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REVEALING NOVEL INSIGHTS ON ECONOMIC STRUCTURE FROM A SPATIAL PERSPECTIVE: EMPIRICAL FINDINGS FROM VIETNAM

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Abstract: Economic structure plays an essential role in distributing resources and shaping the development trend of a country. Although it has become a topic of interest for scholars, most studies focus on analyzing factors affecting the structural transformation process but ignore the correlation in economic structure between localities. This study explores this correlation through the case of a country undergoing a remarkable economic restructuring process—Vietnam. Based on the data from 2010 to 2019, the Moran's index (*I*) is used to assess the level of spatial correlation in the economic structure of localities and the Local Indicator of Spatial Autocorrelation (LISA) is analyzed to determine the specific locations where local spatial correlation occurs. Research results show that the economic structure of localities is unevenly distributed across geographical space. In addition, there exists a spatial autocorrelation phenomenon in localities' economic structure for two sectors—agriculture and industry. At the same time, there is no evidence to show this for the service sector. This discovery confirms the necessity of incorporating spatial factors in research related to economic structure to avoid inaccurate conclusions. From a business perspective, based on the findings of this research, companies can assess the level of competition, risks, as well as business partnership opportunities in different areas, and make appropriate investment decisions. The research results might also serve government agencies regarding planning and functional zoning and formulating and implementing development and economic restructuring policies for various regions.

Keywords: economic structure; spatial autocorrelation; Moran's *I*; LISA; Vietnam

1. Introduction

The role of economic structure is crucial in the shaping and developing a country. Economic structure refers to how industries, business sectors, and other economic segments are organized and function in the economy (Bustos, 2016; Rodrik, 2016). Following Truong Cong et al. (2023), economic structure is defined as the relative shares and importance of different economic sectors (e.g., agriculture, manufacturing, services, etc.) within the overall economy of areas. Besides, economic structure determines how resources such as labor, capital, land, and technology are distributed and used in the economy. This affects the ability to create products, services, and added value in different economic sectors (McMillan & Heady, 2014). Additionally, economic

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structure affects economic development by determining the level of development of industries and services in a country. The development and performance of different economic sectors can create balance and diversification in the economy (Lin, 2019; van Aswegen & Retief, 2020). More specifically, Loayza and Raddatz (2010) argue that economic structure is essential in creating jobs and income for workers. The development of industries and services may create many job opportunities and increase income for the population. Complementing the above view, Constantine (2017) emphasizes that economic structure, not institutions, is the fundamental factor determining economic growth. Economic structure shapes institutional performance, income distribution, and political change, which in turn drives economic performance. Safiullin and Gubaidullina (2018) point out that a stable and efficient economic structure can attract investors and investment capital. The division of work, providing high-quality human resources, and developed infrastructure can create favorable conditions for investment and sustainable economic development (Naumov & Trynov, 2019). From another perspective, da Silva et al. (2014) believe that economic structure affects the level of competition in economic sectors. A highly competitive economic structure can promote innovation and improve product and service quality, and create benefits for consumers.

With the increasing amount of recent scientific evidence on the contributions of economic structure to sustainable development, issues related to it have become a topic of great concern for scientists and policymakers (McMillan & Heady, 2014; Truong Cong, 2022). In addition, global organizations such as the International Food Policy Research Institute and the World Bank have also conducted many in-depth studies over a long period on this issue. However, most of those studies focus on analyzing factors affecting the process of structural transformation while ignoring external factors originating from natural relationships between geographical areas (Truong Cong et al., 2023). Still, any geographical area has uneven development, and the relationships between localities within the area always have specific impacts on each individual's economic activities (Truong Cong, 2021a, 2022). This raises an important question: Whether we need to consider spatial factors in analyzing the economic structure of localities? Results from this question can completely change the research results from previous studies as well as give us an entirely new perspective on the economic structure of geographical areas.

With the purpose of answering the above question, this study analyzes the economic structure of localities from a spatial perspective based on data from a typical developing country, Vietnam. From one of the poorest countries in the world, after more than 35 years of reform since 1986, Vietnam has now become a low-middle income country and also one of the fastest-growing countries in the world. In 2018, Vietnam's GDP growth reached 7.08%, and this figure in 2019 was 7.02% (Truong Cong, 2021a). Despite being strongly impacted by the COVID-19 pandemic, Vietnam's GDP increased by 2.9% in 2020. In addition, GDP per capita increased by nearly 4.9 times from $400 in 1988 to $1,964 in 2018, and more than 45 million people have escaped poverty. Along with this remarkable achievement, it is impossible not to mention the contribution of the economy's transformation from agricultural to non-agricultural activities (Truong Cong et al., 2023). During this period, the contribution of the non-agricultural sector to GDP increased from 53.7% in 1988 to 85.32% in 2018, and this process is still going on in different regions. From being almost dependent on agriculture, the provinces have changed in economic structure with increasing contributions from industry and services. With rapid changes in economic structure, Vietnam is a typical case to study economic structure in both space and time. Hence, this study focuses on examining the similarities in economic structure between geographically adjacent localities in Vietnam over the past decade (2010–2019) using spatial autocorrelation measures, specifically Global Moran's index (*I*) and Local Indicator of Spatial Autocorrelation (LISA). Results from this study will provide specific evidence to answer the question about the role of spatial factors in analyzing the economic structure of geographical areas.

