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Which Economic Sectors Influence Average Household Income? A Spatial Econometric Study of Thailand's 76 Provinces

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Abstract: This study investigates the impact of various economic sectors on household income in Thailand. It is conducted in light of the substantial “digital wallet” scheme initiated by the Thai government, with the goal of providing empirical evidence and suggesting alternative policies for regional development informed by sectoral and spatial insights. The research aims to deepen the understanding of how different economic sectors affect household income, filling a gap in the current understanding of the relationship between sectoral productivity and income. Utilising spatial lag models (SLM), the study analyses data spanning from 2005 to 2021, testing the effects of 19 economic sectors comprising the Gross Provincial Product (GPP) of Thailand's 76 provinces on the average household income. The findings indicate direct associations between agriculture, real estate, professional services, support services, and leisure sectors and household income, alongside pronounced spatial autoregression. This implies that income levels in one province can substantially influence those in neighbouring provinces. This research extends the understanding of economic influences at the regional level and highlights the importance of considering spatial factors in economic policymaking.

Keywords: spatial econometrics; spatial lag model; household income; gross provincial product; regional development; Thailand

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1. Introduction

An essential developmental goal for emerging economies like Thailand is the continuous enhancement of individual and household income, while addressing the pervasive issue of inequality. Achieving this goal is pivotal for the nation's transition to a high-income level. However, this objective is complex and far from straightforward, as developmental trajectories vary among countries and are not deterministic (Kutuk 2022). Therefore, Thailand needs a tailored approach, one that is contextually grounded, to effectively improve individual and household income.

Household income, as one of the crucial indicators of welfare, is shaped by various elements, ranging from demographic factors, employment, and education at the household level, and broader influences like economic shocks, government policies, population dynamics, and the evolution and development of various economic sectors (Aristei and Perugini 2015; Miles 1997; Kalogirou and Hatzichristos 2007; Dachin and Mosora 2012). Traditionally, the impact of sectoral shifts on income has been understood as a linear progression: starting from agriculture, moving to industrial, then to service sectors, and ultimately to knowledge-based industries (Li 2009; Tselios 2009). However, this linear perspective fails to fully capture the complex interactions among different sectors and their collective impact on household income. Therefore, the primary aim of this research is to provide a more comprehensive understanding of how various economic sectors influence household income.

This research is undertaken in the context of a significant economic stimulus initiative, the “digital wallet” scheme. The scheme, spearheaded by the current Thai government led by the Pheu Thai Party formed in 2023, involves issuing a one-time electronic cash incentive of 10,000 Baht (approximately USD280) to eligible citizens. This proposed economic stimulus effort, set for 2024, is designed to rejuvenate the economy, with a particular focus on benefiting the retail, service, and tourism sectors. It is expected to impact 50 million individuals and support around 2.4 million small and medium-sized enterprises (SMEs) in 2024.¹ Experts predict it could enhance the Thai economy by 1.5 to 2 percentage points, potentially leading to a growth rate of around 5%, which is higher than previous forecasts.²Error! Reference source not found.

One key aspect of this one-time stimulus is the scope of eligible spending. The scheme allows recipients to purchase general products, food and beverages, and consumable goods within six months of receipt. However, electronic cash in the digital wallet cannot be used for services, online purchases, alcoholic beverages, tobacco, marijuana, kratom (plant leaves used for their stimulant and pain-relieving effects), vouchers, gold, diamonds, gemstones, debt payments, education, or utility fees.³ While the focus on essential goods and food suggests that the funds will rapidly enter the economy within a short period, there is no empirical study or explanation of how this scheme could lead to long-term benefits.

The Pheu Thai Party also claims that the scheme aims to alleviate poverty, improve welfare, and boost income at the grassroots level.⁴ A significant aspect of this scheme is that the electronic cash is to be spent within the district of the recipient’s residence. This condition is intended to stimulate local economies and distribute income more evenly across the country by encouraging spending within local communities. However, it will likely be funded through government loans, amounting to around 500 billion Baht (approximately 3% of Thailand’s GDP), which has raised questions about fiscal responsibility and potential constitutional and legal issues.^{5,6} Eligibility for the scheme has been a point of debate. Initially proposed to be available to every Thai citizen over the age of 16, the plan was later revised to exclude wealthy individuals.⁷

Considering the magnitude of this scheme, a critical question arises: will it contribute meaningfully to the long-term welfare and income of the Thai population as intended? This question is especially pertinent given that the economic sectors directly benefiting from this scheme are narrow, focused primarily on retail, wholesale, and food services. An additional question is whether this scheme is an effective way to reduce income inequality across communities in Thailand. While the scheme aims to stimulate local economies and promote equitable income distribution, its focus on specific sectors may limit its reach and effectiveness in addressing broader income disparities. Understanding the effects of various sectors on people’s income and their spatial dependencies is crucial for informing the government about potential policy improvements or necessary adjustments.

Therefore, this research is guided by two primary questions: RQ1, “what are the effects of changes in various economic sectors on average household income?” and RQ2, “what are the roles and characteristics of spatial dependencies on the effects of economic sectors and the dynamics of household income?”

To answer these questions, a spatial econometric model was employed to test the effects of 19 economic sectors comprising the Gross Provincial Product (GPP) of Thailand’s 76 provinces on the average household income in these provinces. The study utilised biannual data from 2005–2021 from the National Statistical Office of Thailand. The results of the study reveal that the sectors of agriculture, real estate, professional services, support services, and leisure showed significant direct associations with household income. Furthermore, the study discovered pronounced spatial autoregression, indicating that the income levels in one province could significantly influence nearby provinces. This finding aligns with existing literature emphasising spatial correlation.

The next section of the paper reviews literature relevant to the drivers of household income, followed by sections on data and methods, findings, a discussion, and conclusions. The study aims to provide a comprehensive understanding of the relationship between economic sectors and household income in Thailand, offering insights that could inform future economic policies and strategies.

2. Literature Review

2.1. Factors Affecting Household Income

Household income is increasingly recognised as a crucial indicator of welfare, vital for understanding well-being and economic prosperity. It is typically measured as the aggregate disposable income of all members within a household, serving as a key metric for assessing inequality and poverty across different countries, a method extensively used in empirical literature (Gradin et al. 2008). Traditionally, theories explaining household income have been rooted in neoclassical growth principles, particularly focusing on regional economic convergence (Gebremariam et al. 2010). According to this school of thought, income disparities between regions are expected to diminish over time, with less affluent regions growing at a faster rate (Tselios 2009). However, this view is challenged by endogenous growth models, which argue that regional income disparities might actually widen due to factors such as economies of scale and the concentration of human capital (Yildirim et al. 2009).

The concept of “income mobility”, which emphasises the analysis of longitudinal data, is critical in understanding how individual incomes evolve over time. This approach provides insights into both intragenerational and intergenerational shifts in income (Aristei and Perugini 2015; Ayala and Sastre 2008; Jäntti and Jenkins 2015). It reveals that changes in household income are more complex and less predictable than the neoclassical model suggests. Adding to the theoretical diversity, the “New Economic Geography” posits that a region’s economic activity is influenced by its geographical location and its interactions with neighbouring regions (Yildirim et al. 2009). Thus, according to this theory, neither convergence nor divergence in income levels is predetermined (Yildirim et al. 2009). Empirical studies have shown that regional disparities within countries can sometimes be more significant than those observed between countries.

Considering these various theories and concepts that explain the dynamics of household income, this literature review seeks to explore the factors influencing household income in cities and provinces at both the household and macro levels.

2.1.1. Household Level Factors Affecting Household Income

Four key factors affect household income at the individual level. These factors are demographic aspects, education and human capital, employment status and job nature, and various other income dynamics. Each of these elements plays a crucial role in shaping the financial stability and growth potential of households.

Demographic factors, encompassing age, education, health, and household composition, are central to understanding household income dynamics. Changes in household composition, such as marriage, childbirth, or divorce, significantly influence income, impacting resource division and dependent numbers (Burgess and Propper 1998). Age and gender also play pivotal roles, with female-headed households and younger workers experiencing distinct income mobility patterns (Aristei and Perugini 2015; Engzell and Mood 2023). Additionally, variables such as household size and presence of elderly members influence income growth (Devicienti et al. 2014; Jin and Xie 2017).

Education and human capital investment also significantly influence household income mobility. The education level of household heads, particularly in terms of secondary and tertiary education, plays a critical role in determining income mobility due to better accumulation of human capital, adaptability, and enhanced income growth opportunities (Aristei and Perugini 2015; Engzell and Mood 2023; Jin and Xie 2017; Li 2009).

