



Spatial Interdependence and Competitive Crowding-Out of Financial Inclusion in Asia Pacific Region

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ABSTRACT

The Asia-Pacific region, despite being the world's fastest-growing economy, exhibits pronounced spatial and temporal heterogeneity in financial inclusion (FII). Existing studies tend to assume national independence, thereby overlooking crucial cross-border spatial dynamics. This study investigates the factors affecting FII across a panel of 19 Asia-Pacific countries from 2004 to 2022 using the spatial lag model (SLM) and the spatial error model (SEM), as well as the impact decomposition. Diagnostics confirm time-varying spatial autocorrelation in FII, often characterised by negative divergence in recent years. The spatial impact decomposition reveals that while domestic income growth yields a strong direct impact on local FII, this benefit is significantly offset by a negative indirect spillover to neighbouring countries. This finding confirms a pattern of competitive crowding-out, where financial development in a successful hub draws resources, or capital, away from adjacent markets. Furthermore, the frequent selection of the spatial error model indicates that spatially correlated unobserved institutional and socio-cultural factors (latent spatial heterogeneity) are major drivers of regional FII clustering, particularly concerning income, age, gender and regulatory variables. Policy interventions must evolve from national efforts to coordinated, place-based regional strategies that mitigate competitive displacement and harmonise institutional frameworks to address persistent exclusion among female and ageing populations.

JEL Classification: G21, C21, O53

Keywords: Asia-Pacific countries; Financial Inclusion; Spatial Effect; Competitive Crowding-out

Article history:

Received: 9 February 2026

Accepted: 6 June 2026

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DOI: <http://doi.org/10.47836/ijeam.20.2.02>

© International Journal of Economics and Management. ISSN 1823-836X. e-ISSN 2600-9390.

INTRODUCTION

Financial inclusion is consistently recognised as a crucial mechanism for spurring economic growth and reducing pervasive poverty globally. Within the dynamic Asia-Pacific region, the investigation of financial inclusion is particularly salient, given its status as the world's fastest-growing economy. However, the region presents striking heterogeneity, ranging from financial technology leaders, such as Singapore, which maintains its position as the most financially inclusive market, to various nations that still grapple with providing basic financial access to underserved segments (Principal Financial Group, 2024). This vast disparity exists not only inter-country but also within countries, driven by substantial gaps in income, gender, regulatory environments, infrastructure, and geographical constraints (United Nations Economic and Social Commission for Asia and the Pacific, 2024). Financial inclusion acts as the key driver for economic growth and poverty reduction (Sarma and Pais, 2020; Chakraborty and Abraham, 2021). According to Chakraborty and Abraham (2021), the study highlighted that financial inclusion fosters both economic growth and social empowerment, thereby driving economic development and reducing inequality (Ghosh and Vinod, 2020).

Existing studies have extensively examined the determinants and impacts of financial inclusion, with attention to both structural and individual-level factors. For instance, Ghosh and Vinod (2020) highlight the importance of access to infrastructure and transaction costs, while Ozili (2022) emphasises financial literacy and infrastructure quality. Together, these works underscore that financial inclusion is shaped by a mix of institutional and human-capital dimensions. However, much of this literature treats countries as isolated units, overlooking the spatial interdependencies that may arise when financial inclusion in one country influences outcomes in its neighbours. This gap is non-trivial, as econometric analyses that assume national independence risk ignoring geographically correlated unobserved factors or spatial crowding-out effects, thereby underestimating the true regional impact. In practice, financial inclusion is commonly measured through account ownership, gender and income disparities, and the use of financial products for transactions or insurance (Inoue, 2024) are not merely a domestic phenomenon. Access to credit and insurance can facilitate entrepreneurial activity and business expansion (Inoue, 2024; Widyastuti et al., 2023; Yap et al., 2024), while reforms in infrastructure or regulation in one jurisdiction may spill over, fostering cross-border participation or, conversely, generating competitive pressures. The emergence of digital financial inclusion further complicates this dynamic, as technological innovations increasingly diminish the constraints of geographic distance, making spatial perspectives on financial inclusion both timely and essential.

Financial inclusion is an essential tool for poverty reduction, as it provides low-income groups with access to affordable financial services that improve economic well-being (Nyarko et al., 2023; Omar and Inaba, 2020). In the Asia-Pacific, sustained economic growth since the 1990s has created opportunities for expansion (Athukorala, 2021), but progress in financial inclusion remains uneven. Barriers such as inadequate infrastructure, technological limitations, gender inequality, and geographical constraints continue to slow adoption, particularly in mobile banking (Barajas et al., 2020; Nagaraj, 2021; Irianto and Chanvarasuth, 2025; Le Quoc, 2024). Inequalities in income and access to financial infrastructure further exacerbate these gaps (Asongu et al., 2020; Hasan et al., 2021; Le Quoc, 2024). Inequalities in income and access to financial infrastructure further exacerbate these gaps (Asongu et al., 2020; Cicchiello et al., 2021; Le Quoc, 2024). As a result, financial inclusion in the region is marked by pronounced spatial disparities, with divides between urban and rural areas, across regions, and among socioeconomic groups (Le Quoc, 2024; Sarma and Pais, 2020; Madan, 2020). These persistent gaps highlight the need to account for spatial dynamics, particularly the urban–rural divide and uneven regional distribution of financial infrastructure (Zhong et al., 2022).

Asia-Pacific countries have spatial and socio-demographic differences (Matthews and Stiberman, 2021). Asia-Pacific combines financial innovation with highly uneven access to financial services, which creates strong conditions for observing a competitive crowding-out effect. Asia-Pacific with its various economies widespread the growing of digital payment ecosystem which intensified the competition among the financial service providers. The disparities in income levels or digital infrastructure make it easier to focus on how competition can concentrate services among the users while excluding the vulnerable groups (Autor et al., 2020). Despite the challenges of financial inclusion, the region has some notable achievements in Asia Pacific. For example, Singapore maintains its position as the most financially inclusive market (Principal Financial Group, 2024). According to ASEAN (2025), the financial exclusion level in Southeast Asia decreased from 29 percent

in 2021 to 23 percent in 2022. However, challenges remain, and continuous efforts are needed to improve financial inclusion in the Asia Pacific region. The successful integration of digital technologies became the key to further enhancing financial inclusion and bank performance in the region (Sarma and Pais, 2020). The Asia-Pacific region is the fastest-growing economy in the world and is recognised as an economic powerhouse. Singapore, Japan, Taiwan, Malaysia, Korea, China and Thailand were projected as the 10 most competitive economies in the world out of 140 economies (Khera et al., 2021).

Most studies on financial inclusion emphasise impacts (e.g., poverty reduction, inequality) or its determinants (e.g., accessibility, literacy, technology) (Inoue, 2024; Lee, 2024; Kumar and Ahuja, 2024; Valera et al., 2025; Chletsos and Sintos, 2024). However, a growing body of work has incorporated spatial or spatio-temporal analysis, yielding insights that remain limited in geographic scope or scale. For example, district-level studies in India reveals spatial clustering of financial inclusion outcomes and convergence effects among neighbouring districts. China-based studies show that digital financial inclusion not only localises economic growth (rural vs urban) but also exhibits spillover effects and non-linear threshold behaviours across provinces. Long-run institutional quality effects in Asia-Pacific countries further display variation in income levels. Despite this, cross-country spatial studies in the wider Asia-Pacific by comparing spillovers between nations, over time, and across socioeconomic and geographic gradients appear to be limited. Without such understanding, policies may fail to account for geographical diffusion, regional competition, or spatially correlated unobserved constraints, reducing their effectiveness across the region.

This study introduces the concept of spatial competitive crowding-out to explain uneven financial inclusion across interconnected economies. Unlike conventional spillover effects, which often assume mutually beneficial diffusion, competitive crowding-out reflects an asymmetric process in which financially advanced economies attract a disproportionate share of financial resources, institutional capacity, and capital flows. As a result, neighbouring or less developed economies may experience constrained financial development. This mechanism is grounded in Central Place Theory, which explains the concentration of services in core regions, and Systems Theory, which emphasises interdependence across spatial units. By integrating these perspectives, competitive crowding-out is conceptualised as a spatial process that reinforces regional disparities in financial inclusion.

Hence, this study investigates the spatial effects of financial inclusion across Asia-Pacific countries from 2004 to 2022, with particular attention to spatial autocorrelation patterns and regional disparities. By employing spatial econometric techniques, the analysis reveals potential crowding-out effects among countries in the region. The remainder of the paper is structured as follows: the next section reviews the relevant literature, followed by the methodology and empirical results. The final section discusses the implications, acknowledges limitations, and provides policy recommendations to enhance financial inclusion in the Asia-Pacific. The spatial analysis in this study is guided by four objectives: (i) to identify spatial dependence between each country and its neighbours; (ii) to examine cross-country crowding-out effects; (iii) to detect clusters of financial inclusion, whether high or low; and (iv) to determine the significant factors driving financial inclusion across the region.

PAST STUDIES

This study draws on Central Place Theory (CPT) and systems theory to provide a spatially informed theoretical foundation for understanding financial exclusion. Central place theory explains why financial services tend to cluster in urban centres with higher economic activity and profitability, while rural and sparsely populated areas remain underserved (Butler et al., 2020). Central place theory suggests that urban areas are able to sustain a wide range of services such as commercial banks, Automated Teller Machines, and digital infrastructure, whereas rural areas are often deemed unprofitable, resulting in persistent gaps in financial access. Importantly, Central place theory not only explains the geographic concentration of financial services but also links accessibility to socioeconomic and demographic factors such as income, age, gender, and regulatory environments. While Central Place Theory identifies where financial exclusion occurs, Systems Theory conceptualises a region as an interconnected whole, in which the exclusion of certain subsystems such as marginalised rural populations or socio-demographic groups can weaken regional stability and hinder aggregate financial integration (Mele et al., 2020; Durand and Paoletta, 2013). Within the system, spatial competitive crowding-out emerges as a negative mechanism driven by competition over limited resources.