2. Literature review

One of the fundamental theories that address spatial issues in economic activities is location theory. This theory has also long been a central component of economic geography, encompassing explanations and predictions regarding changes in economic activities as well as the interactions of people, goods, and services within geographical areas. In essence, this theory is built on many interconnected perspectives, including the perspective on land use by von Thünen (1842), industrial location by Weber (1909), the central place of Christaller (1933) and Lösch (1940). In addition to location theory, growth pole theory also plays an important role in analyzing regional economic structure changes. Proposed by Perroux (1955) and developed by Boudeville (1966), this theory posits that development is unbalanced, emerging first in certain points or poles with varying intensity before diffusing throughout the economy. Industries tend to initially develop in urban centers and then expand to surrounding areas. This perspective aligns with the core-periphery theory developed by Friedmann (1966), which suggests that economic centers (the core) often possess innovation potential and high growth rates, which shape the geographical diffusion of innovations, while peripheral regions experience slower or stagnant growth reliant on resource demands from the core.

Based on the theoretical foundations mentioned above, several empirical studies have been conducted to provide specific evidence for these perspectives. In reality, the spatial correlation in economic activities among geographical regions is found in different groups of countries, including developing countries (Aguilar & Hernandez, 2016; Aung & Mar, 2019) developed countries (Meraner et al., 2018), the Asian region (Patel et al., 2019; Tian et al., 2017) Europe (Cimino et al., 2021) and the Latin American region (Aguilar et al., 2003). These empirical research results are also based on different approaches.

Particularly for a group of developing countries, many studies have delved into analyzing the factors contributing to spatial correlation in economic activities. Using data from Landsat 8 satellite imagery and Google Earth imagery, Lokantara and Amo (2021) show that the distribution of economic activities in Bali Province of Indonesia is marked by population growth and an increase in demand for space. Similar to this approach, Mondal and Banerjee (2021) relied on census data from 2001 and 2011 combined with Landsat 2017 and Landsat 2000 satellite images to present evidence of changes in the spatial concentration of economic activities in India. Research shows that peri-urban areas of cities are emerging as new economic spaces and becoming attractions for industries and other commercial activities because of their locational advantages, low-cost land, and cheap labor. Since then, this area has formed a spatial concentration of non-agricultural activities. Similarly, Kannan et al. (2021) analyzed the forces driving the spatial distribution of economic activity by understanding the transformation in agricultural land use. Research results show that urban expansion contributes to promoting the establishment of non-agricultural activities concentrated in areas surrounding urban areas, while a large amount of agricultural land is also converted for other purposes because of the pressure to build industrial facilities, residential areas, infrastructure, and urban-related services.

The survey approach was taken by Nilsson (2019) to examine external impacts on economic activities in localities in the Republic of Rwanda, which is in the Great Rift Valley of Central Africa. The findings show the importance of market linkages and urban knowledge spillovers for non-agricultural activities in peri-urban areas or, in other words, the geographical distance from localities to urban centers will have an impact on the concentration of economic activities in these localities. Therefore, spatially, the closer areas are to urban areas, the higher the rate of non-agricultural activities. In the same vein, Sharma and Chandrasekhar (2014) pointed out that the concentration of secondary sector jobs often appears in areas where people have continuous two-way urban mobility. Huge investment in transportation infrastructure has led to population growth in the vicinity of urban areas, and urban commuting has become easier so that production activities are concentrated in these areas.

Unlike the secondary sector, jobs in the tertiary sector (services) are more concentrated in urban areas where demand for these industry products is very high. Through the survey process, Fafchamps and Shilpi (2003) examined the spatial distribution of economic activities and discovered a strong spatial division of labor in Nepal. Non-agricultural employment is concentrated in and around urban areas, while agricultural wage employment predominates in more rural areas. These findings, according to the authors, are consistent with the von Thünen model of concentric specialization, which has been corrected to take into account urban scale, and thus, the spatial division of labor is closely related to distance from urban areas. Xue et al. (2020) case study approach to the case of Shenyang City showed that the appliance manufacturing industry and the automobile retail industry have complementary spatial integration and weak spatial correlation. This distribution characteristic is due to local policy factors (i.e., should industrial land be located on the city periphery or outside the Ring Road) and economic factors (i.e., the extent to which the dependence of the equipment manufacturing industry and the automobile sales industry is also affected by external factors such as costs).