Employment status and job nature are crucial determinants of household income, with changes such as job loss or transitions between full-time and part-time work having a direct impact on income levels (Debels and Vandecasteele 2008; Jenkins 2000). The type of employment, be it temporary, permanent, or self-employment, significantly influences income mobility, with each employment status offering different levels of security and growth potential (Aristei and Perugini 2015). The occupational type, specifically in the context of urban-rural dynamics, plays a significant role in determining income levels. Higher income is often associated with off-farm activities, indicating a shift from traditional agricultural sources to more diversified income streams (Benjamin et al. 2005; Su and Heshmati 2013). Additionally, the occupation of the household head, particularly in managerial or administrative roles or employment in government or public institutions, is associated with higher income levels (Jin and Xie 2017).

Other income dynamics such as initial income level, different income sources, and expectations also play a crucial role in household income changes. Initial income of the household head is a primary variable influencing per capita income changes, with variability in real income occurring due to different sources, including labour and capital income (Chang and Hanna 1994; Fields et al. 2003). Furthermore, the type of income, whether from wages, property, or social benefits, contributes to overall income mobility, with social benefits often stabilising income during economic fluctuations (Ayala and Sastre 2008).

2.1.2. Macro Level Factors Affecting Household Income

Four key factors affect household income at the macro level, encompassing cities or provinces. It delves into the roles of crises and shocks, government policies, population dynamics, and sectoral composition in influencing household income.

Crises and shocks play a pivotal role in affecting household income at the city or province level. Idiosyncratic and covariate shocks, such as natural disasters, can deeply impact the economic stability of communities. These shocks, along with pressures like rising costs of living, can lead to a gradual descent into poverty (Lázár et al. 2020). Additionally, economic crises, as experienced globally in 2009, can lead to fluctuations in household incomes despite political and social measures (Dachin and Mosora 2012).

Government policies, particularly those focused on investment in education and infrastructure, are instrumental in shaping household income at a regional level. Educational attainment and workforce skills are key drivers of regional economic development, with regions boasting higher levels of education and skilled labour forces better positioned to attract investment, foster innovation, and achieve economic growth (Tselios 2009). This investment in human capital positively affects income collectively, as it enables the workforce to acquire skills relevant to the modern economy, thereby enhancing productivity and economic potential. The impact of education on income distribution is significant, particularly in reducing the income share of the rich and increasing that of the poor, although it does not significantly impact the middle class (Abdullah et al. 2015). Moreover, the distribution of education plays a crucial role, where more equitable distribution leads to lower income inequality. Secondary education, in particular, is noted for its importance in reducing inequality compared to primary schooling. Furthermore, regional economic policies and structural funds, especially in the European Union, play a significant role in promoting economic growth and reducing regional disparities through investments in underdeveloped areas and infrastructure development (Solarin et al. 2023; Tselios 2009).

Population dynamics: The growth and diversity of a population, particularly through migration driven by factors like quality of life and accessibility, also have a profound impact on household income at city or provincial levels. Supply-induced growth, fuelled by migration for reasons such as natural beauty or cultural appeal, not only increases the local labour supply but also directly influences the economic vitality of a region, thereby affecting average household incomes (Carruthers and Mulligan 2008). The presence of a diverse and highly educated immigrant population exemplifies the intricate link between

demographic dynamics and income levels. The varied skills and educational backgrounds of these residents contribute to the economic complexity of the region, influencing average household income (Kalogirou and Hatzichristos 2007).

Sectoral composition and development of industries within a city or province are fundamental to understanding and influencing household income at the macro level. Demand-induced growth, resulting from increased labour demand due to business or industry expansion, can lead to significant job creation and attract people from other areas, thereby affecting household income levels (Carruthers and Mulligan 2008). The type of dominant economic activities in a region and sector specialisation significantly affects regional income disparities (Dachin and Mosora 2012). The spatial distribution of economic activities, including the concentration and clustering of industries, also affects their average income (de Dominicis et al. 2007). Furthermore, the influence of working hours and specific high-paying industries on household income highlights the importance of sectoral specialisation in regional economic performance (Kalogirou and Hatzichristos 2007). These aspects highlight the significant impact of sectoral growth, specialisation, and industrial clustering on the economic development of cities and provinces, ultimately influencing household income at a macro level.

2.2. Economic Sectors' Effect on Income

This research primarily focuses on the impact of sectoral composition and industrial development, as outlined earlier. While the influence of various factors on income has been widely studied, the effect of productivity across different economic sectors on income is not as well-explored. Previous studies have identified infrastructure development within the construction sector as a robust predictor of economic growth across various regions (Resende 2011; Rodríguez-Pose et al. 2012). Additionally, sectoral shifts, particularly from low-productivity activities like agriculture to higher productivity activities, often result in increased GDP per capita (Dachin and Mosora 2012). However, a study by Gebremariam et al. (2010) found that the level of employment in the manufacturing sector, traditionally linked with robust economic growth, did not significantly impact median household income growth.

The transition from manufacturing to service sectors has also led to broader structural changes in the economy, affecting job types and income distribution (Canas et al. 2003; de Dominicis et al. 2007; Petrakos and Saratsis 2000). The influence of sectors such as wholesale and retail trade, finance, insurance, real estate, health, and construction on regional income dynamics is complex and multifaceted. Gebremariam et al. (2010) also noted that employment levels in sectors often seen as indicators of economic maturity, like wholesale, retail, finance, insurance, real estate, and health, do not consistently show significant effects on employment or median household income growth, highlighting their ambiguous role in economic development.

This issue is particularly relevant in the case of Thailand, a developing nation that distinguished itself in the 1990s with a notably higher per capita income compared to other middle-income countries. However, Thailand's income growth has stagnated since the Asian economic crisis in 1997, struggling to achieve a significant breakthrough. This stagnation is evident in the comparison chart provided in the Appendix A (Figure A1), illustrating Thailand's income trajectory in relation to other similar economies.

To the best of our knowledge, there is a notable lack of comprehensive studies directly linking the diversity of economic sectors to average household income in Thailand. Most existing research on regional economic development in the country emphasises the role of specific policies, such as the One Tambon One Product (OTOP) initiative, and their impact on fostering entrepreneurship and growth (Kamnuansilpa et al. 2023). The OTOP initiative has been pivotal in harnessing local skills and resources for the development and commercialisation of products, primarily in sectors like food and beverage, and local craft manufacturing (Moore and Donaldson 2016). However, the predominance of OTOP

products in these limited sectors may inadvertently overlook other economic sectors with significant growth potential.

Moreover, a significant study modelled Gross Provincial Product (GPP) as an outcome variable, highlighting labour in the formal system and the level of investment as key factors influencing GPP (Vajrapatkul 2023). This finding indicates the potential impact of public and private investment in specific economic sectors on the long-term welfare of citizens. Yet, the effects of various economic sectors on household income remain largely unexplored. This gap highlights the necessity to examine the influence of sectoral productivity on income dynamics. Such an investigation could provide valuable insights into Thailand's economic challenges and identify viable avenues for sustainable growth.

This research addresses a research gap stemming from the limited understanding of how specific sectors or the characteristics of sectoral composition affect household income. While shifts from agriculture to industrial sectors are generally understood to improve economic conditions, and the importance of advanced technological sectors is recognised, a comprehensive, comparative analysis of different sectors' impacts on household income is lacking. This research aims to fill this gap by offering a detailed comparative analysis of various sectors and their effects on household income in Thailand. Understanding the specific characteristics of sectoral composition that influence income is crucial for guiding strategic investments and improvements by both public and private sectors.

Therefore, the first research question is: RQ1, what are the effects of changes in various economic sectors on average household income?

2.3. Spatial Effects on Economic Sectors and Household Income

Understanding the effects of economic sectors on household income also requires a comprehensive understanding of spatial influence. The roles of spatial interdependencies from spillover and mobility and regional variations in spatial correlation are significant in shaping economic sectors and impacting household income.

Spatial Interdependencies from Spillover and Mobility: The intricate web of spatial interdependencies is evident in the way regional economies are not only influenced by local factors but also by the economic health of their neighbours through various channels such as trade, labour migration, and sectoral employment concentrations (Basile 2009; Garrett et al. 2007; Gebremariam et al. 2010). Technological diffusion and knowledge spillover play pivotal roles in shaping regional economic landscapes. Studies have shown that these interdependencies, particularly in the context of technological spillovers and factor mobility, are crucial for understanding the dynamics of regional development and the formation of business environments (Basile 2009; Fischer 2011; Gebremariam et al. 2010). Spatial economic policies and developments should be considered within broader, interconnected networks, recognising that changes in one region can have significant ripple effects on others (Patacchini and Rice 2007; Tselios 2009).

Regional Variation from Spatial Correlation: Due to spatial interdependencies, the spatial impact on economic growth shows notable regional variations. This variation is not only a response to different economic stimuli but also reflects the geographic and structural economic differences among regions (Kocornik-Mina 2009; Le Gallo and Ertur 2003). For example, the spatial characteristics of productivity and occupational composition indices demonstrate significant variations in regional income levels (Patacchini and Rice 2007). Studies in China and Japan have highlighted how spatial factors, such as geographical location and proximity, lead to diverse growth patterns and income disparities across regions, challenging the efficacy of traditional non-spatial economic models (Li 2009; Seya et al. 2012; Yu and Wei 2008).