Central place theory and systems theory treat financial inclusion markets as a multi-level spatial system where the spillovers emerge from interconnected provider behaviour rather than isolated areas (Ozili, 2022; Sarma and Pais, 2020). While central place theory explains the structural clustering pattern in which financial service providers concentrate on the “central” nodes, Systems Theory complements this by explaining where competitive pressure in the market pushes firms to replicate similar strategies in neighbouring markets, leading to cross-border convergence. It strengthens the spatial structures and systemic connectedness of the competitive dynamics in financial inclusion that spreads across regions (Demirguc-Kunt et al., 2021; Lee et al., 2023). They interpret not only the geographic clustering of financial inclusion but also the dynamic interactions between countries. Central place theory explains the concentration of the financial services while systems theory accounts for cross-border interdependencies that may lead to competitive crowding-out effects (Chakraborty and Abraham, 2021). This suggests that an integrated framework for analysing financial inclusion in a multi-country setting such as Asia-Pacific is essential, where both geographic concentration and systemic interconnections shape regional financial outcomes.

Exclusion arises when formal financial subsystems fail to extend services to these groups, thereby disconnecting them from the broader financial system (Demirguc-Kunt et al., 2021; Brealey et al., 2020). In this sense, spatially clustered exclusion is not merely a localised issue but one with potential cross-border spillover and crowding-out effects that can undermine inclusive regional development. Most studies in financial inclusion focus on the impacts and factors affecting financial inclusion (Inoue, 2024; Lee, 2024; Kumar and Ahuja, 2024; Valera et al., 2025); few examine how financial exclusion is spatially clustered, particularly across borders, leaving policymakers unaware of the spatial crowding-out effects. Financial inclusion refers to the widespread access to financial services, and it serves as the delivery of an economy’s financial system (Barajas et al., 2020). A high level of financial inclusion increases business activities among the small enterprises, enhances the economic growth in the country, controls inflation, reduces poverty, increases the living standards of the poor and decreases income inequality between the rich and the poor (Ozili, 2022; Ong et al., 2023).

There is still limited research examining the potential competitive crowding-out effects of financial inclusion across regions (Bozkurt and Karakus, 2020; Pradhan and Sharma, 2022; Acharya and Erra, 2024). Central place theory is used to explain the competitiveness that generates the crowding-out effect in financial inclusion markets prioritising central place within the Asia-Pacific region, thereby reducing the effectiveness of services in neighbouring regions (Chakraborty and Abraham, 2021). This study reconceptualises the centrality of place as the digitally mediated access. Financial service providers tend to target low-risk and high-return customers, which leads to the competition within a limited group and the crowding out of a higher risk less digitally connected population. This mechanism is further reinforced by information asymmetry which firms use to shape firm choose their customers on selective-servicing basis. Thus, this study concentrates on the financial services among the Asia-Pacific region and the deepening exclusion within the interconnected financial system. Existing studies provide useful insights but remain geographically narrow and largely country specific. For instance, Acharya and Erra (2024) conducted a cross-state spatial econometric analysis in India and they found no evidence of spatial convergence in financial inclusion, particularly in states with low per capita income, weak infrastructure, and persistent gender gaps. Similarly, Pradhan and Sharma (2022) focused on the spatiotemporal dynamics of financial inclusion in India, showing that access to financial services varies significantly across regions and over time, with income, infrastructure, and financial literacy identified as critical determinants. Outside of India, Bozkurt and Karakus (2020) examined provincial financial inclusion in Turkey, where factors such as unemployment, urbanisation, tourism, education, and crime were found to shape regional disparities. These studies highlight the importance of demographic and regulatory factors—such as income, age, gender, and institutional quality in shaping financial inclusion (Ozili, 2022; Demirguc-Kunt et al., 2021). For instance, higher-income regions often enjoy better financial access, younger populations may accelerate mobile banking adoption, gender disparities continue to limit women’s participation, and supportive regulatory environments foster greater inclusion. Despite these contributions, the literature remains fragmented and predominantly focused on single-country contexts, leaving a critical gap in understanding the cross-country competitive crowding-out effects of financial inclusion, particularly in diverse regions such as Asia-Pacific. Without accounting for these spatial dynamics, policies risk overlooking how financial inclusion in one country may unintentionally restrict access in neighbouring economies by drawing away resources, infrastructure, or financial flows. This study addresses this gap by examining spatial

dependence, clustering, and determinants of financial inclusion across Asia-Pacific countries over time.

Income, age, gender, and regulation are critical determinants of financial inclusion, yet their spatial effects remain underexplored in the Asia-Pacific. Higher-income groups, typically concentrated in urban areas, benefit from stronger financial literacy and greater access to financial services, which in turn attract more providers in line with central place theory (Mitchell and Lusardi, 2015; Klapper et al., 2020; Erra and Acharya, 2020). Age also plays a role: younger cohorts often access credit more easily, whereas older cohorts, despite opportunities for retirement and investment products, face digital literacy barriers that restrict participation in the digital financial ecosystem, creating an age-sensitive gap (Klapper et al., 2020; Acharya and Erra, 2024). Gender disparities further constrain inclusion, with women in marginalised communities lacking access due to identity-related barriers and limited opportunities, even in urban areas where services are available (Demirguc-Kunt et al., 2021; Klapper et al., 2020; Gomez et al., 2025; Nightingale, 2023; World Economic Forum, 2021). Regulatory conditions also matter while stable and supportive environments promote trust, competition, and innovation, restrictive policies such as branch liberalisation limits hinder expansion into underserved areas, with weak infrastructure and limited further constraining digital finance adoption (Chletsos and Sintos, 2024; Barajas et al., 2020; Erra and Acharya, 2020). Besides, empirical evidence shows that financial inclusion reduces inequality but does not consistently alleviate poor, indicating the disconnect between financial development and inclusive outcomes (Soh et al., 2025). Digitalisation increases the opportunities, as financial inclusion influences economic uncertainty based on technological conditions (Salmi, 2024). Meanwhile, limited micro-level constraints affect the understanding of financial mechanisms (Zhang et al., 2024). These studies suggest that financial inclusion is not about access, but about integration across policy, technological advancement and research frameworks.

While prior studies acknowledge the importance of income, age, gender, and regulation, much of the existing literature remains limited to macroeconomic variables or single-country contexts (Bozkurt and Karakus, 2020; Pradhan and Sharma, 2022; Acharya and Erra, 2024; Nguyen et al., 2021). Consequently, the spatial effects of these socio-demographic and regulatory factors on financial inclusion remain underexplored, particularly in a multi-country Asia-Pacific setting. Spatial analysis is therefore needed to uncover disparities in banking infrastructure, digital connectivity, and financial literacy between urban and rural areas (Kumar and Ahuja, 2024). Despite the recognised role of financial inclusion in fostering economic growth and reducing poverty, significant research gaps persist. Existing studies seldom integrate spatial and temporal perspectives, limiting insights into how financial inclusion evolves across regions and over time. Moreover, critical determinants such as income levels, demographic composition, gender disparities, and regulatory frameworks are often neglected, even though they shape financial inclusion outcomes and economic development varies across geographies. This study contributes by integrating systems theory and central place theory to develop spatial competitive crowding-out in financial inclusion across Asia-Pacific regions. Addressing these gaps through a spatial analysis of financial inclusion in Asia-Pacific countries is thus essential for capturing regional variations, spatial dependencies, and cross-border dynamics. Such understanding has direct implications for policymakers, academics, investors, and governments, enabling more effective decision-making to enhance both financial inclusion and bank performance.

DATA AND METHODOLOGY

Spatial dependence is relevant to Asia-Pacific as the region combines strong cross-border financial connectivity which generates spillover effects in competition (Hussain et al., 2024). Financial providers operating in the remittance or digital payment in one region can influence neighbouring markets. At the same time, the variety of regulatory systems encourages the replication of the business models, while the uneven infrastructure allows the dynamics of competitiveness to spread but it results in unequal outcomes. Compared to harmonised systems in the European Union or less financially integrated areas such as Sub-Saharan Africa, Asia-Pacific exhibits both high connectivity and fragmentation in its unique way, making spatial dependence central to explain the spillover of financial inclusion across borders (Petri and Plummer, 2020). This study employs the secondary data over the period from 2004 to 2022 as the latest economic data utilised for the nineteen members of Asia-Pacific countries: Cambodia, China, India, Indonesia, Korea, Laos, Malaysia, Mongolia, Myanmar, Nepal, Philippines, Singapore, Sri Lanka, Papua New Guinea, Thailand, Vietnam, Japan, Bangladesh and Pakistan.

The datasets are obtained from the World Bank Group. The variables are as shown in Table 1 below.

Table 1 Description of Variables

Indicators		Data Source	Denotation
Financial Inclusion	Financial Inclusion Index (FII)	Composite Index	<i>FII</i>
Income	Household Income, <i>per capita</i>	World Bank	<i>HI</i>
Age	Age Dependency Ratio, <i>percent working-age population</i>	World Bank	<i>ADR</i>
Gender	School Enrolment, Primary and Secondary (gross), Gender Parity Index	World Bank	<i>GPI</i>
Regulatory	Political Stability and Absence of Violence and Terrorism Index	World Bank	<i>PSA</i>

Source: World Bank (2022a)

The financial inclusion index has been pre-computed, as this study focuses on the spatial regression. Financial Inclusion Index (FII) is being averaged from the arithmetic mean, geometric mean and entropy method calculation to create the index (Huong et al., 2020). Arithmetic mean treats all dimensions equally; geometric mean gives a balanced score that penalises extremely low values. In contrast, while entropy methods allow data-driven weighting. Before the regression, the transformation is as follows:

$$Y = \ln \frac{FII}{1 - FII} \quad (1)$$

The financial inclusion index includes three dimensions: penetration, availability and usage. The indicators are normalised using min-max transformation to ensure their comparability over time and across countries. The steps started with the outlier detection followed by the correlation analysis, discriminant analysis, normalisation of data and finally aggregation of the three methods to obtain the overall financial inclusion index.

