

Roles of Geographical Heterogeneity on Income Distribution: Empirical Evidence from Thailand

Ronnakron Kitipacharadechatron

Faculty of Economics, Thammasat University, Thailand.

*Padcharee Phasuk**

School of Economics, Sukhothai Thammathirat Open University, Thailand.

Received 25 August 2024, Received in revised form 3 January 2025,

Accepted 30 January 2025, Available online 1 September 2025

Abstract

Income disparity has led to numerous significant issues, prompting the need for a deeper understanding of its causes and impacts. This paper examines the role of geographical heterogeneity in income distribution, providing empirical evidence to support development theory and inform policymakers in designing effective development policies. Secondary data from government surveys and publicly accessible sources, including satellite data, are utilized to conduct the analysis. The econometric model employs the Generalized Method of Moments (GMM), and spatial patterns are investigated using spatial autocorrelation techniques. The findings indicate substantial regional income disparities in Thailand, particularly in the northern and northeastern regions, where economic activity is considerably lower compared to the central region. Furthermore, the results highlight the significant effect of geographical heterogeneity on income distribution, with agricultural areas exhibiting lower income levels relative to regions concentrated in manufacturing and services. These findings underscore the importance of addressing geographical factors in development planning to reduce income inequality.

Keywords: Geographical Heterogeneity, Income Distribution, Spatial Analysis, Thailand

JEL Classifications: O15, I32, D31, C31

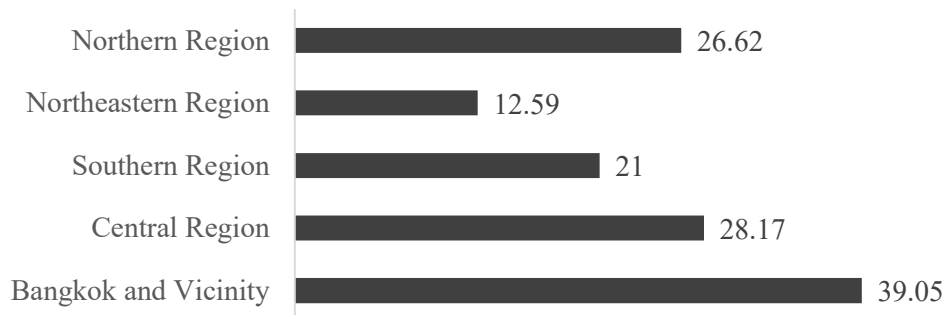
* **Corresponding author:** Email: padcharee.pha@stou.ac.th

1. Introduction

The problem of income distribution has been recognized as one of the major socio-economic challenges that worsens year by year. This issue raises serious concerns for researchers and policymakers alike. The widening income gap has exacerbated problems such as poverty and declining living standards, ultimately reducing overall individual well-being (Ravallion, 2014). Moreover, income inequality directly affects economic growth and sustainability by limiting the effectiveness of government policies (Puttanapong et al., 2022), especially those aimed at stimulating aggregate purchasing power and improving access to essential resources. Therefore, monitoring income distribution remains a critical task for policymakers committed to achieving sustainable development.

Globally, income inequality is a pressing issue, but it is particularly severe in developing countries (Milanovic, 2016), where economic activity is often heavily concentrated in specific areas. This geographical concentration complicates policy implementation (Groot et al., 2014). For example, Thailand has implemented economic development plans since 1961 (Puttanapong et al., 2022), focusing on infrastructure development and economic activity concentration. However, these efforts have predominantly benefited the capital city and nearby regions, leading to persistent income disparities (Prasertsoong & Puttanapong, 2022). Barro (1991) attributed this uneven income distribution to the long-term effects of economic growth, as reflected in the significant differences in average monthly income across regions.

Figure 1: Illustration of the Average Monthly Income per Household.



Note: Units in 1,000 THB

Sources: World Bank, 2021

The variation in income across the country can be attributed to multiple factors. Theoretically, these include education and labor skills (Aigner et al., 1967; Lee et al., 2013; Tinbergen, 1956), technological advancement (Fingleton, 2001; Tinbergen, 1956), government policies, globalization and trade (Lee et al., 2013; Tinbergen, 1956), demographic factors (Aigner et al., 1967; Tinbergen, 1956), and wealth distribution (Banerjee et al., 2002; Tinbergen, 1956). Given these factors, understanding income variation and its distribution is essential for formulating sustainable policies. Numerous studies have documented significant income disparities across various locations, such as France (Piketty, 2003), South Korea (Lee et al., 2013), Thailand (Puttanapong et al., 2022), the Philippines (Estudillo, 1997), China (Zhou & Song, 2016), the USA (Piketty & Saez, 2003), India (Sarkar & Mehta, 2010), and other developing countries (Ravallion, 2014).

However, spatial analysis, particularly in the context of geographical heterogeneity, has yet to provide conclusive evidence. This paper aims to contribute to this gap by exploring income distribution through the lens of geographical heterogeneity, which captures differences in the concentration of economic sectors (e.g., agriculture, manufacturing, and services) across provinces. The study employs and extends Mincer's earnings function (Mincer, 1958) to analyze and explain income disparities in Thailand. The remainder of this paper is organized as follows: Section 2 reviews related literature, Section 3 describes the research methodology, Section 4 presents the results and discussion, and Section 5 concludes with a discussion of the limitations.