These spatial factors add complexity to economic interactions and growth dynamics at both regional and local levels. In Thailand, studies on spatial effects have been somewhat limited. A particular study highlighted that the concentration of multinational enterprises (MNEs) with advanced technological sophistication is predominantly in the Bangkok Metropolitan Area and a few other provinces like Chonburi, with limited

spillovers to first and second-level neighbouring provinces (Sajarattanochoe and Poon 2009). Similarly, economic productivity, as measured by Gross Provincial Product (GPP), is concentrated in these regions (Vajrapatkul 2023).

However, there exists considerable potential for economic improvement. The public and private sectors are uniquely positioned to influence Gross Provincial Product (GPP), as the key factors driving GPP have been identified as labour in the formal system and investments (Vajrapatkul 2023). This potential is further underscored by the observation that local governments have been relatively passive in adopting strategies aimed at attracting businesses (Kamnuansilpa et al. 2023). Additionally, it is important to note that economic productivity, as measured by GPP, exhibits a spatial correlation (Vajrapatkul 2023). This correlation suggests a targeted approach by these sectors, particularly in areas lagging behind, could have a substantial impact on regional economic productivity.

Insights from this research could inform local and national governments to implement policies that attract businesses and investments to disadvantaged provinces to spur household income. Thus, addressing the second research question becomes imperative for a comprehensive analysis of regional economic performance and its impact on households. The second research question is: RQ2, what are the roles and characteristics of spatial dependencies on the effects of economic sectors and the dynamics of household income?

3. Data and Method

3.1. Data

Dependent variable: In Thailand, a crucial dependent variable for assessing economic conditions is the average household income by province, as compiled by the National Statistical Office (NSO).⁸ This dataset encompasses data from 2004 to 2021, covering Thailand's 77 provinces. The NSO typically gathers this information biennially in odd-numbered years. However, an exception occurred in the early years of the dataset, with data for 2004 and 2006 collected prior to 2007. To ensure continuity and consistency in the dataset, the average household income for 2005 was imputed by averaging the incomes of 2004 and 2006. This methodology resulted in a total of eight distinct time periods, each spanning two years. The NSO defines household income broadly, including earnings from employment or self-produced goods, revenue from property, and any form of assistance received from others. This measure serves as a vital indicator for evaluating the financial health and well-being of Thai households, providing insights into regional economic disparities and trends over time. Of the 77 provinces, Bueng Kan was excluded from the analysis because it was established as a new province in 2011, resulting in incomplete data and calculations based on a different annual basis.

Independent variable: Regarding the independent variable, GPP in Thailand serves as a critical economic indicator, mirroring the concept of Gross Domestic Product (GDP) but on a provincial level. The compilation and calculation of GPP is a collaborative effort involving multiple agencies.⁹ The GPP encompasses various economic parameters, including returns on primary production factors such as land rent, labour compensation, interest, and profits. It accounts for total "value added" from all economic activities within each province. The value added, a central element in GPP, represents the net output of a province, calculated as the difference between the production value (Gross Output) and the costs of intermediate goods and services (Intermediate Cost). The NSO adopts the Chain Volume Measures (CVMs) method for calculating GPP. This method, which adjusts for inflation, offers a more accurate depiction of real changes over time through a chain-linked approach.¹⁰ The 19 economic sectors included in Thailand's GPP are categorised into 1 agricultural, 4 industrial, and 14 service sectors, as detailed in Appendix A.

3.2. Spatial Weight Matrix

A spatial weight matrix is a tool used in spatial analysis to represent the spatial relationships among different locations. It quantifies how much influence one location has on another, based on factors like distance, connectivity, or other relationships. This matrix is crucial for spatial econometrics, helping to understand and model spatial dependencies and interactions.

The most commonly used spatial weight matrices in spatial econometrics are the contiguity-based (neighbour) matrices, the inverse distance, and the inverse distance raised to some power or exponential distance decay matrix (Bulty et al. 2023). The selection of spatial weight matrices is characterised by a great deal of arbitrariness, which causes a problem in inference. As the spatial weight matrix should also be theoretically grounded, this research produced the metrics based on the three methods to visually analyse and decide on the one that is most suitable. Each matrix is then row-normalised to ensure comparability.

The contiguity-based (neighbour) method is effective in accounting for provinces in close proximity, emphasising immediate spatial relationships. The inverse distance method, on the other hand, ensures coverage of the entire nation, diminishing the influence of distance but considering all regions. Conversely, the inverse distance-decay method combines the advantages of both the neighbour and inverse distance approaches. While maintaining a focus on nearby provinces, this method also accounts for more distant provinces, thus providing a more comprehensive view of spatial relationships.

The efficacy of the inverse distance-decay method, particularly in highlighting regional influences, is further corroborated by visual maps in the Appendix A (Figure A2). These maps display the weights of three sample provinces—Bangkok, Chiang Mai, and Phuket—and are shown in the appendix. The visualisation reveals that the inverse distance-decay weights are superior in illustrating regional influence, especially in cases like Bangkok, which is surrounded by many other provinces. Therefore, in our analysis, a distance-decay parameter, denoted as α (alpha), was employed to emphasise regional influences over nationwide effects, setting α to 0.01%. This value was chosen to balance the focus between local and broader geographical impacts, aligning with the literature that regional factors are significant in the context of economic interdependencies and regional variation.

3.3. Spatial Econometric Tests

In the field of spatial econometrics, particularly in handling panel data, several tests are conducted to determine the most appropriate model. A key test is the Hausman test, which is essential for choosing between fixed or random effects models. This test evaluates the consistency of an estimator under random effects in comparison to its efficiency under fixed effects. The Hausman test produced a chi-square statistic of 34.016 with 19 degrees of freedom, leading to a significant p -value of 0.0183. This result suggests that the fixed-effects model is more suitable for this analysis.

The Baltagi, Song, and Koh LM2 marginal test, applied using the “splm” package in R (Millo and Piras 2012), is utilised to detect spatial lag or autoregression in the data (Baltagi et al. 2003). Specifically, it aids in addressing RQ2 by allowing us to detect the extent to which economic outcomes in one province are potentially conditioned by those in its vicinity. The robust statistic of 27.854 and the highly significant p -value (<0.001) from the LM2 test in our analysis provide compelling evidence that spatial dependencies are present and influential.

Lastly, the Granger causality test for the panel data, as suggested by Dumitrescu and Hurlin (2012), is employed to assess potential causal relationships. This test is crucial in determining whether one variable can predict another. Identifying these relationships is vital, as they significantly influence the choice of model estimation method. The panel Granger causality test is available in the “plm” package in R (Croissant and Millo 2008).

The test uncovered complex interactions between average household income and various economic sectors, exhibiting direct, inverse, and bi-directional Granger-causality relationships. A notable limitation of this analysis is the biannual frequency of household income data, necessitating its pairing with biannual sectoral GDP data. This limitation restricts the availability of figures to the year immediately preceding the year of the outcome variable. While the results are insightful, caution should be exercised in interpreting their implications due to the discontinuity in data. Nevertheless, the findings suggest potential “simultaneity” between sectoral GDP and household income, highlighting the importance of incorporating appropriate spatial econometric estimators.

3.4. Spatial Lag Model (SLM) with Fixed Effects

The Hausman test indicates the need to incorporate a fixed effect into the selected model. Additionally, the Baltagi, Song, and Koh LM2 marginal test suggests the essential inclusion of a spatial lag. Consequently, this study adopts the Spatial Lag Model (SLM) (Bivand et al. 2021). The SLM, also known as the Spatial Autoregressive Model (SAR), is a fundamental component of spatial econometric models. It focuses on incorporating spatial dependence by including a spatially lagged dependent variable. SLM or SAR is a robust econometric model that has been insightfully used to analyze a variety of outcomes, including economic growth (Álvarez et al. 2016; Amidi et al. 2020), crime (Chanci et al. 2023), COVID-19 cases (Guliyev 2020), and pollution (Xie et al. 2019). In this model, the dependent variable for each spatial unit is regressed not only on the independent variables but also on the values of the dependent variable of nearby provinces (see Equation (1)).

$$Y_{it} = \lambda WY_{it} + X_{it}\beta + \alpha_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the dependent variable for province i at time t . λ is the coefficient for the spatial lag. W is the spatial weights matrix. X_{it} is a matrix of independent variables for province i at time t . α_i is the province-specific fixed effect. γ_t is the time-specific fixed effect. ε_{it} represents the error term for each province at each time point.