For spatial analysis, FII acts as the dependent variable, while independent variables such as household income per capita, age represented by age dependency ratio, gender represented by school enrollment, primary and secondary (gross), Gender Parity Index (GPI) and regulatory represented by Political Stability and Absence of Violence and Terrorism Index are the independent variables.

Spatial Autocorrelation Testing

Firstly, the spatial weight matrix is being assigned. w_{ij} is the spatial weight matrix. The method being employed is based on a distance-based approach where w_{ij} is based on inverse distance or a threshold. The formula is shown:

$$w_{ij} = \frac{1}{d_{ij}} \quad (2)$$

where d_{ij} is the straight-line distance between all pairs of countries. If the countries are closer, then there is more influence on one another. Asia-Pacific regions are closer to each other and tend to be more connected through trade, migration and remittances. Geographic proximity plays a key role in shaping financial interactions, including the diffusion of financial services and the regional spillover effects (Asian Development Bank, 2023; World Bank, 2022b). So, distance-based helps to capture border spillover effects. As financial inclusion in cross-border capital flows is not constrained by physical adjacency, a distance-based matrix provides a realistic representation of spatial dependence across Asia-Pacific region. This approach is consistent with prior spatial econometric studies that examine cross-country interactions using distance weighting. K-nearest is not preferred as it forces countries to have same amounts of neighbour whereas an adaptive kernel lets the spillover varies across countries, making it is may not fully capture the intensity of interaction across geographically dispersed countries (Kim, 2025).

Next, spatial autocorrelation tests are employed to examine the spatial patterns influencing financial inclusion among Asia-Pacific countries. Global Moran's I is used to quantify spatial autocorrelation across geographical areas, whether the patterns are expressed in clustered, dispersed, or random (Thammaboribal et al., 2024; Anselin, 2020). Countries with high financial inclusion are surrounded by other high-inclusion countries, indicating there is a clear spatial pattern and vice versa. The Global Moran's I value ranges from -1, which indicates perfect dispersion, to +1, which indicates perfect clustering. Value 0 suggested a random spatial pattern, which means no real spatial pattern. The formula for Global Moran's I is as follows:

$$I = \frac{n \sum_{i=1}^N \sum_{j=1}^N w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{W \sum_{i=1}^N (x_i - \bar{x})^2} \quad (3)$$

where N is the number of spatial units indexed by i and j . x_i is the value of the variable of interest at location i , $\bar{x}$ is the mean of x , while w_{ij} is the spatial weight between locations i and j and W is the sum of all spatial weights.

Anselin Local Moran's I is a statistic used to identify and visualise local clusters and spatial outliers in data, extended from Global Moran's I . Local Moran's I allows for the assessment of spatial autocorrelation (Thammaboribal et al., 2024; Getis and Aldstadt, 1992) at the level of individual spatial units. The formula for Anselin Moran's I is as follows:

$$I_i = \frac{(x_i - \bar{x})}{s_x^2} \sum_j w_{ij} (x_j - \bar{x}) \quad (4)$$

where w_{ij} is the spatial weight between feature i and j . The results are often visualised in Local Moran's I , typically presented in scatterplots or maps.

Bivariate Moran's I is the extension of Local Moran's I statistic used to quantify spatial correlation between 2 variables, revealing joint clustering, joint dispersion and cross-correlation (Wang et al., 2022; Thammaboribal et al., 2024). The results can be either High-High (HH) clusters, Low-Low (LL) clusters, High-Low (HL) clusters, or Low-High (LH) clusters. High-High and Low-Low clusters indicate areas of positive local spatial autocorrelation, where similar values group together either high values clustering with other high values or low with low and vice versa. The formula for Bivariate Moran's I is as follows:

$$I_B = \frac{\sum_i (\sum_j w_{ij} (d) x_i y_j)}{\sum_i x_i^2} \quad (5)$$

where $x_i y_j$ is the cross value of the first variable at location i and the second variable at neighbouring location j . w_{ij} is the spatial weight of the presenting neighbourhood within a specific distance d .

Spatial Modeling

Conducting spatial regression analysis for financial inclusion involves using various types of data that capture the demographic, economic, and infrastructural factors influencing financial inclusion. The spatial modelling is being conducted through Ordinary Least Squares (OLS), Spatial Lag Model (SLM) or Spatial Error Model (SEM) models. OLS in spatial analysis aims to estimate the parameters of the model in analysing spatial data to minimise the sum of squared differences between observed and predicted values (Thammaboribal et al., 2024). OLS model as follows:

$$FII = \beta_0 + \sum_{i=1}^n \beta_i x_i + \varepsilon_i \quad (6)$$

SLM accounts for the fact that the location may be correlated with the values of the same variables in nearby locations. SLM model as follows:

$$FII = \beta_0 + \lambda WY + x\beta + \varepsilon \quad (7)$$

where λ refers to the spatial error coefficient, W refers to the spatial weight matrix.

SEM assumes spatial dependencies captured through the error term rather than the dependent variable. There may be unobserved omitted spatial variables that influence the dependent variable (Thammaboribal et al., 2024). SEM model as follows:

$$FII = \beta_0 + \lambda W\varepsilon + x\beta + \xi \quad (8)$$

where λ refers to the spatial error coefficient, W refers to the spatial weight matrix and ξ refers to white noise or a vector of uncorrelated error terms.

Although Asia-Pacific includes different levels of financial development, from highly advanced financial centres such as Singapore and Japan and developing countries such as Papua New Guinea, heterogeneity is not a central concern as the study focuses on estimating the average regional spillover in financial inclusion effect rather than country-specific responses (Baltagi et al., 2020; Abban et al., 2025). In the

spatial lag model, extreme values are averaged across neighbours, so there is no single region that dominates the results in the spatial error model; the influence is limited if the residual diagnostics do not show a strong leverage point (Zhang et al., 2021). In addition, the use of a spatial lag model allows the capture of unobserved heterogeneity that is spatially correlated across countries, including the financial development levels and socio-economic conditions that differ across countries. Meanwhile, the explanatory variables such as income, age, gender and regulatory factors serve as proxies for structural differences across countries (Ali et al., 2025). The variables help to control the variation in economic development, thereby partially addressing cross-country heterogeneity within model. the application of logarithmic transformation and winsorisation on data reduces the impact of extreme values (Jaseem and Mohammad, 2024). Thus, the models are appropriate to capture the overall pattern of financial interdependence.

As for robustness checks, spatial lag model and spatial error model play important roles. Spatial lag model captures the spatial spillover in financial inclusion while spatial error model controls for unobserved spatial factors that might bias the residuals (Shen et al., 2020). In sum, the spatial lag model accounts for spatial dependence in the dependent variable, whereas the spatial error model addresses spatial dependence in the error terms. The choice of the most appropriate model is typically guided by statistical criteria such as R-squared (R^2), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) (Thammaboribal et al., 2024). R^2 value ranges from 0 to 100 percent, where 0 percent indicates the model does not account for any variability. The lowest AIC is considered the best, and the Lowest BIC is considered the best, indicating a good balance between goodness of fit and model simplicity (Kuha, 2020; Burnham and Anderson, 2004).

RESULTS AND DISCUSSION

After constructing and averaging the Financial Inclusion Index (FII), Figure 1 presents the geographical heat map of Asia-Pacific countries' FII for the most recent five-year period, 2018–2022.

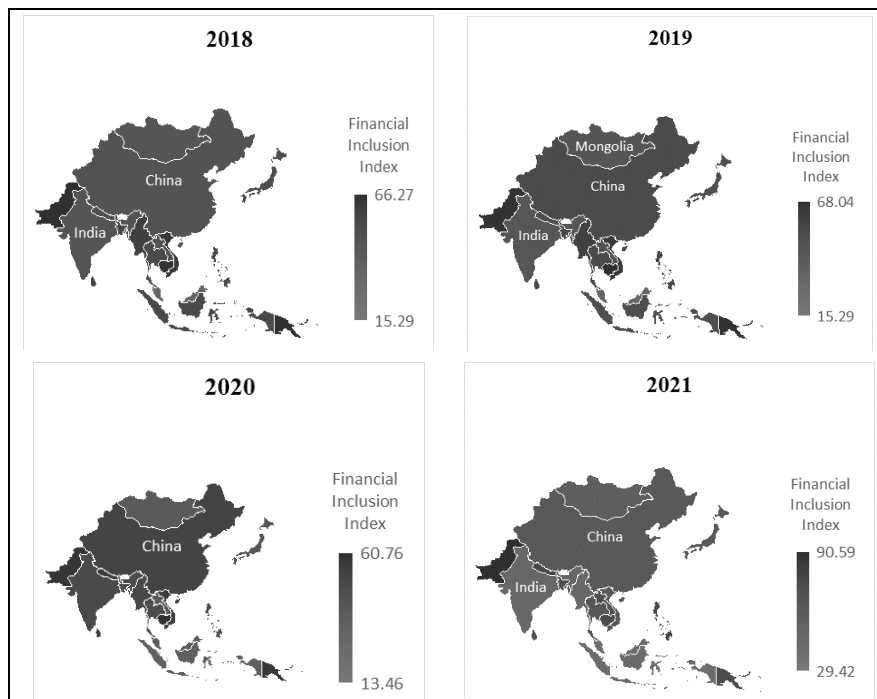


Figure 1 Financial Inclusion Index (2018-2022)

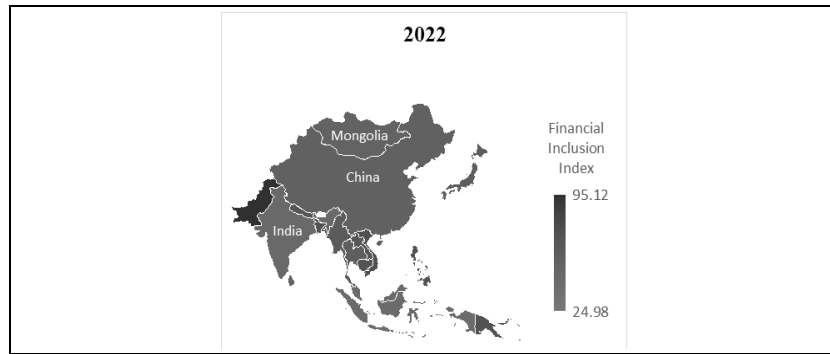


Figure 1 Cont.