2. Literature Review

The existing literature provides extensive insights into income distribution. One of the early pioneers in this field, Adam Smith, addressed the causes of income distribution in his seminal work *Wealth of Nations* in 1776. Smith argued that competition and market structure contributed to income equalization to some extent. However, he also noted that certain factors, such as skill levels and education, led to uneven income distribution. Building on these ideas, Mincer (1958) introduced a framework to quantify income by analyzing years of schooling and work experience. His approach simplified the complex relationship between economic factors and social dynamics, aligning with Smith's concept of income determinants. Mincer's earnings function has since been widely employed by scholars to explore income variation in both micro- and macroeconomic contexts (Lemieux, 2006). For example, Lee et al. (2013) investigated income inequality in Korea from a macroeconomic perspective, employing and adapting Mincer's earnings function to include macro-level variables. Their findings confirmed that the earnings function effectively explained income distribution. Similarly, Aigner & Heins (1967) and Prasertsoong & Puttanapong (2022) analyzed regional income determinants in the United States and Thailand, respectively, from a microeconomic perspective. Both studies demonstrated that Mincer's equation could be used to explain income distribution across regions.

An interesting pattern in the literature is the incorporation of industry density, reflecting geographical heterogeneity, into income distribution studies. Scholars such as Aigner & Heins (1967), Lee et al. (2013), Barufi et al. (2016), and Combes et al. (2008) found varying outcomes depending on the country studied. For instance, geographical heterogeneity significantly influenced income distribution in Korea, the United States, and France. However, in Brazil, no such effect was observed. In the case of Thailand, direct evidence of geographical heterogeneity's influence on income distribution is still lacking. Although the studies of Prasertsoong & Puttanapong (2022) and Puttanapong et al. (2022) provide some insights by exploring agglomeration externalities, a deeper analysis is needed. Agglomeration externalities refer to the benefits businesses and individuals gain by clustering in specific areas, such as cities or industrial zones, which create positive spillover effects that enhance economic growth and productivity. However, geographical heterogeneity encompasses broader aspects, including geospatial characteristics such as natural resources, economic structures, and social conditions across different locations. Therefore, future studies should explicitly include geographical heterogeneity as a key explanatory variable to better understand its role in income distribution. This approach would provide a more comprehensive analysis and fill the current gaps in the literature.

3. Data and Methodology

3.1 Data Sources

This paper utilized retrospective data from secondary datasets, specifically the Socio-Economic Survey (SES) conducted by the National Statistical Office of Thailand in 2021. The dataset includes randomly selected data from over 50,000 households nationwide.

The survey contains detailed household information, and this study focuses on specific variables such as income, age, and years of schooling. These variables were aggregated at the provincial level to suit the objectives of the investigation, particularly capturing the agglomeration externality and geographical heterogeneity, which could not be performed at the individual level. In addition to survey data, this study incorporates publicly accessible VIIRS night-time lights data provided by NASA (Elvidge et al., 2017). The night-time light index, derived from satellite imagery, measures light intensity during nighttime and has become a widely used proxy for socio-economic and economic activity indicators (Shi et al., 2014; Zhou et al., 2015).

The collected data were tested for normality using the Shapiro-Wilk method and analyzed using descriptive statistics, including the mean, standard deviation, median, and interquartile range. These analyses provide a summary of the data, which is presented in tables with accompanying descriptions.

The results indicate that most of the data gathered follows a normal distribution, although exceptions were observed with the night-time light index and economic sector data in certain regions. Notably, the central and southern regions exhibited higher income levels, which align with the trends identified by the night-time light index. This index effectively serves as a proxy for socio-economic status and economic activity within these regions. In contrast, other variables did not show significant deviations, as summarized in Table 1.

Table 1: Illustration of Descriptive Statistics and Normality Testing

Central	Mean	Std. Dev	Median	IQR	Shapiro Wilk
Income (THB/M)	24,640.12	5,292.46	24,030.02	5,716.39	0.258
Age (Year)	42.15	1.99	41.46	2.78	1.110
Schooling (Year)	10.58	0.69	10.46	0.96	0.897
Night-time Light	20.31	13.04	14.98	14.06	4.111 ***
Economic Sectors					
Agriculture (%)	0.15	0.08	0.14	0.14	0.785
Manufacturing (%)	0.25	0.13	0.23	0.16	0.84
Service (%)	0.60	0.10	0.60	0.12	1.57
Northern	Mean	Std. Dev	Median	IQR	Shapiro Wilk
Income (THB/M)	17,582.42	2,449.93	18,000.21	2,708.26	0.845
Age (Year)	44.87	2.41	44.67	3.00	0.581
Schooling (Year)	10.12	0.42	10.09	0.54	1.749
Night-time Light	10.06	1.18	10.25	1.02	0.677
Economic Sectors					
Agriculture (%)	0.29	0.05	0.30	0.06	1.023
Manufacturing (%)	0.12	0.06	0.10	0.04	2.021 **
Service (%)	0.59	0.06	0.60	0.06	1.653 **

