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Decoding the Drivers of Structural Change: Novel Insights from Spatial Panel Data Modeling

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ABSTRACT

Examining the drivers of sustainable development necessitates a comprehensive understanding of structural change. However, existing studies primarily concentrate on the geographical scope of regions, disregarding the intricate interdependencies between areas. This research addresses this gap by employing spatial panel data models to investigate the determinants of structural change, using Vietnam as a case study. The study analyzes a dataset encompassing 63 provinces over a decade (2010-2019). The findings shed light on a previously unexplored aspect: the presence of spatial correlation in the proportion of the non-agricultural sector within the local economic structure. Factors such as agricultural labor productivity, income levels, the transportation system, and FDI capital exert positive influences on structural change. Furthermore, the transportation system and FDI capital have spillover effects on neighboring areas, catalyzing structural transformation. Improved local transportation not only stimulates change within a locality but also fosters connections with urban centers, accelerating structural change in neighboring regions. FDI inflows play a direct role in local structural change, providing investment capital, access to modern technology, and introducing new production forms. Additionally, FDI indirectly supports neighboring areas through domestic enterprise linkages, generating a ripple effect

INTRODUCTION

To be known as the rearrangement of economic activities across the agricultural, industrial, and service sectors, structural change is one of the core economic issues that receive great attention from scholars (Herrendorf et al., 2014; Kuznets, 1973). The role of structural change has been recognized very early in the economic development literature, and the growth path of most developed countries is closely linked to this process (Bustos, 2016; Rodrik, 2016). According to McMillan & Heady (2014), structural change makes the allocation of resources in the economy more efficient and helps to increase productivity sustainably. In addition, structural change is essential in poverty reduction, the first of 17 sustainable development goals (SDGs) the United Nations has adopted (Lin, 2019). Van Aswegen & Retief (2020) argues

that structural change is an effective policy tool in economic recovery after a crisis or fluctuations in many fields. Besides that, this process also supports the improvement of people's incomes and living standards (Loayza & Raddatz, 2010). From the above roles, identifying the determinants of structural change has long been a widely discussed research topic (McMillan & Headey, 2014). However, the existing studies mainly approach this problem in a non-spatial direction. In other words, these studies have ignored the spatial factor in considering the change of economic activities while this factor plays a vital role in economic analysis (Bac et al., 2023; Wu & Gopinath, 2008).

In fact, the topic of spatial factors covers a wide range, is interdisciplinary and has been covered for a long time. However, different fields often have different tools and terminology to address this. As a result, spatially related questions are often solved by techniques that vary across disciplines, and some researchers don't even know that this problem exists in the same branch of social science (Dietz, 2002). For example, in geography, spatial factors can be considered regarding urban structure organization and population distribution (Bac, 2023). Meanwhile, the field of social sciences exploits the effects of spatial factors, such as "neighborhood effects" or "exposure effects," with the mechanism of action through different channels (Chyn & Katz, 2021; Mogstad & Torsvik, 2023). From an economic perspective, the existence of spatial factors and their influence has been recognized in many studies (Topa & Zenou, 2015). However, the spatial factor in this field mainly focuses on the characteristics of the agglomeration economy, while the effects on structural change are rarely mentioned. One of the few recent studies using a spatial approach in analyzing economic structural change in localities is the study of Truong Cong et al. (2023). This study has also shown that the spatial factor plays a vital role in considering the process of structural change. However, the approach of the above study only focuses on the effects of the dominant metropolises characteristics on the change of neighboring localities based on the assumptions of urban-rural relationship. In other words, the above study only stopped considering the process of structural transformation in the spatial separation between urban and rural areas. Therefore, analyzing spatial factors in the process of structural change at the overall scale with the minimization of assumptions is still a big question mark.

With the aim of filling this gap, this study broadens the overall picture of the determinants of structural change from a spatial perspective. Empirical evidence is drawn from a typical developing country, Vietnam. Compared with other developing countries, Vietnam is considered a typical case with a rapid structural change process. After just over 35 years of implementing the "Doi Moi" work starting in 1986, the share of agricultural employment in total employment decreased from 70.88% in 1991 to 37.22% in 2019, while GNI significantly improved from less than 500 USD/year in 1990 to about 1,900 USD/year in 2019 (in 2010 constant dollars). Along with that is the elimination of the economic administrative-command system and its replacement with a market economic model combined with reforms in public administration activities. In addition, Vietnam is also conducting the process of economic opening and international economic integration by participating in many bilateral and multilateral free trade agreements. During the process of structural change, Vietnam has achieved many significant achievements, including stable economic growth, attracting foreign direct investment, diversifying exports, and improving people's living standards. This has helped Vietnam go from being one of the poorest countries to becoming a low-middle income country. Therefore, the analysis of the case of Vietnam will provide great value in identifying the determinants of structural change, especially in developing countries.