Based on Figure 1, a darker colour denotes a larger score, while a lighter colour denotes a lower score. Some countries have a lower score and other countries have a larger score in financial inclusion. The differences in scores highlight the regional inequalities that may hinder economic convergence and equal financial inclusion in the region. Next, Figure 2 shows there are 2 countries with 1 neighbour, 2 countries with 4 neighbours, 1 country with 5 neighbours, 1 country with 8 neighbours, 2 countries with 9 neighbours, 4 countries with 10 neighbours, 1 country with 11 neighbours and 6 countries with 13 neighbours. This method is more suitable if the data exhibit relatively homogeneous spatial patterns (Merk, 2022; Zhang et al., 2024).

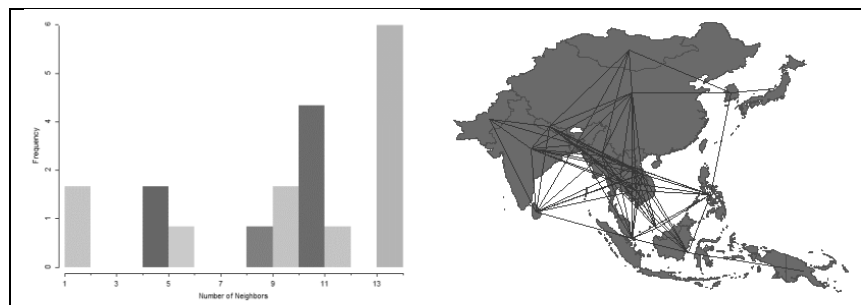


Figure 2 Connectivity Histogram and Connectivity Map

Based on Table 2, the outliers are detected; they are treated by winsorisation, in which correlations are replaced with the less extreme value to ensure that the indicators are free from the outlier distortion. The value has been set as greater than the 95th percentile, equal to the 95th percentile and values that are less than the 5th percentile equal the 5th percentile. Subsequently, Table 3 shows that there is no correlation among all the variables.

Table 2 Summary of Skewness and Kurtosis

Indicator	Skewness	Kurtosis	Outlier
Financial Inclusion Index	0.57	0.09	
Income	3.93	13.74	√
Age	5.89	37.27	√
Gender	4.04	15.49	√
Regulatory	-0.07	-0.56	

Table 3 Pearson Correlation Coefficient

	I1	I2	I3	I4
I1	1.00			
I2	0.00	1.00		
I3	0.17	0.34	1.00	
I4	0.11	0.16	0.00	1.00
I5	0.86	0.00	0.16	0.17

Table 4 shows that the Global Moran's I is significant in 2006, 2007, 2010, 2012, 2020, 2021, and 2022, while Anselin's Local Moran's I is significant in 2006, 2007, 2010, 2021, and 2022. The Z-scores confirm that the spatial distribution of financial inclusion differs significantly from randomness, indicating regional clustering and heterogeneity (Shen et al., 2020). Results are classified into four categories: High-High (HH) and Low-Low (LL), which indicate positive spatial autocorrelation and persistent regional disparities, and

High-Low (HL) and Low-High (LH), which reflect negative spatial autocorrelation and highlight regions requiring policy attention. Notably, in 2021, Anselin's Moran's I (-0.24) is significant at the 5% level, though the cluster map does not display clear patterns, demonstrating that statistical significance may not always translate into visible spatial clustering.

Table 4 Global Moran's I and Anselin Local Moran's I Results at 99 Permutations

	Global Moran's I			Anselin Local Moran's I		
	Moran's Indices	Z-score	P-value	Moran's Indices	Z-score	P-value
2004	-0.09	-0.61	0.22	-0.09	-0.47	0.27
2005	-0.04	0.19	0.36	-0.04	0.19	0.38
2006	-0.15	-1.12*	0.10	-0.15	-1.12*	0.10
2007	-0.16	-1.10*	0.10	-0.16	-1.10*	0.10
2008	-0.02	0.66	0.18	-0.02	0.65	0.18
2009	-0.08	-0.22	0.35	-0.08	-0.41	0.38
2010	0.02	0.90*	0.10	0.02	0.98*	0.10
2011	0.01	0.87	0.15	0.01	0.87	0.15
2012	0.02	1.00*	0.10	0.02	1.08	0.13
2013	-0.10	-0.60	0.28	-0.10	-0.59	0.28
2014	-0.09	-0.35	0.33	-0.09	-0.39	0.35
2015	-0.11	-0.67	0.22	-0.11	-0.48	0.28
2016	-0.10	-0.42	0.30	-0.10	-0.50	0.29
2017	-0.01	-0.45	0.28	-0.10	-0.30	0.44
2018	-0.02	0.67	0.24	-0.02	0.67	0.24
2019	-0.10	-0.55	0.22	-0.10	-0.62	0.25
2020	-0.14	-1.03*	0.10	-0.14	-1.05	0.14
2021	-0.24	-1.78**	0.04	-0.24	-1.78**	0.04
2022	-0.26	-2.52***	0.01	-0.26	-2.62***	0.01

Figure 3 presents the Moran scatter plot and cluster map derived from Anselin's Local Moran's I.

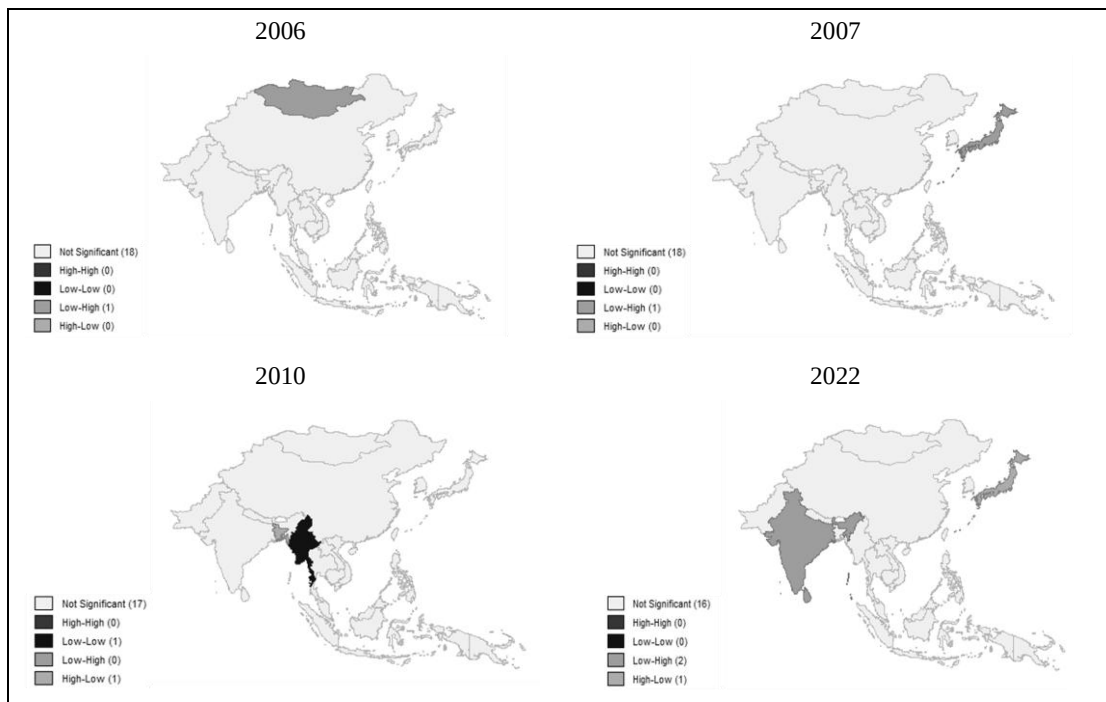


Figure 3 Anselin Local Moran's I (2006, 2007, 2010, 2022)

Table 5 depicts the Bivariate Local Moran's I that is significant between study periods of 2004 to 2022. The results of Bivariate Local Moran's I for household income and financial inclusion in the year 2005, 2006, 2007, 2008, 2009, 2010, 2011 and 2022 are significant. Figure 4 shows Bivariate Local Moran's I for household income, which is significant in either the high FII-high household income, low FII-low household income, high FII-low household income, and low FII-low household income areas on the scatter plot.