Northeastern	Mean	Std. Dev	Median	IQR	Shapiro Wilk
Income (THB/M)	18,086.76	3,078.30	18,396.04	4,473.01	0.085
Age (Year)	42.77	2.14	42.63	2.63	1.549
Schooling (Year)	9.95	0.54	9.90	0.80	0.738
Night-time Light	10.64	0.99	10.46	1.50	0.458
Economic Sectors					
Agriculture (%)	0.32	0.05	0.32	0.09	0.036
Manufacturing (%)	0.09	0.04	0.09	0.03	2.287 ***
Service (%)	0.59	0.05	0.60	0.06	1.623
Southern	Mean	Std. Dev	Median	IQR	Shapiro Wilk
Income (THB/M)	22,624.18	4,669.46	21,826.85	6,224.53	0.218
Age (Year)	38.53	2.72	38.84	4.36	0.809
Schooling (Year)	9.84	0.33	9.79	0.26	0.585
Night-time Light	14.46	7.38	12.46	3.16	4.026 ***
Economic Sectors					
Agriculture (%)	0.22	0.08	0.22	0.06	0.544
Manufacturing (%)	0.10	0.04	0.09	0.04	0.280
Service (%)	0.69	0.08	0.69	0.09	1.727 **

Note: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$

Sources: Author's calculation

3.2 Methodology

This section provides details of the analysis procedure, categorized into three subsections: (1) Theoretical Model, (2) Empirical Model, and (3) Spatial Investigation, as described below.

3.2.1 Theoretical Model Specification

To understand income distribution across the country, this study adopts Mincer's earning function (1958, 1974), which models income as a function of years of schooling and work experience. This model, widely used in empirical economics, assumes that worker experience yields diminishing marginal returns on earnings, typically represented as a quadratic function (Lemieux, 2006). The equation is expressed as:

$$\ln \omega_i = f(sch, exp) = \ln \omega_o + \rho_i sch_i + \beta_i exp_i + \beta_i exp_i^2 + v_i \quad (1)$$

Where:

$\ln \omega_i$ is earnings or income in natural logarithm form.

sch_i is the years of schooling.

exp_i is the worker experience.

exp_i^2 is the worker experience squared.

$\ln \omega_o$ is a earnings without schooling and experience.

v_i is a disturbance term.

ρ_i, β_i is an estimated parameter.

3.2.2 Empirical Model Specification

To extend the theoretical model and align it with the objectives of this study, additional variables such as the night-time light (NTL) index and industrial concentrations are incorporated to capture agglomeration externalities and geographical heterogeneity. However, due to data limitations in the SES dataset, age is used as a proxy

for worker experience, as suggested by Mincer (1974). The empirical model is specified as:

$$\ln INC_i = \alpha_o + \gamma_i SCH_i + \mu_i AGE_i + \eta_i AGE_i^2 + \lambda_i NTL_i + \sum_{n=1}^m \theta_{in} Z_{in} + \sum_{n=1}^m \beta_{in} X_{in} + \sum_{n=1}^m \rho_{in} S_{in} + v_i \quad (2)$$

Where:

$\ln INC_i$ is the average income by province in logarithm form.

SCH_i is the average year of schooling by province.

AGE_i is the average age of workers by province.

AGE_i^2 is the average age of workers by province squared.

NTL_i is the average intensity of night-time light.

Z_{in} is the vector of the region where the province is located.

Given: n = 1 is Central [Base]

n = 2 is Northern

n = 3 is Northeastern

n = 4 is Southern

X_{in} is the socio-economic vector by region.

Given: n = 1 is NTL * Central

n = 2 is NTL * Northern

n = 3 is NTL * Northeastern

n = 4 is NTL * Southern

S_{in} is the vector of industrial concentration.

Given: n = 1 is a proportion of agriculture

n = 2 is a proportion of manufacturing

n = 3 is a proportion of services

α_o is a constant term.

v_i is a disturbance term.

$\gamma_i, \mu_i, \eta_i, \lambda_i, \theta_{in}, \beta_{in}, \rho_{in}$ is an estimated parameter.

Table 2: Details of Variables

Variables	Abbreviation	Details	Source
Average income	INC	Integer in logarithm form	SES dataset (NSO)
Average years of schooling	SCH	Integer	SES dataset (NSO)
Average worker age	AGE	Integer	SES dataset (NSO)
Night-time light intensity	NTL	Integer	VIIRS dataset (NASA)
Location of province	Central, North, Northeast, South	Dummy (1 if province is located in)	SES dataset (NSO)
Socio-economic status	NTL* Central NTL * North NTL * Northeast NTL * South	Integer of NTL multiply by region where the province located.	SES dataset (NSO)
Industrial concentration	Agri, Manu, Serv	Proportions by province (sum = 1)	SES dataset (NSO)

Sources: Author's summary

3.2.3 Model Estimation

The empirical model is applied to two primary analyses: (1) examining the impact of agglomeration externalities on income distribution and (2) analyzing geographical

heterogeneity in income distribution. To estimate the parameters, the Generalized Method of Moments (GMM) is employed due to its suitability for non-linear models and the potential issue of spatial autocorrelation in aggregated provincial data (Goeij & Verbeek, 2000). Ordinary Least Squares (OLS) estimation may not yield unbiased estimates in such cases (Gujarati, 2021).