3. Methodology and data

Regarding the spatial aspect, one of the most basic issues about spatial relationships between research objects is the phenomenon of spatial autocorrelation (Getis, 2008). It refers to the correlation between values of a single variable that can be attributed to their close proximity on a two-dimensional surface (Li et al., 2012). This correlation departs from the assumption of independent observations in classical statistics, as highlighted by Geniaux and Martinetti (2018). Specifically, positive spatial autocorrelation implies that neighboring geographic locations tend to exhibit similar values for a given variable. Spatial correlation is often measured to avoid violating some basic statistical assumptions of specific statistical methods (Lichstein et al., 2002) to ensure the accuracy of the analysis. It has also been quantified to aid spatial prediction (Haining et al., 2009). The importance of spatial correlation lies in the following points: first, by showing the existence of a notable relationship in the distribution of values on the map, spatial correlation requires further research to understand the causes of the observed spatial variation; second, spatial correlation indicates information overlap and has important implications for spatial data analysis methods. Therefore, this study focuses on analyzing the spatial autocorrelation in the economic structure of localities using the Global Moran's *I* and LISA indices. The proportions of agriculture, industry, and services in the economic structure of the localities are utilized to examine the spatial autocorrelation. These analyses are conducted using R software version 4.3.2. The research process is illustrated in Figure 1.

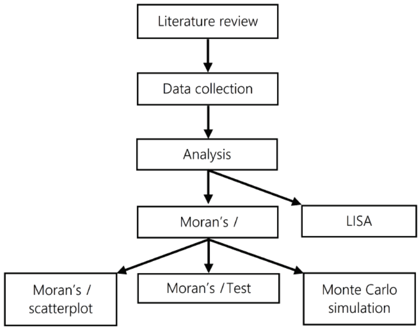

Figure 1. Stages of the research.

3.1. Spatial autocorrelation—Global Moran's I

The spatial autocorrelation of a variable can be quantified in various ways (Cliff & Ord, 1970). Some statistics used to assess the level of spatial autocorrelation include Moran's *I*, Geary's *C*, Ripley's K function, or the variogram (Getis, 2009). Among them, using the Global Moran's *I* is one of the oldest and most widely accepted methods (Zhou & Lin, 2008). The reason for this is that Moran's *I* exhibits more desirable properties in terms of statistical power and sensitivity to spatial weights. One other possible reason for the widespread usage of Moran's *I* is its resemblance to the non-spatial Pearson correlation coefficient (Westerholt, 2022). Although this index does not allow for the specific identification of the geographical areas where correlation occurs, Global Moran's *I* helps evaluate the spatial autocorrelation present in a data set and measures the degree of similarity between objects in the area around them generally. Global Moran's *I* provides a means to test for autocorrelation. Although it has similarities with traditional correlation coefficients, the spatial autocorrelation index is slightly different because it involves complex spatial calculations. The equation of Global Moran's *I* was initially introduced by Moran (1950) and subsequently refined by Cliff and Ord (1973):

$$I = \frac{1}{s^2}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{1}$$

where w_{ij} are the elements of a matrix of spatial weights with zeroes on the diagonal (i.e., $w_{ij} = 0$ with $i = j$). The spatial weight matrix can be established in various ways (distance-based, contiguity-based, etc.). However, in the case of Vietnam, each locality has its own characteristics in terms of natural conditions and area scale, which are clearly defined and classified. Additionally, each locality also applies specific policies and regulations. Therefore, the shared boundaries between spatial units play an important role in determining the spatial influence between localities, and the method of constructing the spatial weight matrix based on contiguity is more suitable for this study. Simply put, $w_{ij} = 1$ if border (i) and border (j) are adjacent and $w_{ij} = 0$ if border (i) and border (j) are not adjacent. y_j denotes the observed value at location *i*. $\overline{y}$ is the mean of *y* variable over the *n* locations and calculated by the Equation 2:

$$\overline{y} = \sum_{i=1}^{n}\frac{y_i}{n} \tag{2}$$

and the sample variance

$$s^2 = \frac{\sum_{i=1}^{n}(y_i - \overline{y})^2}{n} \tag{3}$$

Using the Moran' *I* index to analyze variables as proportions can lead to bias, because proportions are known to be subject to heterogeneity due to different population sizes (Jung et al., 2019; Waldhör, 1995). From here, several different versions of Moran's *I* index for scale variables were developed, such as I_{pop} và I^{*}_{pop}, to control for underlying regional populations (Oden, 1995). However, each index has its own limitations. The test proposed by Oden is powerful in testing for scale heterogeneity, but it has disadvantages when the interest is solely on the spatial correlation (Assunção & Reis, 1999). The primary concern of this study is the similarity in sector proportion in the overall economic structure of each locality. Therefore, this study still uses the standard version of Moran's *I* to simplify the analysis process.