The inclusion of temporally lagged dependent and independent variables was considered. However, this approach posed a potential risk of exacerbating multicollinearity. To address these concerns while still exploring the temporal dynamics of the data, the SLM model was adapted to include temporally lagged independent variables, resulting in SLM_t. In the SLM_{t-1} model, sets of independent variables from previous time periods ($t-1$) were used to predict outcomes in subsequent periods. For instance, in SLM_{t-1}, sectoral Gross Provincial Product (GPP) data from 2020 were utilised to model the average household income of 2021. This approach of employing separate temporally lagged models allows for an enhanced understanding of the temporal impact of economic sectors on average household income, providing valuable insights into the temporal dimension without further complicating the model structure. Additionally, one-period temporally lagged independent variables are used as instrumental variables, a technique that is elaborated upon in the following section. This method further incorporates the temporal dimension into the model without presenting more independent variables.

3.5. Estimation of the Models

In the estimation of SLM model with fixed effects, the Maximum Likelihood (ML) method was initially considered. However, this approach was subsequently dismissed due to signs of simultaneity in the data as shown in the Granger test results. To address these concerns, the Two-Stage Least Squares (2SLS) method was employed as an alternative to ML (Kapoor et al. 2007). The 2SLS approach is particularly adept at mitigating simultaneity issues, making it a more suitable choice for the data at hand (Reed 2015).

In the implementation of the 2SLS method for the panel data model with fixed effects, a specific strategy was adopted for dealing with the endogenous variables, which in this case were the 19 economic sectors. The independent variables were treated as endogenous, and their one-period temporally lagged values were utilised as instrumental

variables in the 2SLS method (see Reed 2015). The Two-Stage Least Squares method for panel data with fixed effects was applied to fit all the models in this study, utilising the “splm” package in R.

3.6. Spatial Autocorrelations

Additional tests conducted to answer RQ2 include the use of Moran’s I, an index that depicts the spatial autocorrelation characteristics of average household income among provinces from 2005 to 2021. In this paper, the global Moran’s I is employed, which typically ranges between -1 and 1 . A value greater than zero signifies positive autocorrelation, whereas a value less than zero indicates negative autocorrelation. This analysis was performed using the “spdep” package in R (Bivand et al. 2015).

The global Moran’s I measure, commonly used to assess spatial autocorrelation, offers a general indication of how similar or dissimilar values are across a geographic space. However, it is limited in identifying specific local patterns, as it summarises the entire spatial distribution into a single statistic. While it can detect overall clustering of high-value and low-value areas or the juxtaposition of high and low values, it cannot discern if both types of clustering coexist. To overcome this, Local Indicators of Spatial Association (LISA) decomposes the global Moran’s I, allowing for the assessment of local spatial patterns (Anselin 1995). LISA can identify local clusters of high values (hot spots) or low values, as well as outliers and regions that deviate from the expected spatial pattern. This method enhances the interpretation of spatial data by highlighting local clusters where similar values are geographically concentrated (HH or LL) or where contrasting values are adjacent (HL or LH), thus providing an intricate understanding of the spatial distribution of economic activities (de Dominicis et al. 2007).

4. Findings

4.1. Descriptive Statistics and Moran’s I of Variables

Table 1 provides a breakdown of the Gross Provincial Product (GPP) for each of the 76 provinces in Thailand, categorised by 19 economic sectors for the year 2021, with all values expressed in million Baht. The sectors range widely from agriculture to other services, with average monthly household income as a dependent variable. The manufacturing sector stands out with the highest mean GPP across the provinces (37,626 million Baht), indicating a strong presence of manufacturing activities throughout Thailand. On the opposite end, the water supply, sewerage, and waste management sector shows the lowest mean (724 million Baht), suggesting a smaller economic footprint in the provinces.

Table 1. Descriptive Statistics, Mean, and Standard Deviation, of the Independent and Dependent Variables of the Year 2021 in million Baht.

Sector	Mean	SD	Min	1st Qu.	Median	3rd Qu.	Max
Agriculture	8447	5773	1208	3974	7104	10,779	27,130
Mining	2595	14,329	0	84	163	605	124,005
Manufacturing	37,626	77,202	290	2195	5225	17,573	353,793
Electricity	3902	7353	147	608	1167	3143	47,664
Water	724	2518	28	100	169	367	21,181
Construction	3964	9354	660	1449	2017	3330	81,588
Retail	21,902	99,299	751	2675	4823	11,047	866,546
Transport	6880	29,289	270	826	1390	2526	248,752
Food	4856	26,770	13	148	385	2074	232,937
Information	8492	56,928	231	564	997	1694	496,946
Finance	11,492	62,048	586	1885	3052	5535	544,070
Real estate	5804	13,546	731	1804	3313	5482	117,443
Professional	2662	18,298	1	15	35	191	159,036

Support	1799	10,214	4	29	87	281	87,715
Public	7064	34,780	502	1324	2060	4424	305,008
Education	4455	7848	433	1483	2626	4475	66,012
Health	3393	8328	408	997	1472	2810	68,858
Leisure	1453	8244	34	106	184	322	68,551
Others	2082	11,506	116	232	391	755	100,478
Household Income (Baht per month)	24,671	5800	15,496	20,671	23,596	27,000	41,129

The substantial standard deviation in the retail (99,299 million Baht) and manufacturing (77,202 million Baht) sectors implies significant disparities in GPP between provinces within these sectors, possibly due to the varying presence of industrial and commercial hubs. The vast range between the minimum and maximum values across most sectors indicates a heterogeneity in economic activity, with some provinces showing very high GPP and others much lower.

The time series chart (Figure 1) tracks the average Gross Provincial Product (GPP) of 76 provinces across 19 sectors from 2005 to 2021. It illustrates a pronounced growth trend in the manufacturing sector, which shows a steady and substantial increase over the years. The wholesale and retail sector also exhibits a significant upward trajectory, reflecting the sector's expansion over the period. Financial and insurance alongside information and communication, though not as pronounced as manufacturing and retail, demonstrate notable growth trends, indicative of Thailand's strengthening service economy.

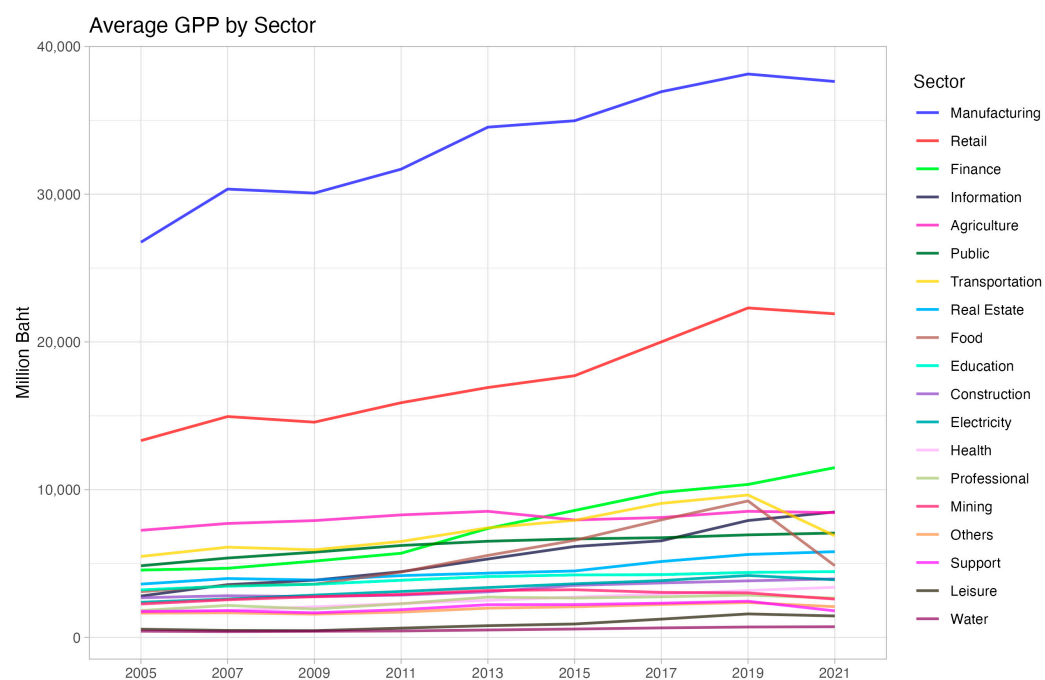


Figure 1. Time Series Chart of the Average GPP by Sector (2005–2021).

However, the chart also captures the impact of the pandemic, particularly on the transportation and accommodation and food services sectors, which experienced sharp declines, reflecting global travel restrictions and reduced consumer spending in these areas during this period. The remaining sectors, including agriculture, education, and health, among others, display relatively stable trends with no significant fluctuations, suggesting resilience or steadiness in their economic output throughout the years.

Regarding the dependent variable, the Moran's I statistics were computed (Table 2). The analysis, underpinned by a distance-decay spatial weighted function revealed

significant positive spatial autocorrelation in all observed years (2005–2021), with Moran’s I values ranging from 0.306 to 0.451 and p -values consistently below 0.001. These results indicate that provinces with similar income levels tend to be geographically clustered. The variation in Moran’s I values across different years suggests fluctuating degrees of this clustering effect. For instance, the highest value in 2005 (0.451) points to a stronger geographic clustering of provinces with similar income levels, whereas the value in 2011 (0.306), though lower, still indicates a significant but less pronounced clustering pattern. Consequently, due to the observed autocorrelation as indicated by Moran’s I, spatial econometric modelling is deemed more appropriate than conventional econometric methods.