3.2.4 Validation and Robustness Testing

After parameter estimation, the model is validated using the bootstrapping method. This involves randomly resampling the data and re-estimating the model to account for disturbance term assumptions (independence and identical distribution). Consistent results in terms of sign, magnitude, and statistical significance indicate model robustness.

3.2.5 Spatial Investigation

This section extends the investigation by examining spatial perspectives through the use of Moran's I statistic (Moran, 1950). Moran's I measures spatial autocorrelation and ranges from -1 to 1, similar to Pearson's correlation coefficient. The formula for Moran's I is given as:

$$Moran's\ I = \frac{n}{S_o} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} z_i z_j}{\sum_{i=1}^n z_i^2} \quad (3)$$

Where z_i is the deviation of an attribute for each feature from its mean, w_{ij} is the spatial weight between feature, n is equal to the total number of features, and S_o is the aggregate of all the spatial weights:

$$S_o = \sum_{i=1}^n \sum_{j=1}^n w_{ij} \quad (4)$$

The standard normal z-score for Moran's I can be calculated as:

$$Z = \frac{I - E[I]}{\sqrt{V[I]}} \quad (5)$$

Where:

$$E[I] = -\frac{1}{n-1}$$

And

$$V[I] = E[I^2] - E[I]^2$$

For a significant cluster pattern to exist in the data, the z-score must fall within the range of -1.68 to 1.68. Moran's I can also be extended to create a Local Indicator of Spatial Association (LISA), which identifies and visualizes spatial autocorrelation patterns using a color scheme (Anselin, 1995). LISA is computed using the following formula:

$$Moran's\ I_i = z_i \sum_j w_{ij} z_j \quad (6)$$

Where:

$$Z = \frac{z_i}{SD_i}$$

The color scheme represents spatial autocorrelation as follows: (1) Dark red: High-value clusters. (2) Dark blue: Low-value clusters. (3) Light red: High values surrounded by low-value clusters. (4) Light blue: Low values surrounded by high-value clusters. These classifications allow for an intuitive understanding of spatial data distribution and clustering patterns (Moran, 1950; Imran et al., 2019).

4. Result and Discussion

The analysis procedures outlined in the previous section yielded results that were divided into two main parts. The first part focuses on analyzing income distribution under geographical heterogeneity at the national level. The second part examines income distribution in terms of spatial patterns at the provincial level.

4.1 Income Distribution Under Geographical Heterogeneity

The empirical results demonstrated that Mincer's (1974) earning function, in its log-linear form as adopted in this paper, is effective for analyzing income distribution in Thailand. The key determinants of income distribution were the age of workers and socio-economic status, which had positive effects on income of approximately 0.359 percent and 0.204 percent, respectively. In contrast, years of schooling had a smaller impact compared to these variables. These findings raise some points of discussion regarding Mincer's (1974) theoretical model, which emphasized the role of education returns. Typically, schooling enhances labor skills and productivity, which in turn increases income. However, in this case, higher income may not solely result from productivity but could include external factors as well (Patrinos, 2024).

Table 3: Illustration of the Estimated Model for Income Distribution and Agglomeration Externality

	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
Age	0.359 ***	0.122	0.452 ***	0.132	0.450 ***	0.133
Age ²	-0.005 ***	0.001	-0.006 ***	0.002	-0.006 ***	0.002
Schooling	0.089 ***	0.036	0.085 ***	0.034	0.087 ***	0.035
NTL	0.204 ***	0.044	0.139 ***	0.046	0.134 ***	0.046
Central	Based					
Northern			-0.094 *	0.054		
Northeastern			-0.154 ***	0.048		
Southern			0.048	0.074		
NTL*Central					Based	
NTL*Northern					-0.042 *	0.022
NTL*Northeastern					-0.064 ***	0.018
NTL*Southern					0.017	0.027
Constant	1.591	2.475	-0.304	2.806	-0.287	2.851
Observations	77		77		77	
Wald Chi-squared	112.21 ***		124.14 ***		128.66 ***	
R-squared (%)	53.80		60.28		60.56	
RMSE	0.160		0.148		0.148	
Robustness Check	Yes		Yes		Yes	

Note: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$

Sources: Author's calculation

Furthermore, incorporating regional variables into the model confirmed the hypothesis that income distribution varies across provinces. Notably, provinces in the

northeastern and northern regions of Thailand exhibited lower incomes, by about 0.154 percent and 0.094 percent, respectively, compared to the central region. This finding highlights the influence of regional economic conditions and the existence of agglomeration externalities (Prasertsoong & Puttanapong, 2022).

To explore these dynamics further, the interaction between the night-time light (NTL) index and regional variables was included in the model. The results revealed that provinces in the northern and northeastern regions, characterized by lower socio-economic status and economic activity, experienced significantly lower incomes. For instance, compared to the central region, economic activity was approximately 0.042 percent and 0.064 percent lower in the northern and northeastern regions, respectively, as shown in Table 3. These disparities are likely due to differences in economic structures; provinces in the central region are predominantly driven by manufacturing and service industries, while the northern and northeastern regions rely heavily on agriculture (Lucas, 1988; Fingleton, 2001; Barufi et al., 2016).

