. Spatial weights matrix (W_N **)**

The critical element of the SAR model is the spatial weights matrix representing the spatial links of your data. In this paper, we study the inter-regional spillover effects of GDP growth among 63 Vietnamese

provinces. Therefore, for Equations (1) , $(3) - (5)$, the spatial weights matrix W_N is the 63×63 spatial weights that are associated with 63 Vietnamese provinces.

The elements of \mathbf{W}_N are constructed using the binary Queen contiguous spatial weight matrix method, which is straightforward in accounting for the inter-regional spillover effects among contiguous provinces. Specifically, each element $w_{ij(i \neq j)}$ is set to be 1 if provinces *i* and *j* are contiguous neighbors (share a common boundary or vertex) and 0 otherwise. The diagonal elements w_{ii} are set to zero. Figure 2 illustrates the map of spatial links transformed into the matrix \mathbf{W}_{N} .

Figure 2. The spatial links of Vietnamese provinces.

3.2. Variable definitions and summary statistics

The Solow growth model of Solow (1956) is regarded as one of the most significant contributions to the theory of economic growth. This model provides a simplified view of the economy as a whole and sheds light on the drivers of economic growth and the reasons for wealth inequality between nations. The Solow model is built based on the neoclassical aggregate production function:

$$
Y = f(A, K, L),\tag{6}
$$

where*Y* is aggregate output, *K* is capital input, *L* is labour input, and *A* measures productivity or the level of technology. Employing the idea of the Solow growth model, we build our model with exogenous variables that are population growth, labor force growth, skilled labor force growth, capital stock, land area, and number of firms. We use two variables to evaluate the economic development of 63 Vietnamese provinces, including GDP growth and GDP per capita growth. All of these variables are collected from the Vietnam General Statistics Office from 2016 to 2020. Figure 3 shows the total GDP per capita of each socio-economic region in Vietnam from 2016 to 2020 (calculated by adding up the GDP per capita of all provinces in each region). Based on this figure, the Red River Delta region has the highest total GDP per capita, followed by the Southeastern region, Mekong River Delta region, Northern Mountains region, South Central region, North Central region, and Central Highlands region. Table 1 below describes the summary statistics of each variable in the SAR model.

Figure 3. Total GDP per capita of each socio-economic region in Vietnam from 2016 to 2020 (Unit: Millions VND).

Variables	Definitions	Mean	Std. dev	Min	Max			
Dependent variables								
Log of GDP growth	Log of the growth rate of real GDP	0.065	0.040	-0.158	0.285			
Log of GDP per capita growth	Log of the growth rate of real GDP per capita	0.084	0.042	-0.132	0.201			
Regressors								
Log of population growth	Log of the growth rate of population	0.009	0.009	-0.012	0.053			
Log of labor force growth	Log of the growth rate of labor force participation rate	0.677	0.031	0.573	0.730			
Log of skilled labor force growth	Log of the growth rate of skilled labor force participation rate	0.193	0.074	0.088	0.485			
Log capital	Log of capital stock from investment	5.047	0.382	4.237	6.415			
Land area	Total land area (unit: 10,000 km^2)	0.525	0.365	0.082	1.649			
Number of firms	Numbers of operating firms (unit: 100,000 firms)	0.105	0.311	0.005	2.396			

Table 1. Summary statistics of variables

Note: We calculate the summary statistics by pooling data for the 2016-2020 period.

4. Results and Discussions

4.1. Moran's I test for spatial correlation

Before modeling data with the SAR model, we first check for the spatial autocorrelation of our data set using Moran's I test (Cliff & Ord, 1981; Bivand & Wong, 2018). The null hypothesis of this test is that there are no spatial dependencies among observations of a variable. Results from Table 2 show high spatial correlations for economic growth among Vietnamese provinces during the period 2016-2020. It proves the efficiency of using the spatial model to examine the inter-regional spillover of economic growth of Vietnamese provinces.

4.2. Spatial autoregressive models' results

We first examine the spatial inter-regional spillover of economic growth among Vietnamese provinces by considering the whole country dataset. Specifically, we model all 63 Vietnamese provinces without regional division. Table 3 illustrates the results when the dependent variable is the Log of the growth rate of real GDP, while Table 4 shows the estimated results when the dependent variable is the Log of the growth rate of real GDP per capita. For both ML and GM estimations, the spatial Hausman tests' p-values confirm that fixed effects models are preferable. Therefore, we focus on the estimated parameters of fixed effects models when discussing the statistical results.