Table 2. Moran’s I Test for Spatial Autocorrelation of Average Household Income.

Year	Moran’s I	p -Value
2005	0.451	<0.001
2007	0.401	<0.001
2009	0.355	<0.001
2011	0.306	<0.001
2013	0.378	<0.001
2015	0.311	<0.001
2017	0.400	<0.001
2019	0.321	<0.001
2021	0.376	<0.001

The map of Thailand displaying the average household income by province in 2021 vividly illustrates the income disparity across different regions (Figure 2). The colour gradient represents various income levels, with lighter shades indicating higher income. Bangkok metropolitan appears as a significant area of high income, as expected due to its status as the capital and economic hub. Additionally, the Eastern region and certain parts of the Southern region also display elevated income figures. Conversely, the provinces in the Northern and Northeastern regions are broadly marked with darker shades, signifying lower average household incomes. The LISA cluster map reinforces these observations by presenting clusters of high-income provinces (H-H) in darker shades, particularly in the Bangkok metropolitan area, some Central region provinces, and the Eastern Economic Corridor. Conversely, clusters in the Northern region, as well as a large area in the Northeastern region, exhibit low-income clusters (L-L).

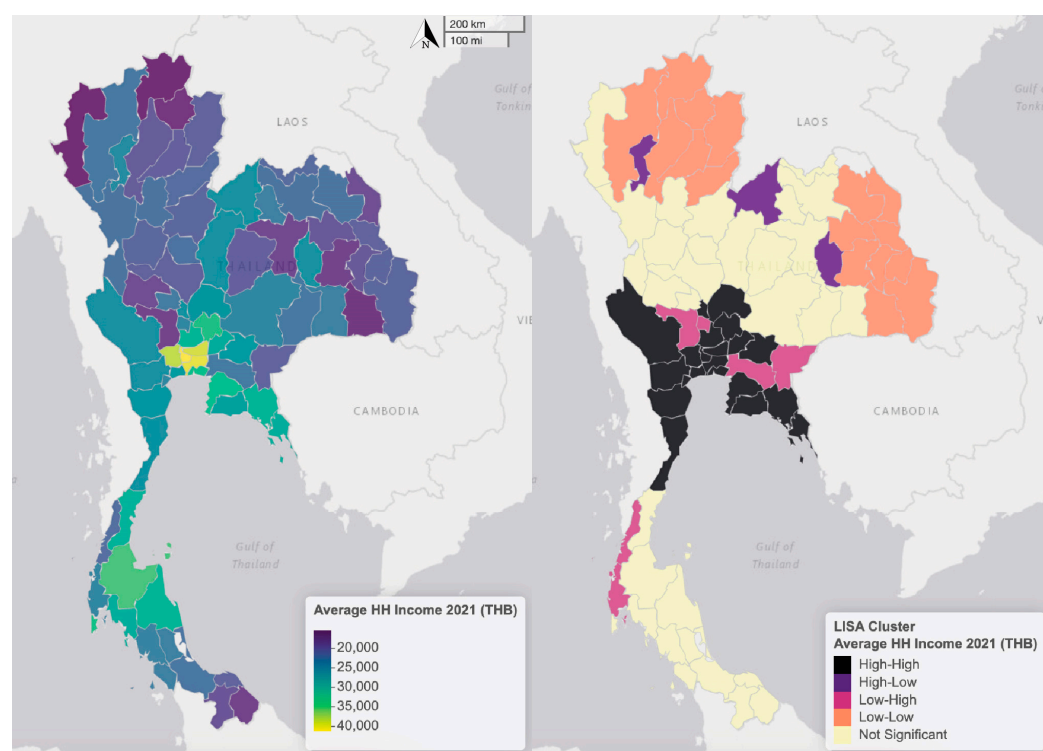


Figure 2. Average Monthly Household Income in Baht by Province and LISA Cluster Map.

4.2. Results of the Spatial Econometric Models

Table 3 presents the empirical results from the application of the SLM and its lagged version, SLM_{t-1} . These models play a pivotal role in shedding light on the impact of sectoral economic activities on income, particularly focusing on the spatial lag effect, denoted by λ . The consistently positive and statistically significant λ values in both models (0.989 and 0.994, with p -values < 0.001) reveal the presence of spatial spillover effects. Specifically, they indicate that household income in one province is positively correlated with the income levels in nearby provinces. This finding implies that the economic health of a region can be, in part, influenced by the financial success of its surrounding areas.

Table 3. The Results of Spatial Lag Models.

Independent Variables	SLM	SLM_{t-1}
Spatial lag coeff. (λ)	0.989 ***	0.994 ***
Agriculture	0.172 **	0.188 **
Mining	−0.038	−0.018
Manufacturing	0.001	0.009
Electricity	−0.016	−0.075
Water	−0.714	−0.140
Construction	0.034	−0.028
Retail	−0.056	−0.061
Transport	−0.022	−0.040
Food	0.024	0.041
Information	−0.034	−0.007
Finance	−0.031	0.026
Real estate	0.560 ***	0.705 ***
Professional	0.471 ***	0.051
Support	0.175	0.470 **
Public	0.071	0.038

Education	0.207	0.076
Health	−0.379 **	−0.514 **
Leisure	0.289 *	0.561 **
Others	−1.030 **	−1.581 ***
Pseudo R ²	0.872	0.874
RMSE	2457	2444

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.001$.

The analysis indicates that certain sectors consistently exhibit a positive correlation with average household income. Notably, the *agricultural* sector—which includes a range of activities from farming to fishing—displays a strong positive link with household income across both models. This relationship highlights the essential role of agriculture in sustaining rural economies and suggests that variations in agricultural output are directly connected to the economic health of provincial households. However, the earlier Granger causality tests cautions against interpreting this link as strictly predictive or causal. It likely points to a symbiotic relationship, where the success of the sector and the growth in household income are mutually reinforcing. Additionally, the *real estate* sector, encompassing property development and sales, shows a significant positive association in both models. This relationship may reflect the immediate economic benefits derived from real estate activities, which could suggest the sector's impact on employment opportunities and local income levels in the short term—and the potential feedback effect of these economic conditions on the real estate sector itself.

Professional, scientific, and technical services, which range from legal and accounting to architectural services, exhibit variability in their influence on household income. They are significantly associated with the average household income in the SLM model. *Administration and support services*, essential to the functioning of both public and private sectors, also show a positive association with income in the SLM_{t-1} model. Finally, the *leisure* sector, which includes arts, entertainment, and recreation, presents a significant positive relationship with household income in the SLM_{t-1} model. This pattern indicates a short-term relationship between leisure-related economic activities and income.

While the SLM and SLM_{t-1} models' results point to significant sectoral associations with household income, the simultaneity and the presence of bidirectional causality emphasise the need for careful interpretation. The two-stage least squares (2SLS) regression employed helps to address simultaneity concerns but does not eliminate them entirely. Thus, while sectoral GPP may be associated with household income, this relationship is intricate and possibly co-determined by income levels themselves.

4.3. Spatial Correlation and Regional Variations in Selected Economic Sectors

The analysis of spatial correlation in five key economic sectors significantly associated with average household income provides valuable insights into how these sectors are geographically distributed and interrelated across regions. Moran's I was computed for two key features of each sector: the Compound Annual Growth Rate (CAGR) from 2005 to 2021, and the sectoral productivity (Gross Provincial Product, GPP) per capita in 2021 (Table 4). The benefit of such an analysis is multifaceted; it not only highlights regions with similar growth patterns or productivity levels but also helps in identifying potential areas of spatial dependency or autocorrelation. This information is crucial for policymakers and investors aiming to understand regional economic disparities and for devising strategies to foster balanced regional development.

Table 4. Moran's I of the CAGR and Productivity Per Capita of the Five Sectors.

Sector		Moran's I	p-Value
Agriculture forestry and fishing	CAGR	0.262	<0.001
	Per Capita	0.353	<0.001
Real estate activities	CAGR	0.051	0.044
	Per Capita	0.316	<0.001
Professional scientific and technical activities	CAGR	−0.059	0.897
	Per Capita	0.074	<0.001
Administrative and support service activities	CAGR	0.045	0.059
	Per Capita	0.173	<0.001
Arts entertainment and recreation	CAGR	0.202	<0.001
	Per Capita	0.063	0.001

The Moran's I results reveal varying degrees of spatial correlation across sectors and attributes. For example, the agriculture, forestry, and fishing sectors exhibit a significant positive spatial correlation in both CAGR (Moran's I = 0.262, $p < 0.001$) and per capita productivity (Moran's I = 0.353, $p < 0.001$). This suggests that regions with high growth or productivity in this sector tend to be geographically clustered. Similar patterns are observed in the real estate activities and arts, entertainment, and recreation sectors, indicating that regions with high productivity or growth in these sectors are likely to be near other regions with similar characteristics.