To further analyze geographical heterogeneity, industrial sector concentration was incorporated into the study. The results indicate that provinces with a higher proportion of agricultural activity had relatively lower income levels, approximately 1.011 percent lower than those driven by other economic activities. Conversely, manufacturing concentration was associated with higher income levels, by about 0.322 percent. However, the results for service sector concentration did not show a statistically significant variation in income levels, as presented in Table 4.

Table 4: Illustration of the Estimated Model for Income Distribution and Geographical Heterogeneity

	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
Age	0.382 ***	0.117	0.335 ***	0.120	0.378 ***	0.122
Age²	-0.005 ***	0.001	-0.004 ***	0.001	-0.005 ***	0.001
Schooling	0.067 **	0.030	0.083 **	0.035	0.088 **	0.036
NTL	0.041	0.051	0.161 ***	0.037	0.198 ***	0.045
Agriculture	-1.011 ***	0.211				
Manufacturing			0.322 **	0.187		
Service					0.205	0.177
Constant	1.903	2.437	2.224	2.450	1.048	2.487
Observations	77		77		77	
Wald Chi-squared	136.22 ***		103.08 ***		107.93 ***	
R-squared (%)	60.93		55.32		54.27	
RMSE	0.157		0.147		0.159	
Robustness Check	Yes		Yes		Yes	

Note: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$

Sources: Author's calculation

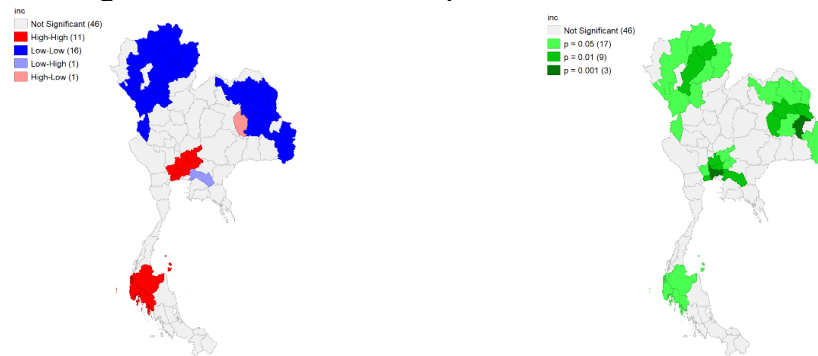
In summary, these findings illustrate the role of geographical heterogeneity in income variation across provinces. Provinces with higher agricultural industry concentrations tend to derive fewer external benefits compared to those with greater proportions of manufacturing or service industries. Lucas (1988) noted that regions benefiting from higher externalities often experience greater economic growth and income. Additionally, persistent income disparities may stem from differences in economic growth and technological advancements over time, leading to migration toward provinces offering better job opportunities and higher incomes, thus reinforcing income inequality across regions.

4.2 Spatial Distribution of Income

The regression analysis from the previous section was extended to spatial analysis using spatial autocorrelation and local indicators of spatial association (LISA) to explore the relationships between geographical heterogeneity and income distribution. These analyses provided deeper insights into spatial patterns of income distribution. The results identified clusters of high-income areas, shown in dark red, located in Bangkok and its surrounding provinces, as well as Surat Thani, Krabi, and Phuket. Conversely, low-income areas, shown in dark blue, were predominantly found in the northern and northeastern regions, with statistical significance.

Geographical diversity findings indicate that most northeastern provinces, along with Tak in the north, rely heavily on agriculture. In contrast, central provinces such as Bangkok, Ratchaburi, Phra Nakhon Si Ayutthaya, Saraburi, and Chachoengsao were primarily driven by the manufacturing sector. Similarly, southern provinces, including Ranong, Chumphon, Surat Thani, and Trang, are primarily reliant on the service sector, as illustrated below:

Figure 2: Illustration of the Spatial Autocorrelation of Income



Note: Moran's I statistics was 0.567

Source: Author's calculation

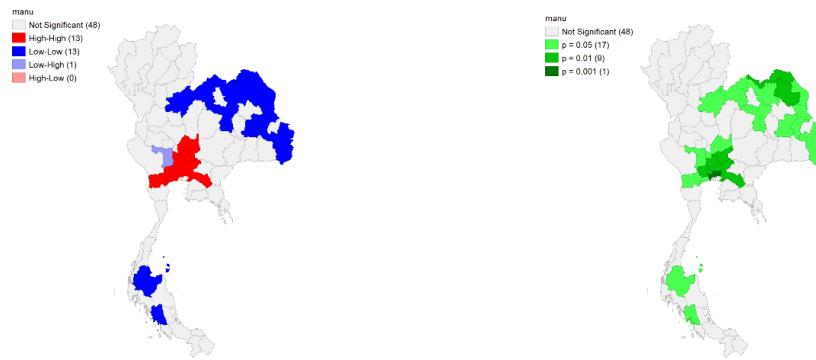
Figure 3: Illustration of the Spatial Autocorrelation of Agriculture Sector Concentration.