Table 5 Bivariate Local Moran's I Results at 99 Permutations

Years	Household Income		Age		Gender		Regulatory	
	Moran's I	Z-score	Moran's I	Z-score	Moran's I	Z-score	Moran's I	Z-score
2004	-0.09	-0.31 (0.36)	0.10	1.08* (0.06)	0.09	0.97* (0.09)	-0.01	0.16 (0.32)
2005	0.06	1.06* (0.10)	0.01	-0.03 (0.48)	0.02	-0.33 (0.34)	0.11	1.24* (0.08)
2006	0.07	1.08* (0.06)	-0.13	-1.36* (0.06)	-0.02	-0.28 (0.25)	0.19	1.78** (0.03)
2007	0.18	1.75* (0.02)	-0.13	-1.41* (0.04)	-0.09	-0.98* (0.09)	0.11	1.38** (0.05)
2008	0.07	0.99* (0.08)	-0.11	-1.54* (0.06)	-0.07	-0.71 (0.15)	0.07	0.92 (0.17)
2009	0.12	1.32* (0.06)	0.17	-1.55** (0.05)	-0.0	0.91 (0.12)	0.07	0.89 (0.11)
2010	0.13	1.25** (0.05)	-0.10	-1.26* (0.06)	-0.13	-1.32* (0.06)	0.06	0.78 (0.13)
2011	0.07	1.18* (0.07)	-0.12	-1.80** (0.05)	-0.12	-1.10* (0.06)	0.05	0.74 (0.19)
2012	-0.005	0.39 (0.18)	-0.13	-1.18* (0.07)	-0.10	-1.18* (0.09)	0.11	1.17* (0.09)
2013	-0.05	-0.36 (0.28)	-0.08	-0.87 (0.11)	-0.06	-0.46 (0.28)	0.07	0.78 (0.19)
2014	-0.02	-0.18 (0.33)	-0.04	-0.54 (0.20)	-0.04	-0.23 (0.39)	0.03	0.17 (0.39)
2015	0.02	0.33 (0.13)	-0.06	-0.33 (0.24)	-0.07	-0.40 (0.24)	0.04	0.26 (0.35)
2016	0.01	0.22 (0.35)	-0.002	0.13 (0.47)	-0.03	-0.05 (0.42)	-0.01	-0.20 (0.36)
2017	-0.02	-0.23 (0.35)	0.03	0.40 (0.24)	-0.01	0.04 (0.50)	-0.02	-0.38 (0.38)
2018	0.01	0.26 (0.37)	0.10	-1.23** (0.05)	0.01	-1.07* (0.06)	-0.06	-1.07 (0.11)
2019	-0.03	-0.43 (0.21)	0.06	0.68 (0.13)	-0.05	-0.34 (0.29)	-0.08	-1.33* (0.07)
2020	-0.04	-0.47 (0.28)	0.08	0.96* (0.08)	0.01	0.19 (0.42)	-0.03	-0.64 (0.17)
2021	-0.04	-0.53 (0.21)	-0.03	-0.25 (0.24)	-0.04	-0.57 (0.20)	-0.01	0.01 (0.45)
2022	-0.21	-1.91** (0.02)	0.01	0.38 (0.29)	0.03	0.51 (0.26)	-0.06	-0.78 (0.14)

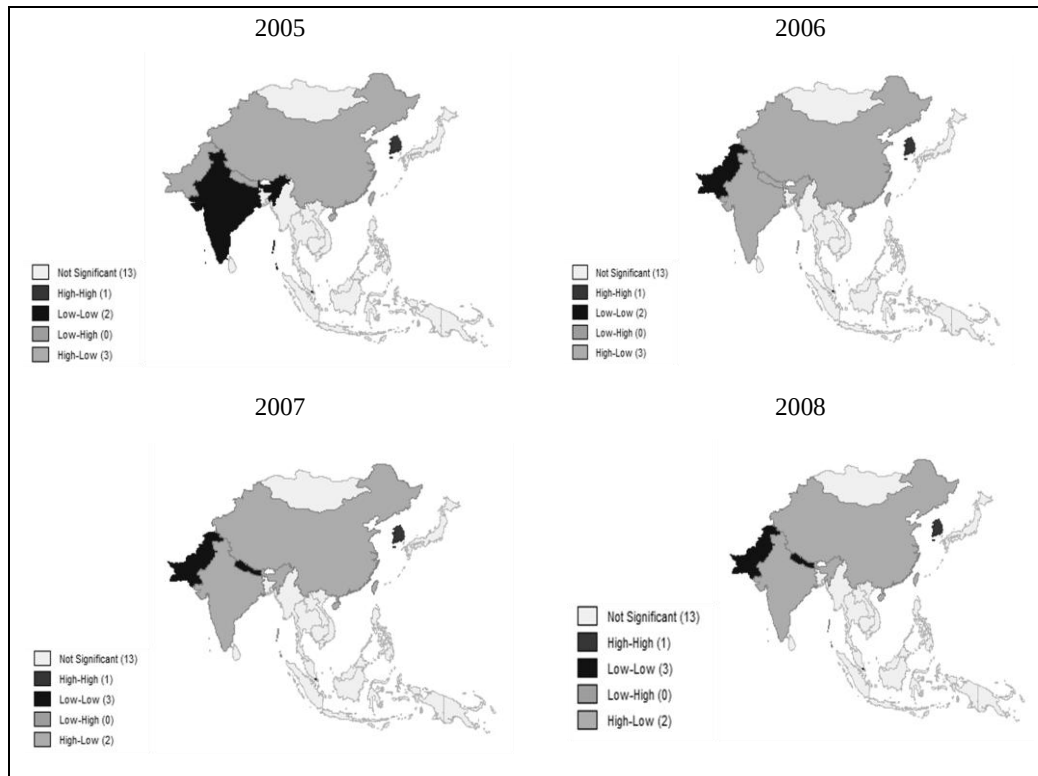


Figure 4 Bivariate Local Moran's I (2005-2011, 2022)

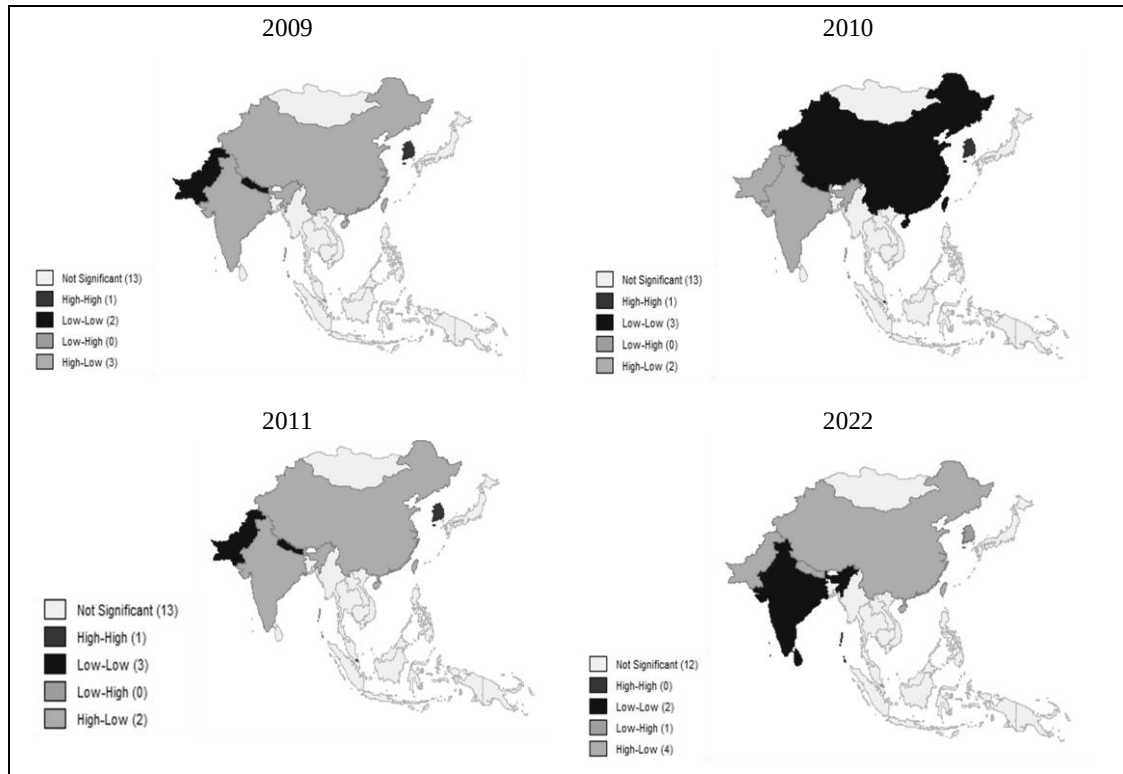


Figure 4 Cont.

Figure 5 depicts Bivariate Local Moran's I for age and financial inclusion. From the results, Bivariate Local Moran's I for age dependency ratio for 2004, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2018 and 2020 are significant, with the high FII-high age dependency ratio, low FII-low age dependency ratio, high FII-low age dependency ratio, and low FII-high age dependency ratio areas on the scatter plot.

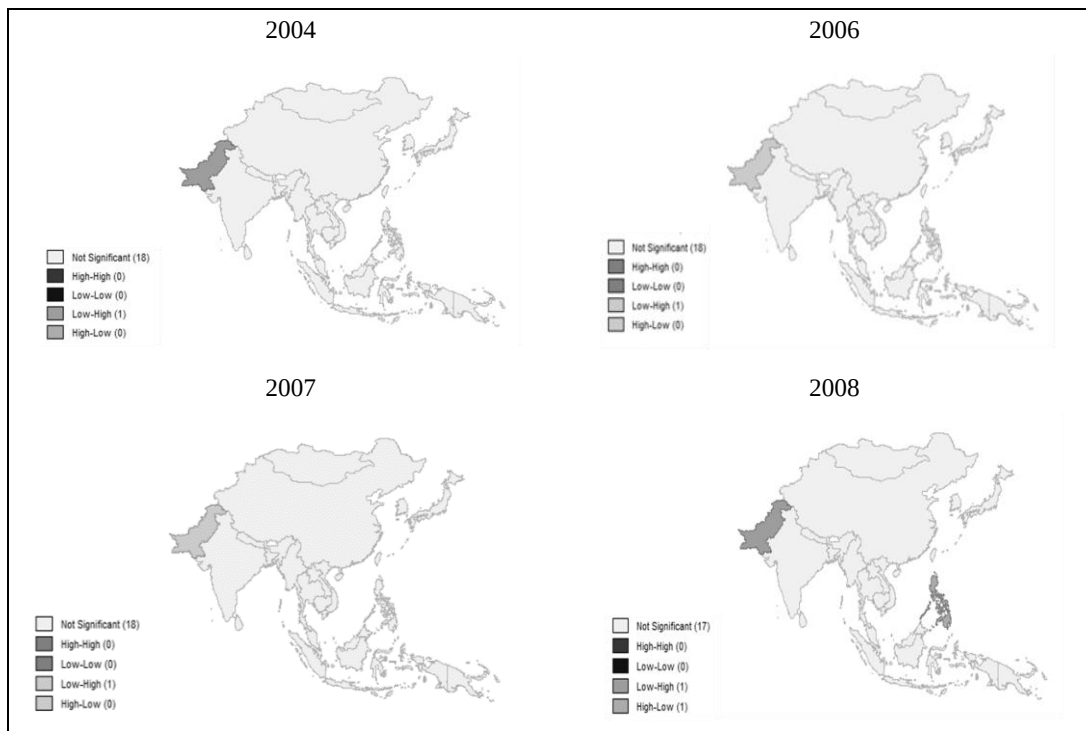


Figure 5 Bivariate Local Moran's I (2004, 2006-2012, 2018, 2020)