The remainder of this study is structured as follows: Section 2 reviews the theoretical background related to the research topic. Section 3 presents the research methods and data. The results of the study and discussion will be presented in section 4. The final section will provide conclusions.

1. LITERATURE REVIEWS

Over a long time, the two main mechanisms used to explain economic structural changes have been income and productivity. The first mechanism involves differences in income elasticity of demand for different products, or other words, heterogeneity in preferences. The income elasticity of demand for non-agricultural goods is higher than for agricultural goods (Kongsamut et al., 2001). As income increases, demand for non-agricultural products increases, leading to a shift of labor from agriculture to non-agriculture (Foellmi & Zweimüller, 2008). Empirical evidence from data from 39 countries in the study by Comin

et al. (2021) shows that income effects mainly drive the sectoral reallocation of these countries. The other mechanism involves differences in technological progress across industries. According to Baumol (1967), if the output rates of the two industries remain constant in an economy with two industries with different productivity, the labor force must increasingly be moved to the non-progressive sector. Sharing the same view, Ngai & Pissarides (2007) argue that the different growth rates of total factor productivity (TFP) across industries are responsible for the change in economic structure, and employment will shift from a high-growth industry to a low-growth industry. Gollin et al. (2002) also suggested that industrialization will be accelerated through improved agricultural productivity. Similarly, the study of Bustos et al. (2019) also shows that the increase in agricultural productivity helps to save a large amount of labor, thereby leading to the redistribution of labor to the industrial sector. High-quality education will improve human capital, improve labor productivity, and lead to positive changes in the economic structure. With the development of a multidisciplinary model, Herrendorf et al. (2014) demonstrate that both income and productivity mechanisms are essential in explaining the process of economic restructuring. Similarly, Martins (2019) also provides solid evidence for the impact of the accumulation of physical and human capital on the rate of structural change.

Extending to the open economy case, McMillan et al. (2014) show that globalization creates opportunities for countries to attract investment and promote structural change. Meanwhile, the study of Mühlen & Escobar (2020) and Amendolagine et al. (2013) also demonstrate that foreign direct investment has contributed significantly to the movement of labor out of the agricultural sector as well as the change in economic structure. Through foreign direct investment activities, geographical areas can access abundant capital and new technologies and techniques for developing non-agricultural sectors. There is already evidence of failure in Latin American countries to undergo structural transformation due to a lack of capital. The economic restructuring process in these countries aims to prioritize the development of heavy industry with capital-intensive characteristics, while this region is characterized by capital-poor (Lin & Monga (2014).

In another approach, Fajgelbaum & Redding (2022) pointed out that the transport system helps geographical areas enhance their internal and external integration, thereby affecting the trade activities of different groups of goods. Similarly, Christiaensen & Martin (2018) also argue that the transportation system will reduce transaction costs for all products, creating an impetus for income growth as well as structural transformation. Meanwhile, Murata (2008) argues that improving the transport system and reducing transportation costs will increase the purchasing power of consumers through a decrease in the price index. This, combined with the heterogeneity of preferences, increases the potential demand for manufactured goods, leading to a shift in demand from agricultural to non-agricultural goods. In addition, the development of the transport system also contributes to the expansion of the market size for non-agricultural goods, leading to the reallocation of labor from the agricultural sector to the non-agricultural sector.