Note: Moran's I statistic was 0.565

Source: Author's calculation

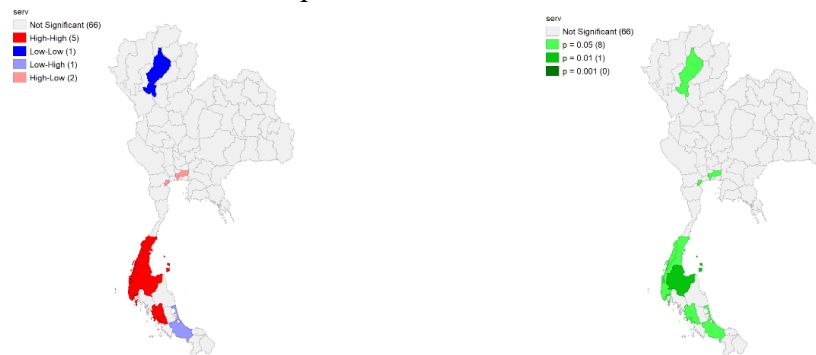
Figure 4: Illustration of the Spatial Autocorrelation of Manufacturing Sector Concentration.



Note: Moran's I statistic was 0.497

Source: Author's calculation

Figure 5: Illustration of the Spatial Autocorrelation of Service Sector Concentration.

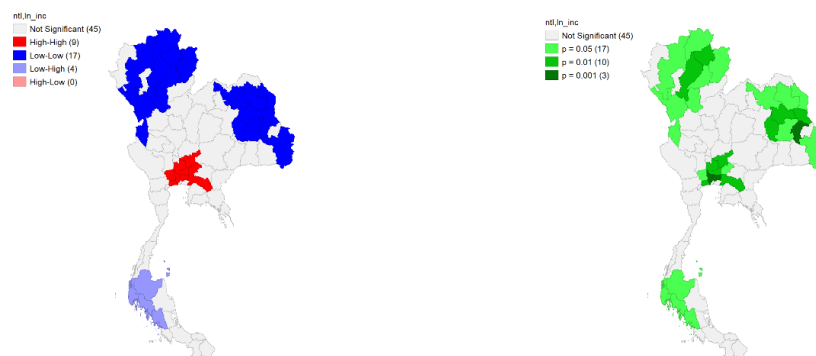


Note: Moran's I statistic was 0.030

Source: Author's calculation

Further mapping of income distribution against geographical heterogeneity revealed that provinces with high socio-economic status, such as Bangkok and its vicinity, Phra Nakhon Si Ayutthaya, and Nonthaburi, tended to have higher incomes. These findings align with the concentration of manufacturing industries. However, certain northern provinces, such as Chiang Mai, Lampang, and Phrae, also displayed relatively high incomes, possibly due to spillover effects from their prominence as tourist destinations.

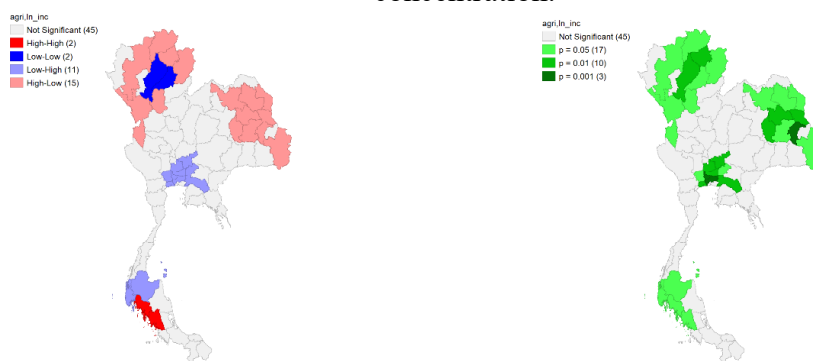
Figure 6: Illustration of the Spatial Autocorrelation between Income and Socio-Economic Status



Note: Moran's I statistics was 0.457

Source: Author's calculation

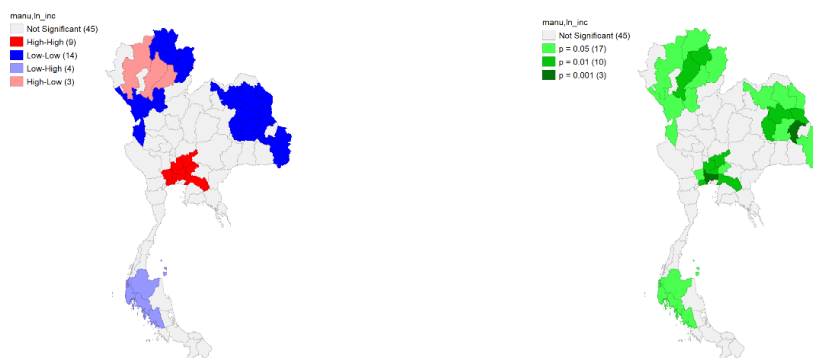
Figure 7: Illustration of the spatial autocorrelation between income and agriculture concentration.



Note: Moran's I statistics was -0.529

Sources: Author's calculation

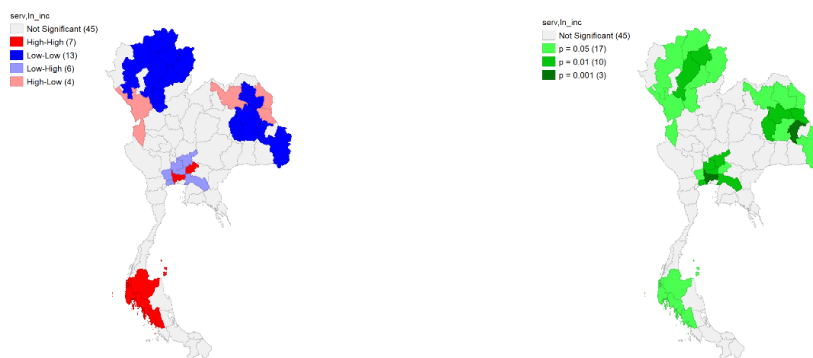
Figure 8: Illustration of the Spatial Autocorrelation between Income and Manufacturing Concentration.