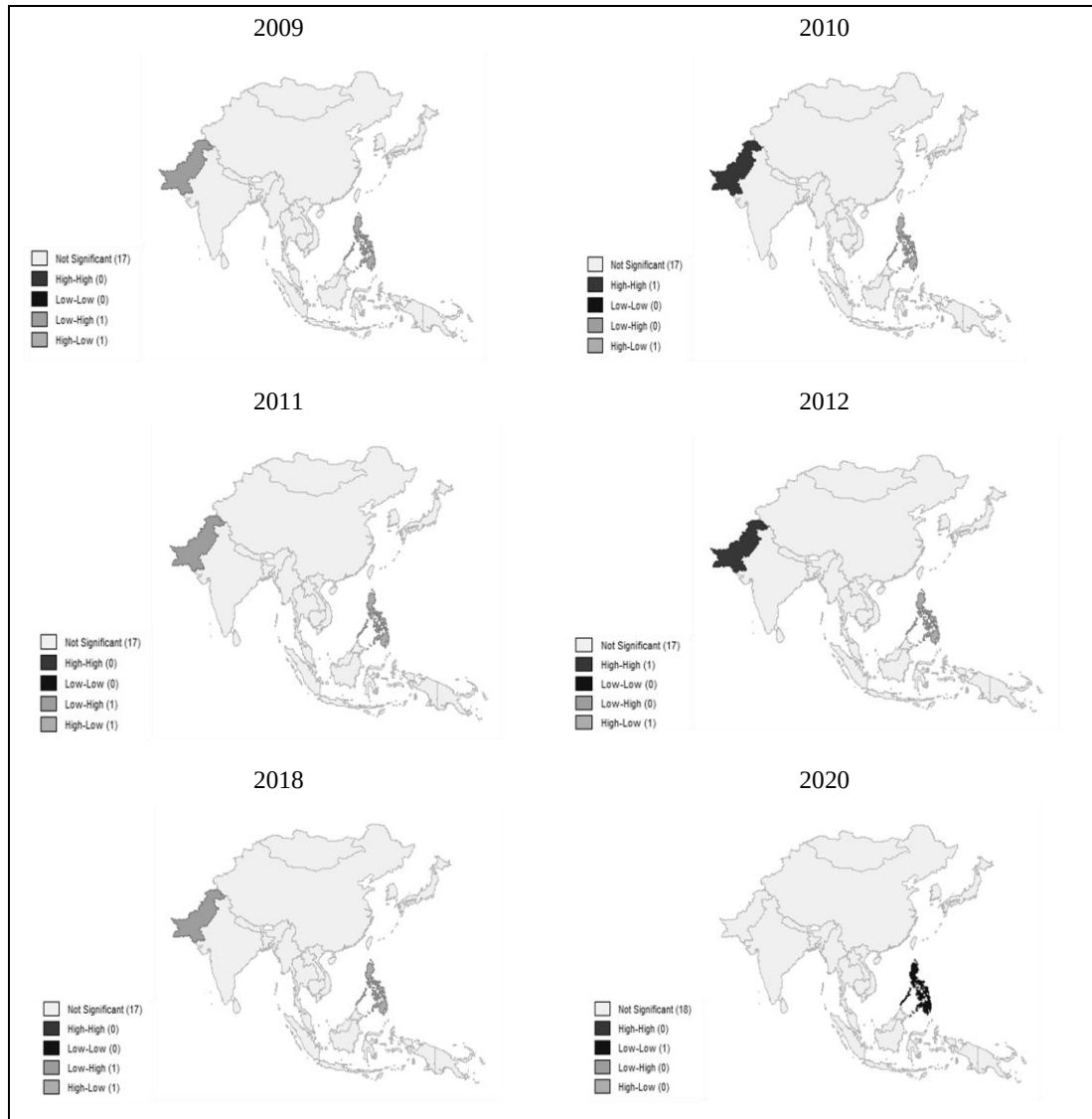


Figure 5 Cont.

From the results, Bivariate Local Moran's I for gender and financial inclusion for 2004, 2007, 2010, 2011, 2012 and 2018 are significant. Figure 6 below shows the scatter plot for gender, highlighting clusters of high FII–high gender parity, low FII–low gender parity, high FII–low gender parity, and low FII–high gender parity. In 2010, the Bivariate Moran's I (-0.13) is significant at the 10% level, though the map does not reveal clear patterns indicating that statistical significance does not always translate into visible spatial clustering.

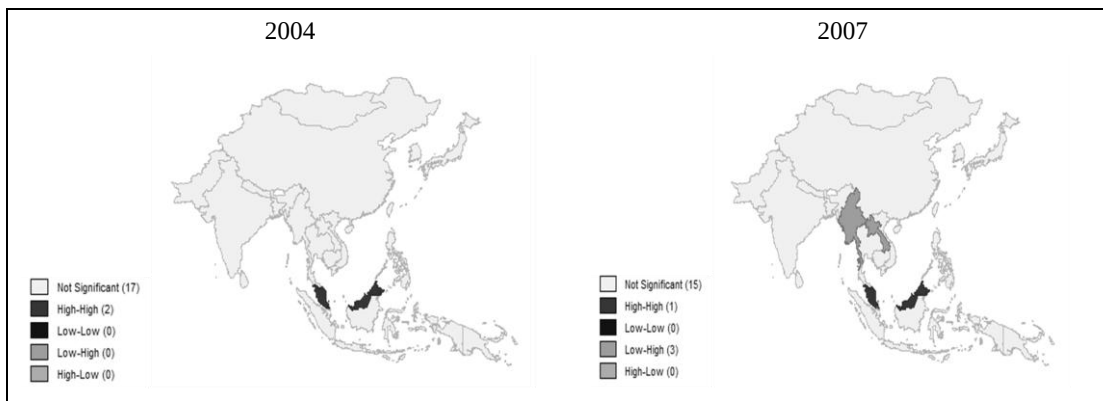


Figure 6 Bivariate Local Moran's I (2004, 2007, 2010-2012, 2018)

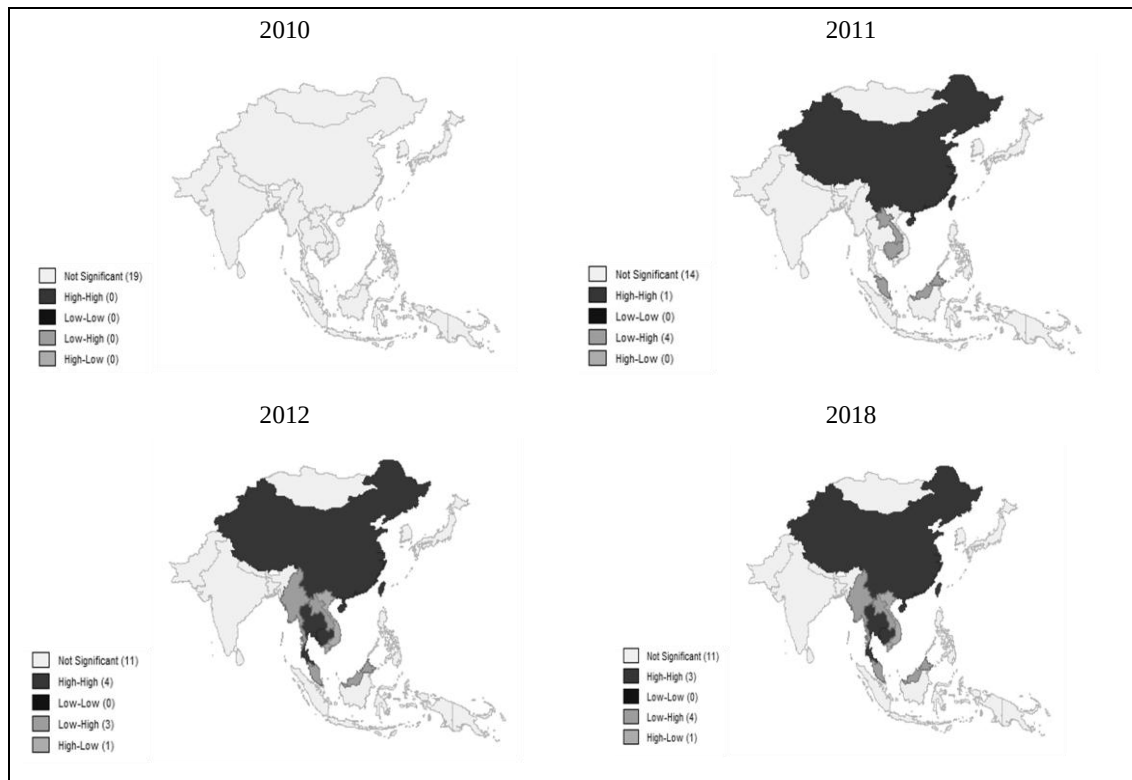


Figure 6 Cont.

The Bivariate Local Moran's I for regulatory is significant in 2005, 2006, 2007, 2012, and 2019. Figure 7 below illustrates the 2012 results, showing high FII–high regulatory clusters and low FII–low regulatory clusters. The Moran's I values were 0.11 (2005), 0.19 (2006), 0.11 (2007), 0.11 (2012), and -0.08 (2019), all significant at the 1% level. Although statistical tests indicate significance, the maps reveal subtle patterns, underscoring that visual clustering does not always align with statistical significance. Positive Moran's I value reflects the spatial clustering of financial inclusion with strong regulation, while negative value indicates divergence. For instance, high FII in the Philippines coincides with strong regulatory environments in Cambodia, Indonesia, Malaysia, Singapore, and Vietnam, suggesting cross-border peer effects. By contrast, Pakistan's higher FII is surrounded by weaker regulatory environments in neighbouring countries, reflecting a regulatory lead that fostered early adoption of microfinance and branchless banking.