In Table 3, both ML and GM estimation of fixed effects models confirm the positive impacts of the skilled labor force, land area, and firm number on real GDP growth. High-skilled labor helps to increase the quality of human

capital, which in turn speeds up economic growth (Kauhanen, 2019). The effects of land area and firm number are obvious since they create more resources for provinces in developing economies. The estimation of the spatial autoregressive parameter (λ) demonstrates the existence of a significant spatial dependence on GDP growth among nearby provinces. More specifically, it proves that the GDP growth of one province is affected by its neighbors. The estimation of the spatial error parameter (ρ) , which illustrates the trend of a noticeable

spatial autocorrelation in the residuals, also confirms the existence of hidden independent variables with spatial autocorrelation.

Dependent variable: Log of the growth rate of real GDP							
	ML estimation		GM estimation				
	Fixed effects	Random effects	Fixed effects	Random effects			
	(1)	(2)	(3)	(4)			
Log of population growth	1.1852	$0.5207*$	0.9182	$0.3420*$			
	(1.0955)	(0.3056)	(0.3331)	(0.1422)			
Log of labor force growth	0.1149	0.1506	0.0157	0.0648			
	(0.1534)	(0.1131)	(0.9281)	(0.0928)			
Log of skilled labor force	$0.4394***$	$0.1125**$	$0.3343***$	$0.1410***$			
growth	(0.0968)	(0.0462)	(0.0650)	(0.0363)			
Log capital	$0.5535***$	$0.0953**$	$0.3894***$	$0.0853**$			
	(0.1945)	(0.0211)	(0.1032)	(0.0194)			
Land area	$0.6487***$	0.0130	$0.5088***$	0.0062			
	(0.1961)	(0.0088)	(0.1123)	(0.0064)			
	$0.0153**$	$0.0084**$	$0.0103**$	$0.0077**$			
Number of firms	(0.0069)	(0.0035)	(0.0072)	(0.0026)			
	$0.5830***$	$0.6492***$	$0.5459***$	$0.6913***$			
	(0.0796)	(0.0647)	(0.0000)	(0.0439)			

Table 3. Estimated parameters of the SAR model for the whole country (Dependent variable is the Log of the growth rate of real GDP)

Note: *significant at 10%, **significant at 5%, ***significant at 1%.

In Table 4, the estimation results are consistent with what we found in Table 3. Population growth, skilled labor force, capital, land area, and number of companies are key factors that positively influence GDP per capita growth.

The estimation of λ and ρ once again confirm those spatial spillovers of GDP per capita growth among provinces. Since the GDP per capita is usually considered as a standard of living, this result means that the increase in prosperity of one province could help to pull up the prosperity of neighboring provinces. However, looking at the magnitude of the estimations, we recognize that the estimated results of λ when the dependent variable is the GDP per capita growth (Table 4) are smaller than that when the dependent variable is the GDP growth (Table 3). It suggests that the spatial transmission of economic size is easier than the spillover of living standards.

Table 4. Estimated parameters of the SAR model for the whole country (Dependent variable is the Log of the growth rate of real GDP per capita)

Note: *significant at 10%, **significant at 5%, ***significant at 1%.

To have more insight into views of the spatial spillover of economic growth among provinces in each region, we separately run the SAR model for each of the seven socio-economic regions in Vietnam. Table 5 provides the estimated results of each region when the dependent variable is the Log of the growth rate of real GDP. Table 6 shows the estimated results when the dependent variable is the Log of the growth rate of real GDP per capita. Focusing on the spatial autoregressive parameter, we find many differences in the spatial spillovers of economic growth among regions.