From a spatial perspective, recent studies have provided empirical evidence on the distribution of economic activities, in which non-agricultural activities are concentrated in certain areas. From the case of China and Japan, Fujita et al. (2004) argue that in an increasingly borderless world economy, the change in the spatial distribution of economic activities in a particular region will likely relate to neighboring regions. Li et al. (2015) analyze the case of Beijing and conclude that industrial and service activities are concentrated mainly in a few localities close to each other and the central urban area. Based on the choice of location of enterprises, research by Yang et al. (2021) shows that the electronic information manufacturing industry in China is spatially concentrated and tends to diffuse outward to neighboring regions in the West. Similarly, López & Páez (2017) show that the Greater Toronto Area's high-tech manufacturing activities and knowledge-intensive services have spatial clustering. This study also shows evidence of sharing key transport infrastructure and access to skilled labor among neighboring localities. Using exploratory spatial data analysis and industrial location quotient, Li et al. (2020) 's study has provided empirical evidence for the existence of spatial effects between the Locality spread from the accumulation of 31 manufacturing industries in Hebei Province, China. In addition, research by Truong Cong et al. (2023) shows that in the condition of separating areas into urban and rural areas, the structural change of rural areas will be promoted from the outstanding characteristics of the urban. Although the influencing mechanism shown in this study is indirect through changes in income and productivity, the study's results also demonstrate that the spatial factor cannot be denied in the analysis of structural change of localities.

2. METHODOLOGY AND DATA

2.1 Spatial autocorrelation

This study considers the spatial factor in analyzing the determinants of structural change, so examining the spatial autocorrelation on the economic structure of localities will be carried out from the beginning through the index reflecting spatial autocorrelation. Moran's I index and Geary's C index are the two most popular indexes for testing spatial autocorrelation. Of these, Moran's I index is more commonly used because of its higher overall stability. Moran's I index was first proposed by Moran's I (1950), then perfected and formulated by Cliff and Ord (1973).

$$I = \frac{N}{W}\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N}(x_i - \bar{\bar{x}})^2} \qquad (1)$$

Where N is the number of locations, W is a spatial weight matrix consisting of elements representing the spatial relationship between localities, where the element is the spatial weight between local i and local j. By convention, values on the diagonal in a spatial weighting matrix take the value 0, or $w_{ij} = 0$ when i = j for all i = 1,.., N. The spatial weight matrix can be constructed through different conditions, such as contiguous or distance characteristics. x_i and x_j are the observation values at local i and j, respectively. $\bar{x}$ is the average value of the observed variables. Moran's I index value ranges from -1 to +1. The value of Moran's I index is usually expressed as the slope of a regression line that describes the relationship between the value of one observation and the mean of its adjacent observations.

2.2 Spatial panel data models

In order to analyze the determinants of structural change in the case of spatial factors, spatial econometric models are used in this study. Elhorst (2010) established a classification of the main spatial econometric models based on three types of spatial interactions extracted from the foundational model of Manski (1993). Endogenous interactions, when the change of a geographical area will depend on the change of neighboring areas; exogenous interactions, where the variation of an area will depend on the observable characteristics of the neighboring regions; spatial correlation when the variation of regions will depend on the same unobserved characteristics. The model that combines all three of these potential spatial interactions takes the form:

$$y_{it} = \rho\sum_{i\neq j} w_{ij}y_{jt} + x_{it}\beta + \sum_{i\neq j} w_{ij}x_{jt}\theta + \alpha + u_{it}$$

$$u_{it} = \lambda\sum_{i\neq j} w_{ij}u_{jt} + \varepsilon_{it} \qquad (2)$$

Variable $\sum_{i\neq j} w_{ij}y_{jt}$ representative variable of the spatial endogenous variable is calculated by the mean value of the dependent variable at the observations in the local neighborhood i. The parameter ρ captures the endogenous interaction effect. x_{it} are the variables that explain the change of local i. β is the parameter of the explanatory variables. $\sum_{i\neq j} w_{ij}x_{jt}$ is the spatially exogenous representative variable. The parameter θ captures the spatial exogenous interaction effect. $\sum_{i\neq j} w_{ij}u_{jt}$is a representative variable of spatial correlation, whereby unobserved features (u_{it}) affecting the change of locality i interact with features affecting the local neighborhood of i. The parameter λ records the correlation effect of unobserved characteristics. And finally, ε_{it} is assumed $\varepsilon_{it} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma^2)$. From the above general model, some models will be created based on the assumption of the existence of spatial interactions: SAC(θ=0), SDM(λ=0), SDEM(ρ=0), SEM(ρ=0; θ=0), SAR(λ=0; θ=0), SLX(ρ=0; λ=0).

2.3 Data

This study uses two data sets, including economic statistics and spatial data. Specifically, economic statistical data is secondary data extracted from statistical yearbooks of localities in Vietnam for the ten years from 2010 to 2019. This data includes the proportion of the non-agricultural sector in economic structure, agricultural labor productivity, the proportion of the land area used for transportation purposes, and realized FDI in localities. Meanwhile, spatial data provides information about geographical relationships between localities, which is extracted from the Global Administrative Regions Database (GADM).