3.2. LISA—Local Moran's I

The Global Moran's *I* spatial autocorrelation index helps measure the degree of spatial correlation and also allows us to make decisions about whether or not to reject the hypothesis of spatial randomness through a statistical test. However, this index does indicate the location at which clustering occurs. This study aims to analyze the characteristics of the regions specifically. Therefore, if there is clustering in the economic structure, it is necessary to answer the question of where that clustering occurs. To do this, the study used LISA indices developed by Anselin (1995). In essence, LISA is any statistic that meets the following two requirements: first, the LISA index for each observation indicates the degree of significant spatial clustering of similar values around that observation; second, the LISA sum for all observations scales with a global indicator of spatial association. Since there are many general spatial autocorrelation statistics, there will be many corresponding LISAs. However, for simplicity, this study focuses on the local spatial autocorrelation index of Moran's *I*. The local Moran's *I* was proposed by Anselin (1995) as a way to determine local clusters and local spatial outliers.

$$I_i = \frac{(y_i - \overline{y})^2}{s^2} \sum_{j=1}^{n} w_{ij}(y_j - \overline{y}) \tag{4}$$

where I_i represents the Local Moran's *I* index for the locality (*i*). The remaining symbols in the equation are explained similarly as in the equation for calculating Global Moran's *I* mentioned above; then:

$$I = \sum_{i=1}^{n} \frac{I_i}{n} \tag{5}$$

3.3. Data

For the data used in describing and analyzing the relationship in the spatial distribution of the economic structure, this study uses spatial and economic statistical data of all 63 localities at the sub-national level during the period 2010–2019. In particular, spatial data are extracted from the Global Administrative Regions Database—GADM (Global Administrative Areas, 2022) and economic statistical data are extracted from the Annual Statistical Yearbooks of the localities (General Statistics Office, 2019). Spatial data from GADM include information about location, coordinates, and administrative zoning of localities. Economic statistical data provide information about the contribution proportion of sectors in the economic structure, and these values are taken in the section "National accounts, budget, banks, and insurance" of the statistical yearbook.

4. Results and discussion

4.1. The descriptive statistics

Table 1 presents the descriptive statistics of economic structure data for localities in Vietnam from 2010 to 2019. The average proportion of the agricultural sector during this period was approximately 25.299%, ranging from a minimum of 0.618% to a maximum of 58.120%. Conversely, the industrial sector's proportion varied between 9.900% and 89.493%, with an average of 33.700%. Similarly, the service industry accounted for a proportion ranging from 8.127% to 73.227%, averaging 38.837%. These findings highlight the service sector's significant contribution to the economic structure, while the agricultural sector's average contribution remains the lowest. Moreover, the standard deviation (*SD*) value reveals the level of fluctuation in each industry's distribution among provinces and cities. A higher *SD* indicates greater variation in contribution shares, while a lower *SD* suggests closer alignment. In this context, the industrial sector exhibits the highest *SD* at 16.514, whereas the service sector demonstrates the lowest *SD* at 10.120.

Table 1. Descriptive statistics of variables

Variables	Mean	*SD*	Min	25%	Median	75%	Max
Agriculture	25.299	13.087	0.618	15.010	25.744	35.358	58.120
Industry	33.700	16.514	9.900	21.496	29.154	42.230	89.493
Service	38.837	10.120	8.127	32.875	38.598	44.279	73.227

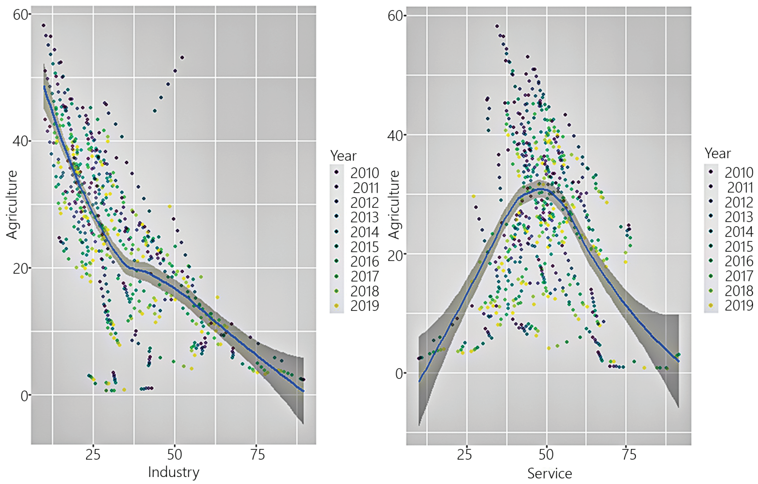

Figure 2. Non-agricultural share in Vietnam's provinces.