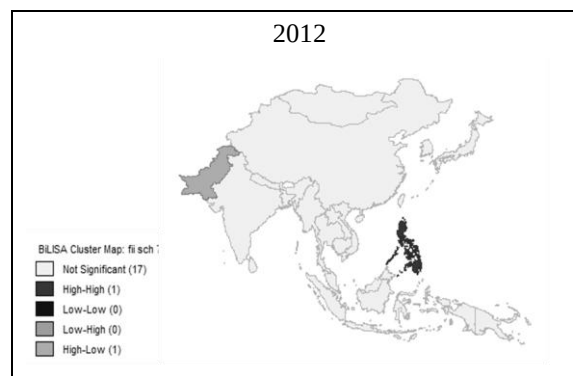


Figure 7 Bivariate Local Moran's I (2012)

Spatial Modeling

Firstly, the LM Lag test is used to detect spatial lag dependence in the dependent variable. If only LM lag is significant, it supports spillover or crowding effects across regions. Then, the spatial lag model (SLM) is the final model. The LM Error test checks for spatial error dependence. Spatial error dependence occurs when the error terms of the model are spatially correlated. If it is significant, it means there is no direct spillover but shared underlying conditions across neighbours. Then, the spatial error model (SEM) is the final model.

Meanwhile, if both the LM lag and the LM error are insignificant, there is no strong evidence of spatial dependence; the model remains an ordinary least squares model. When both the LM lag and the LM error are significant, this indicates that there are spillover effects or omitted spatial factors or both. Thus, proceed with robust LM lag and robust LM error diagnostics. If robust LM Lag is significant, then the spatial lag model (SLM) is the final model. If robust LM error is significant, then the spatial error model (SEM) is the final model. If both robust LM lag and robust LM error are insignificant, it remains an ordinary least squares (OLS) model (Arbia and Nardelli, 2023).

Based on the results from Table 6, the LM error and robust LM error tests are significant in 2006; therefore, a spatial error model (SEM) is appropriate. It shows that spatial dependence is in the error term, not directly in the dependent variable. Financial inclusion is influenced by spatial factors, such as household income. All four tests are significant in 2007 indicating an absolute spatial independence. There is spatial dependence in financial inclusion; spatial correlation in the error term or spatial interaction for both exists at the same time. The final model depends on the significance of the robust LM lag or robust LM error. As for 2004, 2008 to 2016 and 2018, both LM lag and LM error are insignificant. However, robust LM lag is significant in 2004 and both robust LM lag and robust LM error in 2008 to 2016 and 2018 are significant, this implies that the spatial dependence might exist. Still, it is not stable enough to justify a spatial model. It remains as ordinary least squares model. For 2021 and 2022, both LM lag and LM error are significant indicating that the initial LM test suggests spatial dependence, but robust LM lag and robust LM error do not confirm these effects. It is due to weak spatial structure in 2021 and 2022, thus the ordinary least squares model is retained

Table 6 LM Lag and LM Error Results for Household Income

Years	LM Lag	LM Error	Robust LM Lag	Robust LM Error
2004	2.55	0.88	0.60*	0.94
2005	0.01	0.21	1.75	1.95
2006	2.03	2.68*	2.01	2.70*
2007	3.00*	3.85**	4.34**	5.20**
2008	0.07	0.58	3.30**	3.80**
2009	0.22	0.42	2.69*	2.90*
2010	0.24	0.06	7.10***	6.92***
2011	0.16	0.0005	7.59***	7.44***
2012	0.26	0.70	4.54**	4.98**
2013	1.32	1.60	2.73*	3.01*
2014	0.86	0.50	3.05*	0.50*
2015	0.00	0.04	3.37*	3.41*
2016	0.39	1.42	2.66*	3.69**
2017	0.03	0.002	0.38	0.35
2018	0.01	1.10	4.53**	5.62***
2019	0.73	0.62	0.16	0.05
2020	0.03	0.13	0.97	1.08
2021	2.89*	2.80*	0.97	1.08
2022	3.15*	2.73*	0.80	0.39

The results in Table 7 show that LM Error and robust LM Error are significant in the year 2004; a spatial error model (SEM) might be appropriate. It shows that spatial dependence is in the error term, not in the dependent variable directly. Financial inclusion is influenced by spatial factors, age dependency ratio. As for 2005 to 2009, 2011 to 2012, 2018 to 2019, 2021 and 2022, both LM lag and LM error are insignificant. However, both robust LM lag and robust LM error in 2005 to 2009, 2011 to 2012, 2018 to 2019, 2021 and 2022, except in 2013, only robust LM lag is significant, this implies that the spatial dependence might exist. Still, it is not stable enough to justify a spatial model. It remains as ordinary least squares model. All four tests are significant in 2007 indicating an absolute spatial independence. There is spatial dependence in financial inclusion; spatial correlation in the error term or spatial interaction for both exists at the same time. The final model depends on the significance of the robust LM lag or robust LM error.

Table 7 LM Lag and LM Error Results for Age

Years	LM Lag	LM Error	Robust LM Lag	Robust LM Error
2004	1.74	3.12*	2.21	3.59**
2005	0.17	0.004	5.13**	4.96**
2006	1.15	1.00	3.16*	3.01*
2007	0.41	0.04	3.25*	2.89*
2008	0.20	0.03	3.02*	2.84*
2009	0.05	0.14	4.56**	4.65**
2010	5.37**	4.52**	8.00***	7.15***
2011	0.87	1.59	7.91***	8.63***
2012	0.06	0.01	6.10**	6.02**
2013	1.13	0.60	2.57*	2.05
2014	0.75	0.31	1.58	1.14
2015	0.02	0.15	2.12	2.25
2016	0.33	0.23	0.88	0.78
2017	0.71	1.28	0.37	0.94
2018	0.03	0.18	3.92**	4.07**
2019	0.69	2.09	3.56**	4.96**
2020	0.91	0.77	1.91	1.06
2021	3.14	3.07	0.12*	0.06*
2022	3.26	3.03	0.25*	0.01*

Table 8 shows all four tests are significant in 2010, which indicate that there is an absolute spatial independence. There is spatial dependence in financial inclusion, spatial correlation in the error term and spatial interaction for both existing at the same time. The final model depends on the significance of robust LM lag or robust LM error. As for 2004, 2007, 2009, 2011 to 2017 and 2021, both LM lag and LM error are insignificant. However, both robust LM lag and robust LM error in 2004, 2007, 2009, 2011 to 2017 and 2021, this imply that the spatial dependence might exist. Still, it is not stable enough to justify a spatial model. It remains as ordinary least squares model.

Table 8 LM Lag and LM Error Results for Gender

Years	LM Lag	LM Error	Robust LM Lag	Robust LM Error
2004	0.44	0.41	3.16*	3.12*
2005	0.20	0.12	1.42	1.34
2006	1.48	1.67	0.56	0.74
2007	0.42	0.64	2.56*	2.78*
2008	0.18	0.22	1.45	1.49
2009	0.12	0.30	3.19*	3.37*
2010	6.56***	8.20***	12.25***	13.89***
2011	0.95	1.64	8.26**	1.64**
2012	0.09	0.03	5.76***	2.70***
2013	1.20	0.76	3.49*	3.05*
2014	0.81	0.35	2.94*	2.48
2015	0.04	0.30	5.60***	5.86***
2016	0.29	0.12	3.62**	3.50*
2017	0.40	0.13	4.66**	4.38**
2018	0.09	0.01	1.64	1.56
2019	0.57	0.54	0.33	0.30
2020	0.93	0.31	2.04	1.42
2021	3.15	3.08	0.50*	0.43*
2022	4.65	5.12	0.78	1.25

Based on Table 9 below, all four tests are significant in the year 2010 showing that there is an absolute spatial independence. There is spatial dependence in financial inclusion, spatial correlation in the error term and spatial interaction for both existing at the same time. The final model depends on the significance of robust LM lag or robust LM error. As for 2004, to 2009 and 2011 to 2015, both LM lag and LM error are insignificant. However, both robust LM lag and robust LM error in 2004, to 2009 and 2011 to 2015, this imply that the spatial dependence might exist. Still, it is not stable enough to justify a spatial model. It remains as ordinary least squares model. In 2021 and 2022, both LM lag and LM error are significant indicating that the initial LM test suggests spatial dependence, but robust LM lag and robust LM error do not confirm these effects. The ordinary least squares model is more appropriate.

Table 9 LM Lag and LM Error Results for Regulatory

Years	LM Lag	LM Error	Robust LM Lag	Robust LM Error
2004	0.78	2.14	3.44*	4.80**
2005	0.03	0.00	4.82**	1.79**
2006	1.07	0.80	10.58***	10.32***
2007	0.14	0.07	4.57**	4.50**
2008	0.06	0.00	6.86***	6.81***
2009	0.00	0.01	3.18*	3.19*
2010	3.80**	2.80*	5.35**	4.35**
2011	0.38	0.27	3.48*	3.37*
2012	0.10	0.07	8.69***	8.65***
2013	1.28	0.99	6.72***	6.43***
2014	0.88	0.44	3.48*	3.04*
2015	0.01	0.20	3.59**	3.78**
2016	0.34	0.23	0.76	0.65
2017	0.57	0.55	0.02	0.01
2018	0.21	0.18	0.07	0.04
2019	0.91	0.38	1.11	0.59
2020	0.06	0.07	0.00	0.01
2021	3.35*	3.33*	0.05	0.03
2022	4.70**	5.02**	0.49	0.81

Table 10 below depicts the final models of income, age, gender and regulatory. Based on LM tests, spatial dependence is suggested. The best-fitting model is based on the final model selection workflow. After estimating ordinary least squares, spatial lag, and spatial error models. The final models are chosen based on the overall results, with the model preferred for its lower Akaike Information Criterion and significance of key variables. Based on the results, only the final models of the spatial lag model (SLM) and spatial error model (SEM) for income, age, gender, and regulatory are reported. The highlighted areas denote cases where ordinary least squares is the appropriate specification. The spatial lag model results indicate that financial inclusion in one region depends not only on local factors but also on neighbouring regions, reflecting spatial crowding-out or diffusion effects. This suggests that policies that enhance financial inclusion in one country may generate positive spillovers in adjacent economies, particularly in high-income regions with strong financial potential. In contrast, the spatial error model results highlight the role of unobserved spatially correlated factors influencing financial inclusion, underscoring the need for tailored, region-specific interventions; for example, outreach and education programs targeting older populations. According to Rahman et al. (2022), models are estimated with different subsamples to capture changes over time. To check whether the crowding-out effect holds consistently across the 2004 to 2022 study periods or not, the sample is split into four sub-samples: Precrisis (2004-2007), Crisis (2008-2012), Recovery (2013-2019) and COVID-19 (2020-2022). Results for the coefficients are similar in sign and magnitude, showing that spatial crowding-out or diffusion effects are robust over time. Spatial interdependence remains stable after the COVID-19 pandemic or the boom of digital fintech. The sample results for income, age, gender, and regulatory are presented in Table 11.