3. RESULTS

3.1 The descriptive statistics

Table 1 shows the descriptive statistics for the model variables. The non-agricultural sector's proportion in localities ranges from 39.05% to 93.42% between 2010 and 2019, with an average of around 69,601%. There are significant variations in labor productivity within the agricultural sector across localities, with the highest recorded at 128.88 million VND/year and the lowest at 6.63 million VND/year. The average income per capita of localities is 2.451 million VND/year, with variations of up to 6 million VND among different areas. The proportion of land allocated for transportation purposes ranges from 0.685% to 16.570%, averaging approximately 4.933%. Furthermore, the average foreign direct investment (FDI) inflow to localities during the 2010-2019 period is approximately 0.201 billion USD. Notably, the highest recorded level of FDI inflow reaches 4.101 billion USD.

Table 1. Descriptive statistics of variables

Variables	*Description*	*Mean*	*SD*	*Min*	*Max*
Pro	Labor productivity in agriculture (Million VND/year)	25.901	16.473	6.630	128.880
Inc	Income per capita (Million VND/month)	2.451	1.061	0.840	6.990
Trans	The proportion of land area used for transportation purposes (%)	4.933	3.786	0.685	16.570
FDI	FDI inflows (Billion USD)	0.201	0.458	0.000	4.101
NonA	The proportion of non-agricultural sectors in the economic structure (%)	69.601	11.540	39.050	93.420

Source: Author

3.2 Spatial autocorrelation

The Moran I scatter plot (Figure 1) depicts the relationship between each observation's value and its neighbors' mean. The horizontal axis of the histogram represents the scale of the values of the observations, while the vertical axis represents the weighted mean scale of the neighboring observations. Moran's I value is the slope of the least squares regression line of the observations. Most of the observations in the sample are distributed in the lower left and upper right corners, and over time the observations in these two regions are increasing. Therefore, the sample's observations' regression line has an upward slope. In other words, the proportion of non-agricultural sectors in the economic structure of provinces in Vietnam is similar to that of neighboring localities, and this trend has become increasingly obvious over time.

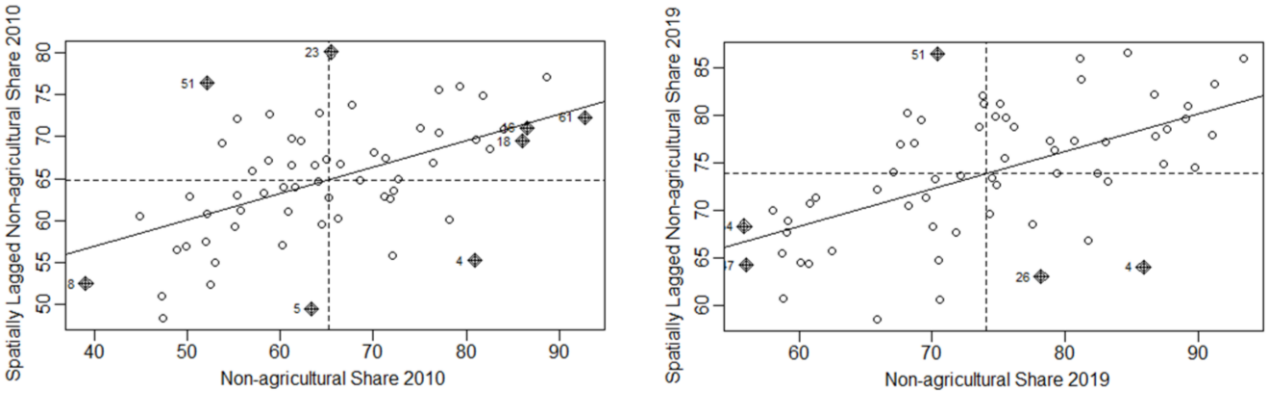

Figure 1. Moran scatterplot of non-agricultural share in Vietnam's provinces

Source: Author' calculation

Statistically, Table 2 shows that Moran' I index values ranged from 0.3680 to 0.4022 with an average value of 0.3786 during the period 2010-2019. In addition, Moran's I index test results always give a P-value less than 0.05. This shows that the proportion of non-agricultural sectors in the economic structure of localities is not distributed independently in space but is correlated, in which localities located next to each other have a similar proportion of non-agricultural sectors in the economic structure (positive auto-correlation).