Regarding the relationship between sectors in the economic structure of localities, Figure 2 shows the correlation between the proportion of agriculture compared to the industry and service sectors of localities. It can be seen that the relationship between agriculture and industry is an inverse relationship. In other words, the proportion of industry in the economic structure of localities will increase when the proportion of agriculture decreases. Meanwhile, the correlation between the agricultural sector and the service sector in the economic structure is an "inverted V" relationship. This means that as the agricultural sector contributes more and more to the economic structure, the service sector's contribution also increases. However, at a certain stage, when the proportion of the agricultural sector in the economic structure decreased, the proportion of the service sector continued to increase. In general, this result is similar to the comments of McMillan and Heady (2014) and Truong Cong (2021a) when they said that the process of structural transformation is associated with a gradual decrease in the proportion of the agricultural sector and an increase in the proportion of the non-agricultural sector in the economic structure.

4.2. Spatial distribution of economic structure

Figure 3 describes the spatial distribution of the economic structure of localities in 2019. It can be seen that the proportion of industries in the economic structure among localities is different. The high proportion of the agricultural sector in the economic structure only appears mainly in southern localities, while the high proportion of non-agricultural sectors mainly appears in northern localities. Besides, the two regions show superiority in the non-agricultural proportion in the economic structure. This is quite similar to the case of both developed and developing countries such as Germany (Kies et al., 2009), Korea (Roh et al., 2023), Bangladesh (Hassan et al., 2020), India (Kannan et al., 2021; Mondal & Banerjee, 2021), the Republic of Rwanda (Nilsson, 2019), or Latin American countries (Aguilar et al., 2003). In these countries, the distribution of economic activities is also not uniform across localities. Some industries have specific characteristics associated with certain regions.

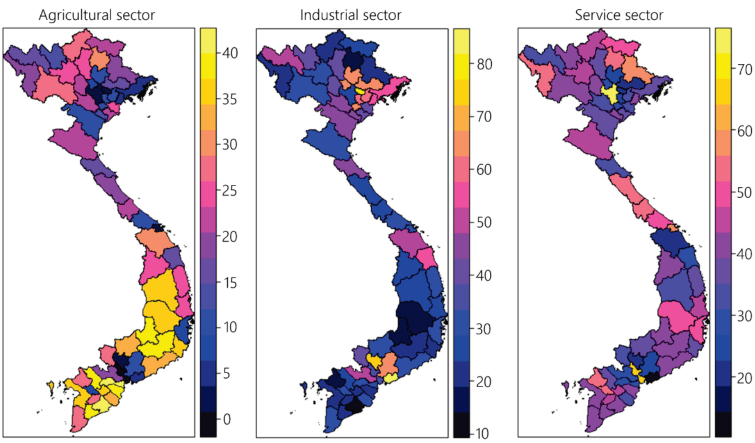

Figure 3. Sectoral shares (in %) in Vietnam's provinces, 2019.

4.3. Global Moran's I

The Moran's *I* scatter plot (Figure 4) is utilized to visually represent the correlation between the value assigned to each specific observation and the average value of its neighboring observations. The *x*-axis of the plot corresponds to the observation values, while the *y*-axis represents the weighted average of the neighboring observations. By observing the dashed lines on the graph, one can ascertain the sample's overall mean, which effectively divides the plot into four distinct regions (Anselin, 1996). The value of Moran's *I* signifies the slope of the least squares regression line derived from the observations. In this study, three separate industries are depicted in their respective charts. Concerning agriculture and industry, most observations within the sample tend to cluster in the lower-left and upper-right quadrants. The lower-left quadrant signifies observations with values below the overall average, and the average values of neighboring observations are correspondingly lower than the overall average. Conversely, the upper-right quadrant indicates observations with values surpassing the overall average, and the average values of neighboring observations also exceed the overall average. Consequently, the regression lines for observations relating to the shares of agriculture and industry exhibit an upward inclination. On the other hand, the service sector presents scattered observations across all the four regions of the chart. Nevertheless, the upper-left and lower-right quadrants encompass the majority of observations. Specifically, the upper-left quadrant reflects observations with values exceeding the overall average, whereas the average values of neighboring observations fall below the overall average. The lower-right quadrant encompasses observations with values lower than the overall average, while the average values of neighboring observations surpass the overall average. Therefore, the regression line for observations regarding the proportion of the service industry tends to exhibit an upward slope, albeit not significantly pronounced. In summary, the proportion of agriculture and industry in the economic structure of Vietnamese provinces aligns with that of neighboring localities, while the proportion of service industries displays an opposing trend.