Note: Moran's I statistics was 0.135

Sources: Author's calculation

Figure 9: Illustration of the Spatial Autocorrelation between Income and Service Concentration.



Note: Moran's I statistics was 0.030

Sources: Author's calculation

5. Conclusions and Limitations

The findings of this paper reveal a strong relationship between geographical heterogeneity and income distribution, particularly when compared to agglomeration externalities. By investigating Mincer's earning function, the analysis focused on agricultural regions, which played a significant role in determining income. The results suggest that income distribution varies across provinces due to limitations in economic diversification, such as market size and industrial structure. These factors drive economic specialization, with provinces that emphasize manufacturing and services tending to exhibit higher income levels. However, the empirical results for Thailand indicate that both agglomeration externalities, arising from knowledge spillovers, and geographical heterogeneity, stemming from resource endowments, also contribute significantly to income variations. This phenomenon can be attributed to the increasing returns and spillover effects associated with these sectors (Lucas, 1988; Fingleton, 2001), which were evident in the correlation between income and socio-economic status or the night-time light index. Conversely, regions focusing primarily on agriculture encounter competitive market conditions where all production leads to consistent returns, thus resulting in income conditions that lack exponential growth.

The outcome of this paper was consistent with the findings of Davis & Weinstein (1999), who discovered that the manufacturing sector had a crucial role in economic development since the manufacturing sector contributed to the leading industries in the country, and consequently the wages or income in that area will be higher compared to others. Moreover, the findings of Fingleton (2001) and Acemoglu & Ventura (2002) highlighted the cause of the income variation across regions: variation in income across regions was a result of differences in technological advancements and spillover effects, impacting economies of scale, in particular the province or region that held manufacturing concentration, which can lead to increased production efficiency.

Furthermore, achieving higher production efficiency not only lowers production costs but also creates opportunities for exporting goods to other regions with higher production costs. Consequently, these outcomes significantly contribute to increased income levels within manufacturing concentrations. However, this finding was contested by Barufi et al. (2016), who examined the income of labor in Brazil and found that there was no statistically significant contribution from the manufacturing sector to income.

The main contribution of this paper was to provide insightful evidence of the income distribution in Thailand within the framework of geographical heterogeneity. On the basis of these findings, it was implied that different economic activities significantly affected income as well as being meaningful indicators in explaining how income changed across regions.

The limitations of this paper lie in the lack of survey data from the government agencies, since data provided every four years brought about the out-of-date problem, while the data covered also led to the problem of omission bias in the results. Moreover, aggregating the micro-data level into provincial data was likely not to fit with spatial econometric approaches compared to the generalized method of moment since all samples were randomly selected from different locations, which might bring about bias in the results.

To overcome these conditions, future researchers should be aware of the datasets used in the work and try to compare results from various types of estimation. Ultimately, dynamic analytical approaches such as spatial-temporal frameworks should be employed to examine the agglomerated evolution of income across provinces.