Table 2. Moran's test of the spatial autocorrelation

	2010	*2019*	*2010 - 2019*
Moran's I	0.3680	0.4022	0.3786
Standard deviate	4.6524	4.793	4.712
Variance	0.0075	0.0076	0.0075
P-value	1.641e-06	8.215e-07	1.127e-06

Source: Author' calculation

3.3 Regression results

With panel data, the Hausman specification test (Hausman, 1978) helps to distinguish between models with individual effects that are not correlated with explanatory variables and models where this correlation exists. The test results from Table 3 show that the unobserved characteristics are correlated with the explanatory variables in the model of the existence of endogenous interaction and spatial correlation (p-value <0.01). Therefore, the following models will be analyzed considering the existence of fixed effects.

Table 3. Robust Hausman Test to spatial effects

Test		*Value*	*df*	*p-value*
Robust Hausman Test	Spatial correlation	187.32	1	< 2.2e-16
	Endogenous interaction	75.36	1	2.64e-15

Source: Author' calculation

The Lagrange multiplier test in the fixed effects model allows one to select the spatial interaction type in the analytical model. The results from Table 4 show that the LMLag test for endogenous interactions and LMErr for spatial interactions both have a P-value <0.05, so no spatial interaction can be removed from the model. Besides, the strong Lagrange multiplier test also has a P-value <0.05, which shows that it is impossible to conclude which model will be selected in the analysis. The model selection must be based on the following criteria: Akaike's analytical models.

Table 4. Lagrange multiplier tests results

Test	*Null hypothesis*	*Value of Test*	*P-value*
Lagrange multiplier tests (LM)			
LMLag	No endogenous interaction (ρ=0)	35.414	2.666e-09
LMErr	No spatial correlation (λ=0)	63.039	2.027e-15
Robust Lagrange multiplier tests (RLM)			
RLMLag	No endogenous interaction (ρ=0) when the model already contains spatial correlation (λ=0)	8.9269	0.00281
RLMErr	No spatial correlation (λ=0) when the model already contains endogenous interaction (ρ=0)	36.552	1.486e-09

Source: Author' calculation

The regression results of the six spatial models with panel data are presented in Table 5. Among these models, the Spatial Durbin Model (SDM) exhibits the smallest Akaike Information Criterion (AIC) value, indicating its suitability for analysis. Therefore, the SDM model is chosen for further examination. According to the SDM model, several factors have a significant positive impact on the proportion of non-agricultural sectors in the economic structure of localities at a 5% significance level. These factors include agricultural labor productivity, per capita income, transport system development, and local FDI capital. Moreover, it is important to note that, in addition to the local internal factors, the development of transport infrastructure and the presence of FDI capital in neighboring localities also contribute positively to the structural change of the locality. This implies that the interplay between neighboring areas and their economic characteristics plays a role in shaping the structural change within a given locality.

Table 5. The regression results of the models

Variables	*SAR*	*SEM*	*SLX*	*SAC*	*SDM*	*SDEM*
Pro	0.076*** (3.530)	0.063** (2.853)	0.116*** (2.853)	0.071*** (3.754)	0.086*** (4.282)	0.086*** (4.260)
Inc	1.288*** (10.048)	1.160*** (10.927)	1.131*** (11.115)	0.623*** (10.185)	0.895*** (10.501)	0.892*** (10.499)
Trans	3.146*** (8.287)	3.583*** (8.6180)	2.489*** (8.002)	2.446*** (7.992)	2.592*** (7.356)	2.598*** (7.418)
FDI	0.049** (2.463)	0.0241* (2.337)	0.291* (2.387)	0.025* (2.280)	0.032** (2.444)	0.032** (2.440)
W*Pro			0.025 (0.050)		0.017 (0.044)	0.017 (0.390)
W*Inc			0.440 (0.716)		0.430 (0.494)	0.400 (0.808)

W*Trans			2.044*** (9.727)		2.070*** (9.173)	2.136*** (9.394)
W*FDI			0.243*** (10.125)		0.236*** (10.358)	0.233*** (10.352)
ρ	0.482*** (13.081)			0.755*** (14.749)	0.624*** (14.180)	
λ		0.371*** (8.1315)		0.638*** (8.945)		0.212*** (8.387)
Log-Likeli-hood	-1337.212	-2517.305	-1311.517	-2033.726	-1242.532	-2378.946
AIC	2812.424	5172.61	2779.063	4207.452	2649.063	4921.892
BIC	3119.179	5479.365	3089.216	4518.652	3013.612	5286.441