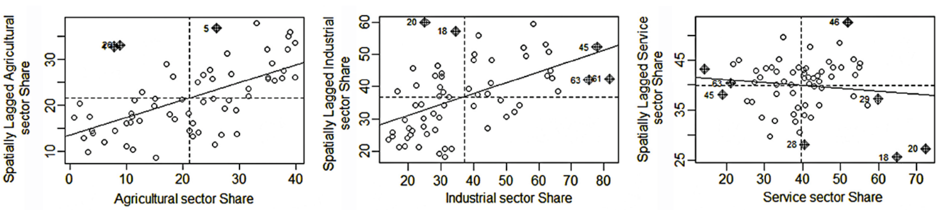

Figure 4. Moran's *I* scatterplot of sectoral shares in Vietnam's provinces, 2019.

Statistically, the change in the Global Moran's *I* value of the agricultural sector has little change in 2010–2019, fluctuating between 0.382 and 0.413. The Global Moran's *I* change for industry over this period can be divided into three periods. During 2010–2014, the Global Moran's *I* value fluctuated little, with an average value of about 0.334. This value then dropped to 0.275 in 2015 before starting a gradual upward trend in 2015–2019. This is entirely the opposite of the service industry. The absolute value of the Global Moran's *I* index tends to decrease gradually in 2010–2014, then increase suddenly in 2015 before gradually decreasing in 2015–2019. The *p*-values in the test of the Global Moran's *I* for the agriculture and industry are always less than 0.01, while this value is always greater than 0.05 for the service throughout the period 2010–2019.

Since Vietnam's terrain is characterized by an S-shape, with the area expanding at the top and narrowing in the middle, the spatial weight matrices are characterized by irregularly distributed polygons (Wang et al., 2018). This feature can make the Global Moran's *I* test value sensitive. Therefore, this study uses the Monte Carlo method to examine the density plot of the permutation or the obtained probability of the Global Moran's *I* value. The curve in Figure 5 depicts the expected distribution of Global Moran's *I* value in case the proportion of sectors in the economic structure is randomly distributed across provinces. The vertical line of the graph shows the statistical value of the actual Moran's *I*. For 2010, the Global Moran's *I* value for agriculture and industry lies to the right and away from the distribution, while that for the service sector lies in the center of the distribution.

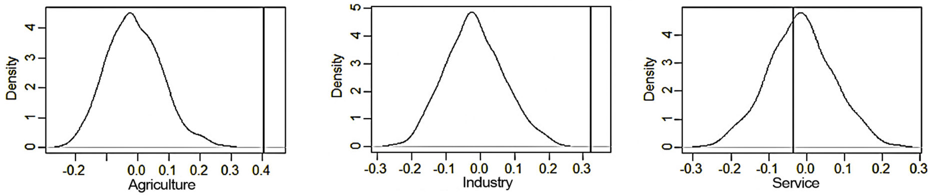

Figure 5. Density plot of the permutation outcomes—Monte Carlo simulation of Global Moran's *I* 2010.

Similarly, for 2019, the value of the Global Moran's *I* of agriculture and industry remains outside the distribution, although the distance to the distribution is smaller than in 2010. Meanwhile, the Global Moran's *I* for the service industry in 2010 is located in the middle of the distribution center (Figure 6).

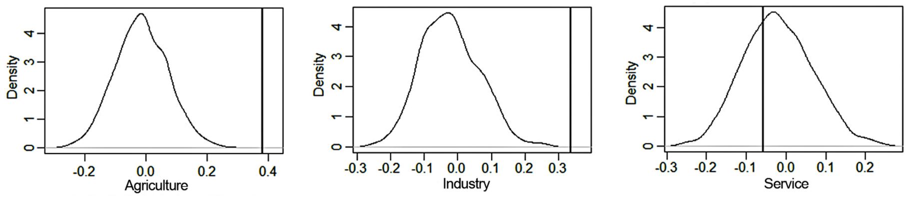

Figure 6. Density plot of the permutation outcomes—Monte Carlo simulation of Global Moran's *I* 2019.

It can be seen that autocorrelation in the economic structure of localities in Vietnam only occurs in the agricultural and industrial sectors. This result is consistent with observations about the existence of correlations between geographical areas in agricultural and industrial activities in certain developing countries, such as Mexico (Aguilar & Hernandez, 2016), Myanmar (Aung & Mar, 2019), India (Patel et al., 2019), and Bangladesh (Hassan et al., 2020). Furthermore, this result also mirrors the cases reported in specific regions of developed countries such as Germany (Kies et al., 2009; Meraner et al., 2018), Italy (Cimino et al., 2021), and South Korea (Roh et al., 2023). However, unlike previous studies by Mondal and Banerjee (2021) or Sharma and Chandrasekhar (2014), non-agricultural activities, including industry and services, are spatially correlated. The analysis results from this study show no clear evidence that spatial autocorrelation occurs in the service industry. This can be explained through Vietnam's economic characteristics. This country is currently undergoing industrialization, with a focus on concentrating resources to develop specific industries. As a result, these industries grow from major urban centers and gradually spread across the surrounding geographic areas, creating clear clustering patterns. On the other hand, the services industry is only developing in a few specific locations that possess distinctive characteristics without following a clear systematic pattern. Therefore, it does not generate a distinct clustering phenomenon in space.