Conversely, sectors such as professional, scientific, and technical activities, and administrative and support service activities show no significant spatial correlation in their CAGR (Moran's I = −0.059, $p = 0.897$ for the former and Moran's I = 0.045, $p = 0.059$ for the latter). This suggests a more dispersed spatial distribution of growth rates across regions.

Figure 3 offers a comprehensive visual analysis of five key economic sectors in Thailand, showcasing the CAGR from 2005 to 2021, productivity per capita in 2021, and LISA cluster maps for each sector. In the *agricultural* sector, the CAGR maps reveal a pronounced cluster of high growth across the entire Northeastern region, contrasting with low growth in the Central region and the deep South of Thailand. However, the productivity per capita maps indicate a starkly different scenario; the Northeastern region is identified as a low productivity cluster in agriculture, while the Southern region boasts high productivity. This contrast suggests that although the Northeastern region has seen substantial growth, it still lags in productivity, indicating a potential area for targeted development. The *real estate* sector presents a strong dichotomy. The Bangkok Metropolitan area and the Eastern provinces are highlighted as regions of high productivity per capita. The Eastern region also emerges as a high-growth area, pointing to a significant divergence in growth and prosperity within the real estate sector across the country.

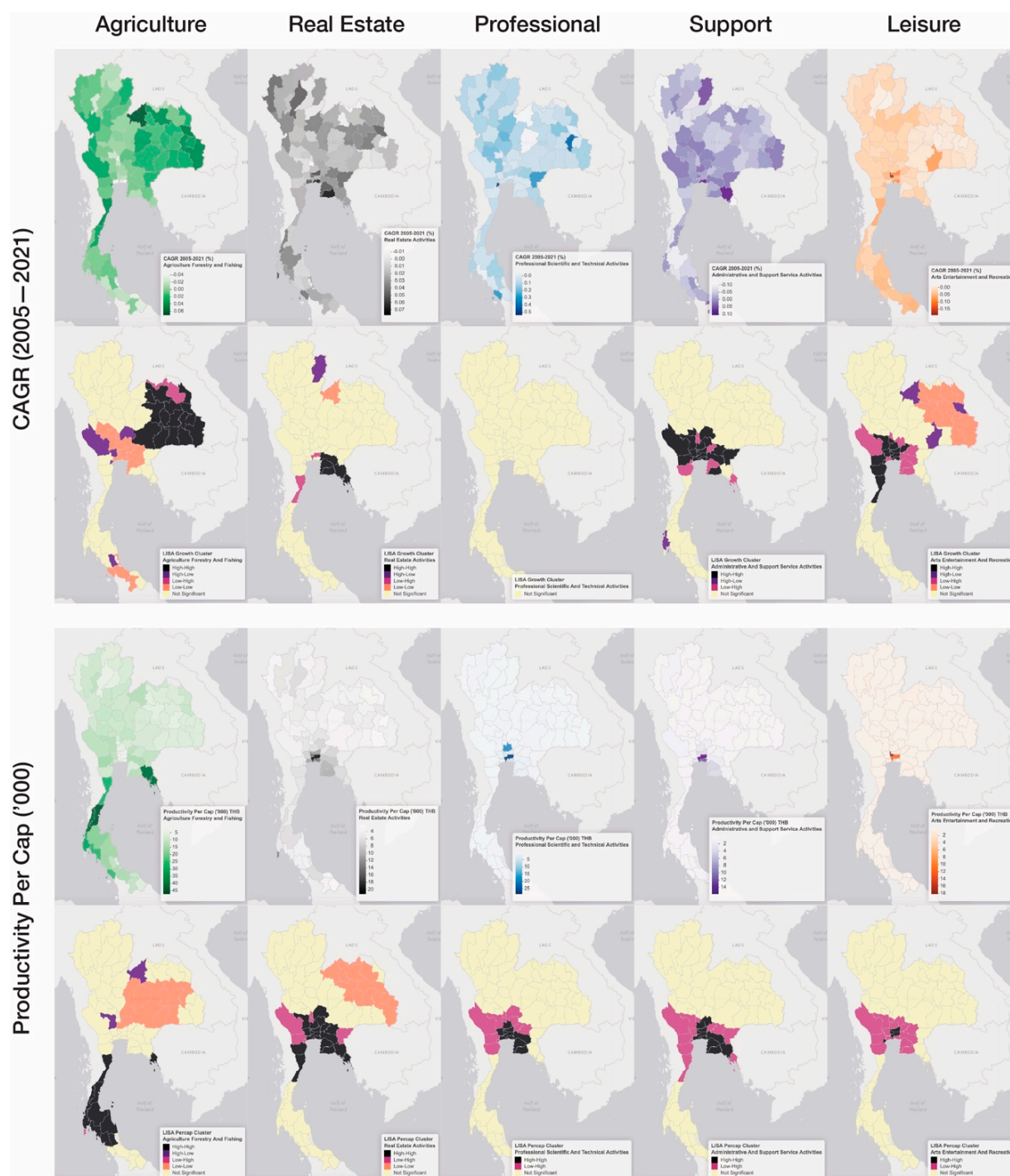


Figure 3. CAGR and Productivity Per Capita of the Five Sectors and the LISA Maps.

The *professional, scientific, and technical services* sector does not exhibit a clear growth pattern according to the global Moran's I results. Nevertheless, the productivity per capita is highly concentrated in the Bangkok Metropolitan area and the Eastern region, reinforcing these areas as economic hubs for advanced services. *Administrative and support service* activities' growth, while lacking spatial correlation globally, demonstrates regional high-growth clusters in the Bangkok Metropolitan area and parts of the Central and Eastern regions through the LISA Cluster maps. The pattern for productivity per capita mirrors that of professional activities, with high values clustered in Bangkok and the Eastern region. For the *leisure* sector, encompassing arts, entertainment, and recreation, there is a consistent concentration of high productivity per capita in Bangkok and its neighbouring

provinces, Nonthaburi and Pathum Thani. The central area of Thailand is noted for the sector's growth, whereas the Northeastern region is distinctly marked by low growth.

The LISA cluster maps presented in Figure 3 are invaluable for discerning the distinctive characteristics and trends within Thailand's key economic sectors. These maps highlight the spatial variability and disparities that exist, providing crucial insights that can inform and shape development policies by public sector entities.

5. Discussion and Conclusions

5.1. Discussion of the Findings

In the analysis of RQ1, "what are the effects of changes in various economic sectors on average household income?", the study leverages the data from official sources to develop predictive models. Specifically, it employs Spatial Lag Models (SLM) and their temporally adjusted variants (SLM_{t-1}) to delve into the effects of sectoral Gross Provincial Product (GPP) on household income. The findings indicate a potential simultaneity issue, suggesting that sectoral productivity (GPP) and average household income may be mutually reinforcing, rather than exhibiting a straightforward causal relationship.

To mitigate the simultaneity issue, a 2SLS estimator with fixed effects was employed. The analysis revealed that five sectors—agriculture, real estate, professional services, support services, and leisure—demonstrate a significant association with average household income in either or both models. Conversely, health-related sectors and other services show a negative association with average household income. These findings contribute to an expanded understanding of sectoral effects on income.

In the context of Thailand, the growth of key economic sectors is often seen as indicative of increased household income. Agriculture, for instance, employs about 30 percent of the labor force. However, this sector is characterised by relatively low income and productivity.¹¹ Therefore, improvements in agricultural productivity are strongly associated with an increase in average household income. Additionally, the sectors of professional, scientific, and technical activities, along with administrative and support activities, can be viewed as integral to enhancing 'business capacity' within a province. These sectors contribute significantly to innovation, competitive advantage, and management efficiency, all of which are closely linked to average household income.

The real estate and leisure sectors also emerge as distinct markers of increased average household income. However, there may be a bi-directional relationship at play, as these sectors are likely to benefit from the increased disposable income of the populace. The study observes no direct correlation between sectors such as retail, wholesale, and food services, and average household income, which calls for more in-depth analysis. Nonetheless, this absence of apparent relationships should be interpreted with caution due to the potential for multicollinearity in datasets of this nature.

Traditional economic theories often outline a linear transition from agriculture to industrial, service, and knowledge sectors, highlighting the transformative impact of each stage on economic development (Kuznets 2019). This paper presents an original examination of the impact of sectoral GDP at a provincial level on household income. While this study is contextually bound to Thailand, and its applicability to other settings may be limited, it provides critical lessons for economic policy. The findings serve as an empirical foundation for strategies aimed at fostering household income growth and highlight the importance of sector-specific policies.