Note: t-statistics in parentheses; *** p < 0.01; **p < 0.05; * p < 0.1

Source: Author' calculation

Table 6 provides a comprehensive overview of the impacts of local characteristics on the change in the economic structure of neighboring localities. The table presents both direct and indirect effects, which elucidate the influence of these characteristics on the economic structure of specific localities. The direct effects in Table 6 demonstrate the impact of these characteristics on the economic structure of a given locality. On the other hand, the indirect effects highlight the influence of the characteristics of one locality on the economic structure of another locality. By examining these direct and indirect effects, we can gain valuable insights into the interconnectedness and spillover effects of local characteristics on the structural changes observed in neighboring localities.

Table 6. Direct, indirect and total effects

Variables	*Direct Effect*	*Indirect Effect*	*Total Effect*
Pro	0.092*** (4.482)	0.037 (0.403)	0.129 (-0.239)
Inc	0.905*** (10.499)	0.667 (0.582)	1.572 (0.208)
Trans	2.732*** (7.418)	1.864*** (5.279)	4.596*** (6.486)
FDI	0.038** (2.444)	0.019*** (2.125)	0.057*** (2.327)

Note: z-statistics in parentheses; *** p < 0.01; **p < 0.05; * p < 0.1

Source: Author' calculation

4. DISCUSSION

Testing spatial autocorrelation using Moran's I index reveals a strong correlation in localities' economic structures. Neighboring localities exhibit similar proportions of non-agricultural sectors, providing solid evidence of autocorrelation, which is overlooked in previous studies.

The spatial econometric analysis shows that changes in agricultural productivity, income, transportation systems, and foreign direct investment impact structural change. Increasing agricultural labor productivity releases workers to engage in non-agricultural activities, increasing the proportion of non-agricultural sectors (Ngai & Pissarides, 2007; Bustos et al., 2019). Higher local per capita income promotes non-agricultural sector development. These findings align with studies by Foellmi & Zweimüller (2008), Kongsamut et al. (2001), and Comin et al. (2021). Expanded transport infrastructure enhances internal and external integration, promoting non-agricultural sectors through consumer goods market expansion (Fajgelbaum & Redding, 2022; Murata, 2008). Foreign direct investment plays a vital role in structural change,

reallocating labor across sectors and facilitating efficient transformation, as seen in Mühlen & Escobar's (2020) study.

Besides local internal characteristics, the analysis using spatial panel data models emphasizes the role of transportation system development and foreign direct investment (FDI) inflows in neighboring areas in driving local structural change. This finding supports the hypothesis that structural change determinants extend beyond a locality's internal characteristics. Improved transportation systems in neighboring areas facilitate market expansion and connectivity with metropolises, accelerating structural change through increased flow of labor, goods, capital, and information (Truong Cong et al., 2023; Bac et al., 2023). Additionally, FDI inflows into neighboring areas foster local structural change by establishing linkages with domestic enterprises. Such interactions and knowledge spillovers lead to learning and imitation by domestic firms, driving local structural change (Amendolasine et al., 2013; Görg & Seric, 2013, 2015).

CONCLUSION

This study explores the determinants of structural change, incorporating spatial factors overlooked in previous research. Using spatial model analysis and panel data from 63 provinces in Vietnam (2010-2019), the study identifies the significant roles of agricultural labor productivity and per capita income in driving structural change. Transport system development and FDI capital have crucial impacts, promoting non-agricultural sector growth and creating spillover effects on neighboring localities. These results highlight the interconnectedness of spatially proximate areas in structural change. Considering spatial correlation is essential for a comprehensive understanding of the factors influencing localities' structural change and avoiding incomplete conclusions.

Being the first study to examine the determinants of local structural change with spatial factors, there are limitations that need addressing. Firstly, this study focuses on the general perspective of income and productivity transformation without analyzing specific driving factors. Future research can delve into these factors to gain deeper insights. Secondly, the spatial matrix used in the model is simplistic, relying only on adjacency without considering distance, limiting the quantification of factor influence. Future studies can incorporate more sophisticated spatial matrices accounting for distance to provide accurate depictions. These limitations provide valuable suggestions for further research, urging the exploration of specific drivers of structural change and refinement of spatial modeling techniques for comprehensive understanding.

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