4.4. Local Moran's I

The results of calculating the local Moran's *I* index show that the phenomenon of spatial clustering in the economic structure of localities has only two forms: high-high (HH) clustering and low-low (LL) clustering, while the high-low and low-high clusters do not exist in all the three sectors of agriculture, industry, and services in the period 2010–2019. In general, the number of localities where clustering occurs changes over time (Table 2). Specifically, for HH clustering, the number of clusters in the agricultural sector increases over time while the industrial sector decreases. Clustering in the service industry during the period only took place very limitedly in a few localities, and at some points, this clustering disappeared. For LL clustering, the number of localities where clustering occurs in agriculture tends to decrease, while in industry, it tends to increase. The LL clustering for the service industry is similar to the HH clustering when only a few localities appear, and this appearance only occurs a few times.

Table 2. Number of clusters in sectors 2010–2019

Year		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Number of HH clusters	Agriculture	7	8	9	7	8	8	8	9	9	9
	Industry	8	8	9	8	7	5	5	5	5	7
	Service	2	2	1	2	2	0	0	1	1	1
Number of LL clusters	Agriculture	8	7	7	8	6	7	7	6	6	7
	Industry	6	6	6	6	6	4	5	7	7	7
	Service	1	0	0	0	0	0	0	0	0	1

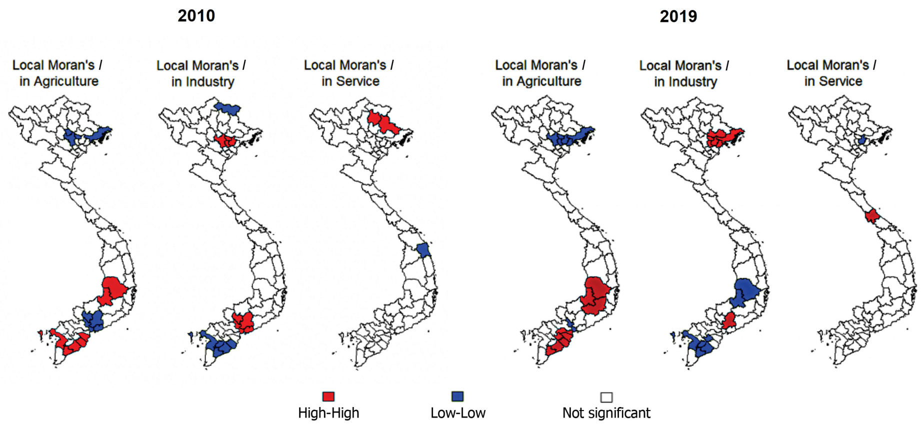

Figure 7. Local indicators of spatial association cluster map of sectoral share 2010 and 2019.

Visually, the clustering of sectors is shown in Figures 7. In general, clustering in agriculture and industry only occurs in the northern and southern regions of Vietnam, while clustering in the service industry takes place in localities located in the northern and central regions. For 2010, the clustering of both agriculture and industry took place in four separate areas. Specifically, there were two HH clustering areas and two LL clustering areas. Meanwhile, the service industry has only two areas where clustering occurs: one is a HH clustering area, and one is a LL clustering area.