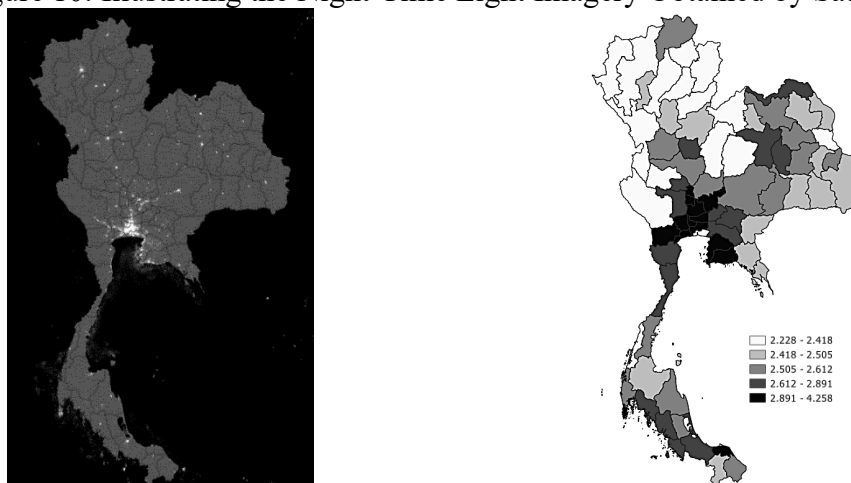
References

- Acemoglu, D., & Ventura, J. (2002). The world income distribution. *The Quarterly Journal of Economics*, 117(2), 659-694.
- Aigner, D. J., & Heins, A. J. (1967). On the determinants of income equality. *The American Economic Review*, 57(1), 175-184.
- Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, 27(2), 93-115.
- Barro, R. J. (1991). Economic growth in a cross section of countries. *The quarterly Journal of Economics*, 106(2), 407-443.
- Banerjee, A. V., Gertler, P. J., & Ghatak, M. (2002). Empowerment and efficiency: Tenancy reform in West Bengal. *Journal of Political Economy*, 110(2), 239-280.
- Barufi, A. M. B., Haddad, E. A., & Nijkamp, P. (2016). Industrial scope of agglomeration economies in Brazil. *The Annals of Regional Science*, 56(1), 707-755.
- Combes, P. P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters!. *Journal of Urban Economics*, 63(2), 723-742.
- Davis, D. R., & Weinstein, D. E. (1999). Economic geography and regional production structure: An empirical investigation. *European Economic Review*, 43(2), 379-407.
- Estudillo, J. P. (1997). Income inequality in the Philippines, 1961-91. *The Developing Economies*, 35(1), 68-95.
- Fingleton, B. (2001). Theoretical economic geography and spatial econometrics: Dynamic perspectives. *Journal of Economic Geography*, 1(2), 201-225.
- Goeij, P., & Verbeek, M. (2000). *An empirical analysis of affine term structure models using the generalized method of moments*. Belgium: Center for Economic Studies, Erasmus University Rotterdam.
- Groot, S. P., de Groot, H. L., & Smit, M. J. (2014). Regional wage differences in the Netherlands: Micro evidence on agglomeration externalities. *Journal of Regional Science*, 54(3), 503-523.
- Gujarati, D. N. (2021). *Essentials of econometrics*. California: SAGE Publications.
- Imran, M., Sumra, K., Abbas, N., & Majeed, I. (2019). Spatial distribution and opportunity mapping: Applicability of evidence-based policy implications in Punjab using remote sensing and global products. *Sustainable Cities and Society*, 50, 1-12.
- Lee, H. Y., Kim, J., & Cin, B. C. (2013). Empirical analysis on the determinants of income inequality in Korea. *International Journal of Advanced Science and Technology*, 53(1), 95-109.
- Lemieux, T. (2006). The “Mincer Equation” thirty years after schooling, experience, and earnings. In S. Grossbard, S. (Ed.) *Jacob Mincer a pioneer of modern labor economics* (pp.127-145). Springer, Boston, MA.
- Lucas Jr, R. E. (1988). On the mechanics of economic development. *Journal of monetary economics*, 22(1), 3-42.
- Milanovic, B. (2016). *Global inequality: A new approach for the age of globalization*. Massachusetts, USA : Harvard University Press.
- Mincer, J. (1958). Investment in human capital and personal income distribution. *Journal of Political Economy*, 66(4), 281-302.
- Mincer, J. A. (1974). Age and experience profiles of earnings. In J.A.Mincer (Ed.), *Schooling, experience, and earnings* (pp. 64-82). New York, NY: National Bureau of Economic Research.

- Mincer, J. A. (1974). Schooling and earnings. In J.A.Mincer (Ed.), *Schooling, experience, and earnings* (pp. 43-63). New York, NY: National Bureau of Economic Research.
- Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, 37(1/2), 17–23.
- Patrinos, H. A. (2024). Estimating the return to schooling using the Mincer equation. *IZA World of Labor*, 1-11. Retrieved from <https://doi.org/10.15185/izawol.278>
- Piketty, T. (2003). Income inequality in France, 1901–1998. *Journal of Political Economy*, 111(5), 1004-1042.
- Piketty, T., & Saez, E. (2003). Income inequality in the United States, 1913–1998. *The Quarterly Journal of Economics*, 118(1), 1-41.
- Prasertsoong, N., & Puttanapong, N. (2022). Regional wage differences and agglomeration externalities: Micro evidence from Thai manufacturing workers. *Economies*, 10(12).
- Puttanapong, N., Luenam, A., & Jongwattanakul, P. (2022). Spatial analysis of inequality in Thailand: Applications of satellite data and spatial statistics/econometrics. *Sustainability*, 14(7).
- Ravallion, M. (2014). Income inequality in the developing world. *Science*, 344(6186), 851-855.
- Sarkar, S., & Mehta, B. S. (2010). Income inequality in India: Pre-and post-reform periods. *Economic and Political Weekly*, 45 (37), 45-55. Retrieved from <https://www.jstor.org/stable/25742070>
- Shi, K., Huang, C., Yu, B., Yin, B., Huang, Y., Wu, J. (2014). Evaluation of NPP-VIIRS night-time light composite data for extracting built-up urban areas. *Remote Sensing Letter*, 5(4), 358–366.
- Tinbergen, J. (1956). On the theory of income distribution. *Weltwirtschaftliches Archiv*, 77 (1956), 155-175.
- Zhou, Y., Ma, T., Zhou, C., Xu, T. (2015). Nighttime light derived assessment of regional inequality of socioeconomic development in China. *Remote Sensing*, 7(2), 1242–1262.
- Zhou, Y., & Song, L. (2016). Income inequality in China: Causes and policy responses. *China Economic Journal*, 9(2), 186-208.

Appendix

Figure 10: Illustrating the Night-Time Light Imagery Obtained by Satellite.



Source: Author's collection and calculation

Figure 11: Illustration of the Administrative Map of Thailand



Source: Author's summation