Table 10 Final Models of Income, Age, Gender and Regulatory

Years	Income	Age	Gender	Regulatory
2004	SLM	SEM	SEM	SEM
2005				
2006	SEM	SEM		SEM
2007	SEM			
2008				
2009	SEM			
2010	SEM	SEM	SEM	SEM
2011		SEM	SEM	
2012	SEM			
2013	SEM	SLM	SEM	SEM
2014	SEM		SLM	SEM
2015				
2016	SEM			
2017			SLM	
2018		SEM		
2019		SLM		
2020				
2021	SEM	SEM	SEM	SEM
2022				

Table 11 Results for Income (HI), Age (ADR), Gender (GPI), Regulatory (PSA)
Financial Inclusion and Income 2004

Variables	OLS		SLM		SEM	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
Constant	4.21	0.49	26.28***	0.00	8.36**	0.02
W_LNFII	-	-	-0.95***	0.00	-	-
LNHI	3.02***	0.00	3.09***	0.06	2.36***	0.00
λW	-	-	-	-	-1.00***	0.00
Best Fit Model	√					
R ²	0.4459		0.6214		0.5775	
AIC	134.72		131.56		131.86	
BIC	136.61		134.39		133.75	
Financial Inclusion and Age 2004						
Constant	97.66**	0.02	128.27***	0.00	112.88***	0.00
W_LNFII	-	-	-0.90***	0.01	-	-
LNADR	-18.07*	0.07	-20.38***	0.01	-22.07***	0.00
λW	-	-	-	-	-0.67*	0.08
Best Fit Model	√					
R ²	0.1827		0.3832		0.4139	
AIC	142.11		140.60		135.01	
BIC	144.00		143.43		136.99	
Financial Inclusion and Gender 2010						
Constant	27.10***	0.00	5.50	0.24	28.96***	0.00
W_FII	-	-	0.77***	0.00	-	-
LN GPI	1.69	0.37	2.30**	0.09	2.78**	0.02
λW	-	-	-	-	0.82***	0.00
Best Fit Model	√					
R ²	0.0477		0.4189		0.4897	
AIC	141.14		136.10		132.07	
BIC	143.03		139.00		134.00	
Financial Inclusion and Regulatory 2004						
Constant	26.30***	0.00	39.91***	0.00	26.62***	0.00
W_LNFII	-	-	-0.58	0.13	-	-
PSA	3.62*	0.08	3.34*	0.06	4.71***	0.01
λW	-	-	-	-	-0.63*	0.10
Best Fit Model	√					
R ²	0.1729		0.2619		0.3640	
AIC	142.33		142.92		136.61	
BIC	144.22		145.75		138.50	

Note: (*), (**) and (***) indicate the respective 10%, 5% and 1% significance.

Since only the robust LM lag is significant in 2004, the initial model suggested is the ordinary least squares model. However, based on the results for financial inclusion and income, R² for the model shows that 62.14 percent of the variation in *LNFI* can be determined by *LNHI*. The lowest Akaike Information Criterion suggests spatial lag model is the final model. Below is the spatial lag model 2004:

$$LNFI_i = 26.28 - 0.95W_LNFI + 3.09LNHI_i + \varepsilon \quad (9)$$

The baseline model estimates *LNFI* at 26.28 when the independent variable is zero and spatial dependence is not considered. The spatial lag coefficient of -0.95 indicates that a 1% increase in neighbouring countries' *FII* reduces the focal country's *FII* by 0.95%, reflecting competition across regions. Conversely, a 1% increase in *LNHI* raises *LNFI* by 3.09% under spatial lag, suggesting that financial inclusion in one region depends on both local income and neighbouring regions' inclusion levels. The spatial lag model results underscore the importance of spatial dependence, where policies promoting financial inclusion in high-income regions can generate multiplier effects across borders.

As only the LM error and robust LM lag are significant in 2004, the initial model suggested spatial error model as the final model. From the results on financial inclusion and age, R² for the model shows that 41.39 percent of the variation in *LNFI* can be determined by *LNADR*. The lowest Akaike Information Criterion suggests spatial error model is the final model. Below is the spatial error model 2004:

$$LNFI_i = 112.88 - 0.67\lambda W\varepsilon - 22.07LNADR_i + \xi \quad (10)$$

The baseline estimates values *LNFI* at 112.88 when the independent variable is zero and spatial error dependence is excluded. The spatial error coefficient of -0.67 indicates negative spatial dependence in unobserved factors. Meanwhile, spatial error model indicates a crowding effect through the explanatory

variable, rather than the spatial error term. A 1% increase in LNADR reduces LNFII by 22.07%, indicating a crowding-out effect. The spatial error model results highlight the presence of unobserved spatially correlated factors influencing financial inclusion through age, underscoring the need for region-specific outreach and financial education programs tailored to older populations.

Since all four tests are significant in 2010, the final model depends on the significance of the robust LM lag or robust LM error tests. From the results on financial inclusion and gender, the R^2 for the model shows that 48.97 percent of the variation in *LNFII* can be determined by *LNGPI*. The lowest Akaike Information Criterion suggests that the spatial error model is the final model. Below is the spatial error model 2010:

$$LNFII_i = 28.96 + 0.82\lambda W + 2.78LNGPI_i + \xi \quad (11)$$

The baseline estimates value LNFII at 28.96 when the independent variable is zero and spatial error dependence is excluded. The spatial error coefficient of 0.82 indicates positive spatial dependence in unobserved factors. Additionally, a 1% increase in LNGPI increases LNFII by 2.78%. The spatial error model results suggest that spatially correlated unobserved factors, such as gender norms, legal constraints, or broader socio-economic environments influence women's financial inclusion. Strengthening regional collaboration and sharing best practices can help advance women's financial rights and narrow gender disparities.

Although robust LM lag and robust LM error are insignificant, the initial model suggested is an ordinary least squares model, as LM lag and LM error are initially insignificant. However, based on the results of financial inclusion and regulatory, R^2 for the model shows that 36.40 percent of the variation in *LNFII* can be determined by *PSA*. The lowest Akaike Information Criterion suggests spatial error model is the final model. Below is the spatial error model 2004:

$$LNFII_i = 26.62 - 0.63\lambda W + 4.71PSA_i + \xi \quad (12)$$

The baseline estimates values LNFII at 26.62 when the independent variable is zero and spatial error dependence is excluded. The spatial error coefficient of -0.63 indicates negative spatial dependence in unobserved factors. Moreover, a 1% increase in PSA raises LNFII by 4.71%. The presence of spatial dependence in the error terms implies that unobserved regional factors shape the effects of regulatory frameworks on financial inclusion. Strengthening regional institutional capacity and ensuring consistent enforcement of regulations are therefore essential.

CONCLUSION

This study provides a regional overview of financial inclusion across nineteen Asia-Pacific countries from 2004 to 2022, highlighting spatial dynamics and heterogeneity. Visualisations and spatial econometric models reveal distinct clusters, where high or low financial inclusion in one country influences its neighbours through spatial crowding-out and aggregation effects. Global Moran's I, Anselin Local Moran's I, and Bivariate Local Moran's I confirm significant spatial dependencies, while regression results show that income, age, gender, and regulation remain critical determinants of inclusion. The findings are consistent with past studies that documented exclusion among low-income, ageing, and female populations, particularly in weakly regulated environments, and emphasise regulatory harmonisation to reduce uneven access across borders and lagging regions. Policy implications suggest that governments should adopt place-based strategies tailored to low-income and ageing communities, supported by mobile banking and financial literacy programs. Gender-responsive financial policies and harmonised regulatory frameworks are essential to close persistent gaps, especially for women and informal segments. The identified demographic and regulatory drivers also serve as proxies for evaluating progress in financial inclusion across countries. Regional collaboration, knowledge sharing, and dissemination of best practices are crucial for sustaining improvements. If a neighbour is crowding out financial inclusion, macroprudential policies should be designed to limit the excessive sovereign exposure in the banking sector. Credit allocation to underserved communities, enabling the lending expansion to unbanked users could be one way. Besides, the presence of spatial dependence detected in spatial error models

and spatial lag models suggests the fiscal effects are not based on individual regions but the investment responses spillover across neighbouring regions. This implies that regional policy is more effective than isolated intervention. At the regional cooperation level, enhanced financial integration among ASEAN countries is taking place in the development of digital finance. For example, cross-border digital payment interoperability which allows the linking of Quick Response (QR) payment systems in neighbouring regions. Meanwhile, the crowding-out coefficient was consistent across from 2004 to 2022 through the estimation of sub-samples, it suggests that public borrowing persistently displaces private investment. Therefore, it is important to prioritise fiscal expansion, giving the priority is given to productive public investment rather than consumption-based expenditure. Finally, the heterogeneity is explicitly acknowledged as the limitation of this study, while further research could further refine analysis through sub-regional estimations and based on income-group stratification to better capture the differential effects between advanced and developing economies.

ACKNOWLEDGEMENT

Financial support from Universiti Malaysia Sarawak is greatly acknowledged.

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