Compared to 2010, the clustering of industries in 2019 is quite similar. The number of areas where clustering occurred did not differ at the two-time points, but the location and number of localities in the clustering area by sector did. In particular, for the industry, in 2010, there were two clustered areas in the north and two clustered areas in the south. In 2019, there were three clustered areas in the south and only one clustered area in the north. Meanwhile, the clustering position in the service industry is reversed. Specifically, the HH clustering that took place in the north in 2010 has changed into a LL clustering in 2019, and the LL clustering that took place in the central region in 2010 has changed into a HH clustering in 2019. The places where HH clustering occurs for industry and LL for agriculture are the areas with large urban areas. This clustering characteristic can essentially be explained through the impact of agglomeration economics (Glaeser, 2010) and core-periphery theory (Friedmann, 1966). Regarding agglomeration economics, manufacturing enterprises, especially in the industrial sector, often tend to focus on exploiting the advantages of agglomeration, such as sharing, connecting, and learning (Truong Cong, 2021b). In particular, sharing is characterized by infrastructure, facilities, suppliers, and workers. These features benefit from economies of scale. Suppliers and workers will create favorable conditions that allow for more specialization, a more scientific supply of intermediate goods, and easier replenishment of supplies between sectors (Ellison et al., 2010; Rosenthal & Strange, 2001). From a connectivity perspective, when labor and supplier markets are large and diversified, there will be a better match between employers and workers or between intermediate suppliers and suppliers (Finney & Kohlhase, 2008). In terms of learning, new companies must go through a learning process about how to best organize and operate, and in densely concentrated areas, businesses have more learning opportunities (Duranton & Puga, 2004). If agglomeration economics explains the concentration of industries, the core-periphery theory answers the question of why clustering occurs in large cities and neighboring localities. The economic center (core) is usually a large metropolitan area that dominates the peripheral areas. Metropolises often have high innovation (improvement) and growth potential, shaping innovations' geographical diffusion (Bac et al., 2022; Truong Cong, 2021a). Peripheral regions experience slow or even stagnant growth and may rely for growth largely on the resource needs of the core region. During the industrial phase, industry grew with increasing employment of migrants from neighboring localities. This change also led to a shift from using a human workforce to mechanization and automation of production. Furthermore, during the industrial phase, other growth centers emerged through economic growth and diffusion. These areas experienced a decline in the proportion of the agricultural sector and were replaced by industry. The main cause of the decrease in concentration is the increasing production costs related to labor and land in the core region. This diffusion is associated with increased interaction between urban system elements and transport infrastructure construction.

Generally, the spatial clustering of autocorrelation between agriculture and industry is closely related. The area where HH clustering occurs in the agricultural sector will simultaneously create low-low spatial clustering in the industrial sector and vice versa. This trend is increasingly evident over time. The explanation for this phenomenon is the characteristics of the economic restructuring process. In the case of Vietnam, this is a country undergoing a transition towards "industrialization", so the proportion of the agricultural sector has decreased, mainly replaced by the proportion of the industrial sector. This differs from Latin American countries restructuring towards "de-industrialization" (Rodrik, 2016; Szirmai, 2012; Timmer et al., 2015). In these countries, the proportion of agriculture in the economic structure is mainly replaced by the service industry.

5. Conclusion

This study analyzes the spatial distribution of the economic structure of sub-national level localities in a typical developing country, Vietnam. Through spatial autocorrelation analyses, research results show the uneven distribution of economic structure between localities. However, this distribution shows a certain rule for the agricultural and industrial sectors, while there is no clear evidence of a rule for the service sector. Specifically, the proportion of industry in the economic structure of localities is often high for localities located next to large urban areas, while the proportion of agriculture in these localities is often low. On the contrary, localities located far from large urban areas have a low proportion of industry in the structure, while the proportion of agriculture is high. Besides, in geographical space, there is a positive autocorrelation in the economic structure for two industry groups: agriculture and industry. In other words, the proportions of agriculture and industry in nearby localities tend to be similar. This becomes increasingly apparent over time. From a theoretical perspective, these findings affirm the necessity of integrating spatial factors, often overlooked, in the study of economic structure. From a business perspective, based on research findings on businesses, the level of competition, risk, and business partnership opportunities can be assessed in specific regions, thereby making informed investment decisions. From a policy standpoint, these discoveries play a crucial role in providing a scientific basis and guiding the construction and implementation of policies aimed at promoting the development of specific economic sectors.

Regions exhibiting concentration or positive spatial autocorrelation will be potential locations for investing in the development of centers for functional areas or hubs for specific industries. This helps to limit resource dispersion by spreading investments across multiple different localities, thereby enhancing investment efficiency. Additionally, the concentrated nature of the industrial sector around major cities partly demonstrates the role of these cities in driving the industrialization process of regions. Therefore, policies aimed at promoting the industrialization process of localities in certain countries, especially developing ones, need to be closely linked to the function of urban centers. Through investment in infrastructure development to connect with major cities, localities will have opportunities to undergo economic structure transformation more rapidly.

While the specific patterns and trends identified in this study are based on the context of Vietnam, they can serve as a reference point for understanding similar processes in other countries. However, it is important to note that the applicability of the conclusions and trends to other countries may vary depending on the specific socio-economic, geographic, and cultural contexts of each country. Therefore, caution should be exercised when directly applying the findings of this study to other countries without considering these contextual factors.

Unlike previous studies that only consider the economic structure of geographic regions based on either spatial or temporal aspects, this study chooses to analyze both factors to provide a more comprehensive view of the process of change and distribution of the economic structure. Although it brings forth these characteristic new discoveries, this study still has certain limitations. First, determining the spatial weight matrix in this study is based on the adjacent characteristics of localities, so it is difficult to accurately determine the correlation range of localities. Second, this study only stopped at determining the existence of the phenomenon of spatial autocorrelation in the economic structure without analyzing the specific impacts of the factors that create this phenomenon. These are also specific suggestions for future research.

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