In response to RQ2, "what are the roles and characteristics of spatial dependencies on the effects of economic sectors and the dynamics of household income?", the application of SLM and subsequent analysis have been instrumental. The findings demonstrate a pronounced spatial autoregression, suggesting that the household income of one province can be significantly influenced by the income levels in nearby provinces. This aligns with existing literature that emphasises spatial correlation (Basile 2009; Garrett et al. 2007).

The study also conducted global Moran's I and LISA analyses on household income, growth, and GPP per capita across five key sectors. These analyses yield a two-part answer to RQ2. First, there is an apparent spatial autoregressive effect on household income, with a cluster of high-income provinces centred around the Bangkok Metropolitan region and the Eastern region, confirming a previous study (Sajarattanochoe and Poon 2009). This reflects agglomeration principles outlined in the literature, including backward linkages, innovative activity, and skilled labour pooling, which foster economic activity concentration in specific regions (Barrios et al. 2009).

Second, sectors such as agriculture, real estate, professional and support services, and leisure, identified as potential income drivers, are predominantly clustered in this same high-income region. While existing literature discusses the convergence hypothesis, where lower-income regions gradually align with higher-income counterparts (Chambers and Dhongde 2016; Gebremariam et al. 2010), this study reveals a contrasting scenario in Thailand's economic landscape. The spatial concentration of key sectors around affluent areas like Bangkok and the Eastern region signals enduring spatial inequality. However, this could be viewed through the lens of a "Kuznets-like" structural process, characterised by a shift from agricultural to industrial and service-based sectors and an initial increase in income inequality, potentially reducing over time (Kuznets 2019). Thailand may not have reached the point where spatial inequality begins to diminish.

Despite theoretical frameworks suggesting otherwise, this study's evidence implies that the spatial concentration of wealth and economic activities in already prosperous areas might not adequately address regional income disparities, given the low growth trajectories of these sectors across different regions. Consequently, addressing spatial inequality emerges as a critical task, necessitating collaborative efforts from both public and private sectors. The subsequent section delves deeper into strategies and recommendations, underlining the vital role of policy interventions in promoting equitable regional development.

5.2. Policy Implications

The findings of this research raise questions about the long-term effectiveness of Thailand's digital wallet scheme. The SLM models demonstrated no direct association between the wholesale, retail, and food service sectors and household income throughout the study period. While these results do not entirely dismiss the value of the economic stimulus or downplay the importance of these sectors—which are integral to Thailand's economy and interconnected with other sectors—they do highlight the need for a more considered approach in policymaking. The lack of direct influence between these sectors and the improvement of household income suggests that a more strategic sector- and place-based policy could be more effective.

5.2.1. Accelerating Industry Clusters and Innovation Districts

The sectoral and spatial insights from this research highlight the need for policies that specifically address these issues. The first key implication centres on accelerating economic clusters to boost household income throughout Thailand while concurrently addressing the spatial inequality identified in the study. The findings entail the crucial role of industry clusters in regional development, a strategy globally recognised for promoting economic growth (Stimson et al. 2006).

In Thailand, economic clusters, especially in advanced manufacturing within affluent regions like the Eastern area, have been a focus for decades (Klaitabtim 2016). However, the existing top-down approach often misses the distinctions of local realities (Kamnuansilpa et al. 2023). This study's insights, particularly concerning five key sectors—agriculture, real estate, professional services, support services, and leisure—suggest a more refined approach to implementing cluster policies.

Firstly, the sectors of professional, scientific, and technical services, along with administrative and support services, can be simultaneously regarded as sectors aimed at

driving ‘business capacity’ in a province and are strongly associated with average household income. This research found that the improvement of business capacity is related to increased income. These findings echo the calls within Thailand for improvements in business processes, strategic planning, technical expertise, and coordination to bolster the functioning of industry clusters (Lengwiriyakul and Jarernsiripornkul 2017; Phochathan 2016; Thongprasert et al. 2023; Vanarun 2019).

This leads to the concept of “innovation districts”, a variant of small-scale economic clusters, which can significantly enhance the business capacity of enterprises and other sectors within a province. Innovation districts, leveraging the presence of universities and colleges as anchors, can facilitate public, private, and community collaborations. The integration of these educational institutions is pivotal for enhancing clusters in Thailand (Abhinorasaeth et al. 2021; Hansamorn et al. 2019). The existing literature also links the role of higher education institutions to regional income growth (Liu et al. 2018; Ramos et al. 2010; Su and Heshmati 2013; Teslenko et al. 2021). The innovation districts not only drive innovation and business capacity but also contribute to the vibrancy of real estate and leisure sectors (Taecharungroj and Millington 2022).

Innovation districts in Thailand should aim to break away from a one-size-fits-all, prescriptive nationwide policy. Different regions may require distinct types of innovation districts, tailored to their unique economic landscapes and resource availability. The effectiveness of small-scale, place-based development has been recognised as crucial for regional progress in Thailand (Moore and Donaldson 2016; Suranartyuth 2011). These districts would provide a conducive environment for nurturing new businesses, fostering research and development, encouraging collaboration across various sectors and fostering specialisation which is important for regional growth (Piras et al. 2012). In this context, a strategic focus on high-value agriculture as a spearhead project in innovation districts nationwide could be highly beneficial. Such a focus would leverage Thailand’s agricultural strengths, driving innovation in a sector that directly affects a large portion of the population. By integrating advanced technologies and practices into agriculture, these districts could significantly enhance household income, particularly in rural areas.

5.2.2. Improving Regulatory Framework and Province Branding

While Thailand already has various business-friendly regulations, such as tax incentives and streamlined licensing processes, these benefits have predominantly been geared towards top-down clusters in wealthier regions, with a focus on attracting large-scale investments and enhancing export opportunities (Klaitabtim 2016). To foster more inclusive economic growth, it is essential for government policies to extend support to businesses within the five strategic sectors, especially small-scale enterprises. In addition to offering tax breaks and reducing regulatory burdens, there is a need to provide more comprehensive support, including human capital development and funding opportunities.

Another crucial aspect of place-based policy that could significantly enhance strategic sectors and income levels is the concept of “place branding” for provinces. Place branding goes beyond merely attracting tourists; it can be a powerful tool in drawing investment, entrepreneurs, and businesses to targeted provinces (Che 2008; Cleave et al. 2016; Mabillard and Vuignier 2021; Roozen et al. 2017; Rothschild et al. 2012; Sparvero and Chalip 2007; Wisuchat and Taecharungroj 2022). By effectively presenting the unique business opportunities and quality of life each province offers, place branding can play a pivotal role in mitigating spatial inequality and boosting income. The combination of business and quality of life factors has been recognised as an important driver of regional growth (Carruthers and Mulligan 2008). In Thailand, where place branding has traditionally focused on tourism, pivoting towards promoting it for business, investment, and talent attraction could direct resources to and stimulate agglomeration within key economic sectors.

5.3. Conclusions

This research offers significant insights into the dynamics of household income and spatial economic interactions in Thailand, with a focus on the effects of various economic sectors and spatial dependencies. Notably, agriculture, real estate, professional services, support services, and leisure sectors emerge as significant predictors of household income. The study's exploration of spatial effects reveals critical spatial autocorrelation patterns. This emphasises the importance of considering regional interdependencies and variation in economic policymaking. The identification of high-income clusters around the Bangkok Metropolitan and Eastern regions, juxtaposed with the enduring spatial inequality in other areas, calls for a more progressive approach to economic development. Policy implications drawn from this research suggest alternatives to the substantial digital wallet scheme and emphasise the need to accelerate industry clusters and innovation districts, especially in less affluent regions, to promote equitable economic growth. The research advocates for a more inclusive regulatory framework and strategic use of place branding to attract investment and encourage regional development.

The limitations of this research are primarily rooted in its data constraints and the choice of econometric model. A key limitation is the temporally limited nature of the bi-annual average household income data spanning from 2005 to 2021. This biannual frequency restricts the temporal resolution of the analysis and may overlook subtler year-to-year variations that could offer deeper insights. Another notable limitation is the challenge posed by the often less normally distributed data, particularly with provinces like Bangkok exhibiting outsized levels compared to others. While a log transformation could have normalised the data distribution, it was not performed due to the presence of zero values in some sectors of certain provinces. Also, the potential multicollinearity among the independent variables is another limitation. The interpretation, especially regarding the size of the effects and the absence of certain relationships, should be approached with caution. Further study utilising machine learning (ML) techniques is advisable. The SLM employed in this study is a robust spatial econometric model for panel data that effectively accounts for spatial autoregressive characteristics. However, it is important to acknowledge that there are alternative models and techniques that could further enrich the analysis. These alternatives, potentially offering different perspectives and insights, could be considered in future research to overcome some of the limitations of the current study and provide a more comprehensive understanding of the phenomena.

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Appendix A

Appendix A.1. Nineteen Sectors Comprising Thailand's Gross Provincial Products

Appendix A.1.1. Agriculture

- *Agriculture, forestry, and fishing:* Farming; Animal breeding and stocking, animal hunting and related service activities; Forestry and logging; Fisheries and aquaculture.