In Figure 5, from the estimation of λ , we can identify that among three regions in the north (Northern Mountains, Red River Delta, and North Central), only the Red River Delta region has significant positive economic growth transmissions. In contrast, we find no evidence of spatial spillovers of economic growth in the other two regions (or a very low spillover effect in the case of the Northern Mountains with GM estimation). Recalling from Figure 3, the Northern Mountains and North Central regions are two of the least

developed economic regions in the country, while the Red River Delta has the highest total GDP per capita in Vietnam. This result shows that the magnitude of economic growth spillovers depends on each region's economic development level. Regions with more developed economies usually have higher economic linkages among members than less developed regions. Moving to the south, the other four regions have significantly positive estimations of λ (even for Central Highlands, the region with the lowest total GDP per capita in Vietnam). However, the magnitude of λ in Central Highlands is lowest compared to other regions in Southern Vietnam, once again supporting the finding that economic growth spillovers depend on the level of economic development of each region. More interestingly, when looking at the seven socio-economic regions of Vietnam as a whole, the further south, the greater the degree of economic growth spillover. It means geographical location and regional culture can also drive the differences in economic linkages among regions.

In Figure 6, when using GDP per capita growth as a dependent variable, we also find evidence of the dependence of economic growth spillovers on economic development and geographical location. Among the three regions in the north, the Red River Delta has the highest estimation for λ . All regions in the south have significant positive economic transmissions, and the further south, the greater the degree of economic growth spillover.

Table 5. Estimated parameters of the SAR model for each social-economic region Table 5. Estimated parameters of the SAR model for each social-economic region

(Dependent variable is the Log of the growth rate of real GDP) (Dependent variable is the Log of the growth rate of real GDP)

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4.3. Robustness checking with diff erent types of weights matrices

To verify the robustness and sensitivity of our results to different specifications for weights matrices, we follow Esiyok and Ugur (2017) to create two other weights matrices based on the distance between provinces with different cut-off values. We build the first alternative weights matrix $(AW1)$ based on neighbors within 186 kilometers of the capital of the host province. Neighbor provinces within a distance of 186 kilometers of the host province will take the value of 1 in the weights matrices and 0 otherwise. This cut-off value guarantees having at least three neighbors for each host province. The second alternative of the weights matrix (AW2) is all neighbors within a radius of 350 kilometers from the capital of the host province, ensuring that each host province has at least seven neighbors. As distance increases, the level of spatial dependence is expected to decrease at a quadratic rate. As a result, closer neighbors receive heavier weights than distant neighbors. In calculating the distance between provinces, we use capital cities as reference points. As provinces grow in size, so do the distances between them.

Table 7 illustrates the results of our SAR model with these two specifications for weights matrices. The estimated results of spatial parameters again confirm significant spatial linkages of economic growth among nearby provinces, proving our findings' robustness in different weights matrices' specifications.

Table 7. Estimated parameters of the SAR model for the whole country (Dependent variable is the Log of the growth rate of real GDP)

Note: *significant at 10%, **significant at 5%, ***significant at 1%. AW1 is the weights matrix base on neighbors within 186 kilometers of the capital of the host province. AW2 is the weights matrix base on neighbors within 350 kilometers of the capital of the host province.

5. Conclusions and suggestions

To achieve inclusive growth and sustain the growth momentum, it is increasingly recognized that the regional economy is of critical importance. Given the divergence in economic growth potential in Vietnam, this study examines the spatial spillovers of economic growth among provinces in seven Vietnamese socio-economic regions. We analyze the panel data of 63 Vietnamese provinces from 2016 to 2020 using the spatial autoregression (SAR) model. The results confirm strong regional economic linkages and the spillover effects of economic growth among Vietnamese provinces. The magnitudes of spatial parameters show that the spillover of growth in economic size seems to be easier than the transmission of growth in living standards. When looking at each socio-economic region, the empirical results find that economic growth spillovers depend on each region's economic development level; geographical location and regional culture can also drive the differences in economic linkages among regions. From the above results, we make some suggestions for policymakers in developing the regional economy in Vietnam. First, the less developed economic regions have the lowest regional linkages. Therefore, the government should put more effort into boosting the economic connections among provinces in these regions, which will help improve each province's economy. Second, since economic growth transmission is affected by geographical location and regional culture, the central government should have separate policies for each region to develop the regional economy effectively.

This study has some limitations. The data used in our analysis is annual data, which is low-frequency. To solve this, future studies can address the spillover of economic growth among regions using nighttime lights. This could be a good proxy of economic growth, and as high-frequency data, it is easier to collect (Bickenbach et al., 2016; Chen, 2020; Zheng et al., 2020; Sun et al., 2021; Puttanapong et al., 2022). We can also extend this study by using the spatial Durbin model (SDM) and the spatial error model (SEM) to account for the direct and indirect effects of exogenous variables on economic growth or spatial dependence on the errors.

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