Appendix A.1.2. Industrial

- *Mining and quarrying*: Coal and lignite mining; Production of crude oil and natural gas; Mining of metal ores; Mining Nonmetal Mine and other quarries; Service activities that support mining and petroleum production.
- *Manufacturing*: Production of food products, beverage, tobacco products, textile, clothing, leather goods, wood and products from wood and cork, paper and products processed from paper, coke and petroleum products, chemicals and chemical products, pharmaceutical products, rubber and plastic products, products made from non-metallic minerals, aluminium alloy, products made from fabricated metal, computer products, electronics and optical equipment, electrical equipment, machinery and tools, vehicles, trailers and semi-trailers, other transportation equipment, furniture, and other types of products; Repair and installation of machinery and equipment; Printing and reproducing recording media
- *Electricity, gas, steam, and air conditioning supply*
- *Water supply, sewerage, waste management, and remediation activities*: Water storage, supply, and distribution; Waste management; Waste collection, treatment, and disposal; Recycling of waste; Treatment activities and other waste collection services

Appendix A.1.3. Services

- *Construction*: Building construction; Civil engineering work; Special construction work
- *Wholesale and retail trade and repair of motor vehicles and motorcycle*
- *Transportation and storage*: Land transport and pipeline transport; Water transportation; Air transportation; Warehouse-related activities and transportation support; Postal and delivery of documents/items.
- *Accommodation and food service activities*: Accommodation; Guesthouses; Food and beverage services.
- *Information and communication*: Publishing, selling, or distributing; Film, video, and television program production, Recording and distribution of music; Television program management and broadcasting; Telecommunications; Computer program preparation and consulting; Information services.
- *Financial and insurance activities*: Financial service; Insurance and Pension Funds; Activities supporting financial services and insurance.
- *Real estate activities*
- *Professional, scientific, and technical activities*: Legal and accounting; Head office activities; Management consulting; International trade business representative; Architecture and engineering, testing and technical analysis; Scientific research and development; Advertising and market research; Other professional, scientific, and technical activities; Veterinary.
- *Administrative and support service activities*: Renting and leasing; Recruitment; Travel business agent, travel organising and reservation business; Security and investigative service activities; Service activities for buildings and landscaping; Business support services.
- *Public administration and defence; compulsory social security*
- *Education*
- *Human health and social work activities*: Human health activities; Caregiving; Social welfare.
- *Arts, entertainment, and recreation*: Creative arts and entertainment; Library, archives, museum, and cultural activities; Gambling; Sports and recreation activities.
- *Other service activities*: Activities of member organisations; Religious organisations; Repair and maintenance; Personal services; Household services; Homemade products; Activities of international organisations

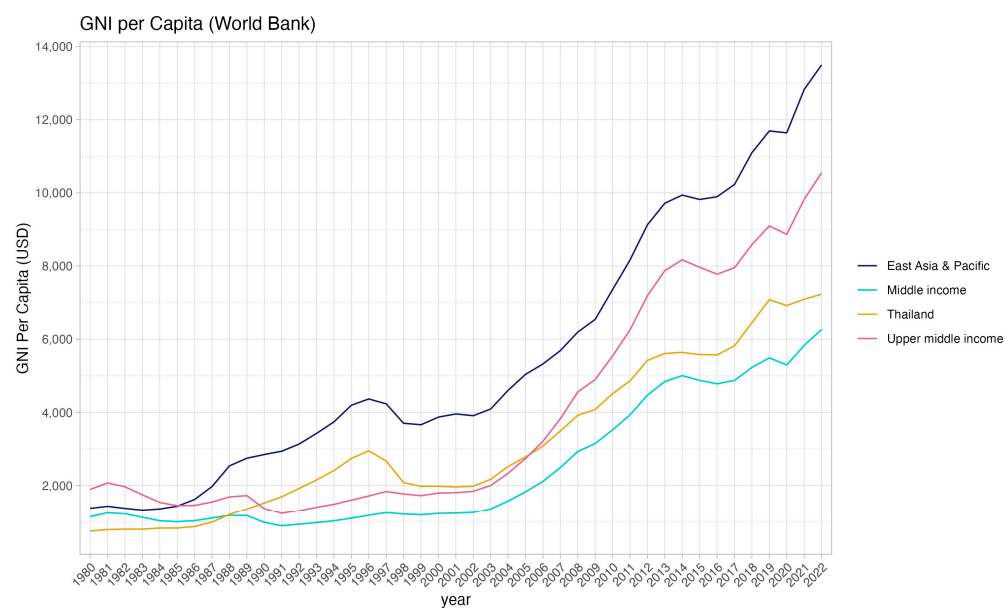


Figure A1. GNI Per Capita Comparison between Thailand, East Asia & Pacific, Middle Income, and Upper-Middle Income Countries.

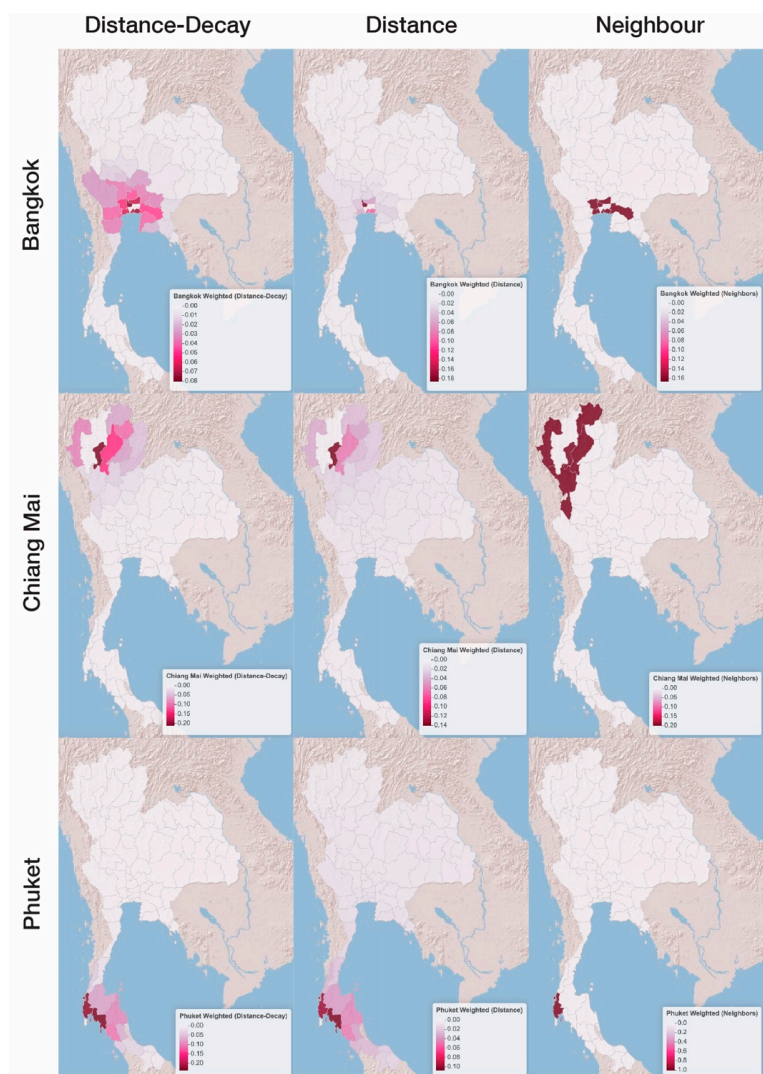


Figure A2. The visual representation of spatial weights on Bangkok, Chiang Mai, and Phuket using the three methods.

Notes

1. <https://www.thailand-business-news.com/economics/111713-digital-wallet-scheme-aimed-at-boosting-businesses-and-stimulating-the-economy> (accessed on 13 January 2024).
2. See note 1 above
3. <https://plus.thairath.co.th/topic/politics&society/103921> (accessed on 13 January 2024).
4. <https://ptp.or.th/> (accessed on 13 January 2024).
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8. The average household income by province in Thailand can be accessed at <http://statbbi.nso.go.th/staticreport/page/sector/th/08.aspx> (accessed on 13 January 2024).
9. The GPP data of Thailand can be accessed at https://www.nesdc.go.th/main.php?filename=gross_regional (accessed on 13 January 2024).
10. The collection and calculation of GPP can be retrieved from Office of the Official Information Commission (OIC) at <http://webcache.googleusercontent.com/search?client=firefox-b-d&q=cache%3Aoic.go.th%2FFILEWEB%2FCABINFOCEN-TER4%2FDRAWER052%2FGENERAL%2FDATA0002%2F00002224.PDF> (accessed on 13 January 2024). The document was produced by the Comptroller General's Department.
11. <https://thailand.un.org/en/103307-thai-agricultural-sector-problems-solutions> (accessed on 13 January 2024).

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