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A Spatial Autoregressive Model on the Effect of E-Money, Fintech Lending, and ATM Usage on Economic Performance across Provinces in Sumatra

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This study investigates the spatial courting between digital economic signs and local monetary overall performance throughout ten provinces in Sumatra, Indonesia, from 2019 to 2022. As digitalization hastens economic and business sports, devices together with fintech lending, e-cash, debit card usage, and e-commerce are increasingly more diagnosed as capability drivers of regional increase. But, the unequal distribution of digital infrastructure and monetary literacy across regions raises issues approximately the inclusivity of these benefits. constructing upon current findings by using Miranti et al. (2024), this research employs spatial econometric fashions—particularly the Spatial Lag model (SLM) and Spatial mistakes model (SEM)—to evaluate how digital variables influence provincial financial overall performance while accounting for spatial spillover consequences. The results reveal that fintech lending and debit card usage exert a positive and significant impact on economic growth, whereas the effect of e-money is negative, suggesting potential substitution effects or access constraints. Spatial dependency is also evident, as demonstrated by the significant lambda coefficient in the SEM model. These findings highlight the importance of spatially coordinated digital policies, particularly in addressing disparities and enhancing digital financial inclusion. The study concludes with policy recommendations aimed at fostering inclusive and spatially balanced digital economic development in Sumatra.

Keywords: digital finance, spatial econometrics, regional economic performance, fintech, Sumatra, e-money, spatial spillover

Introduction

Regional economic disparities remain a persistent issue in Indonesia's development agenda, particularly outside Java. Sumatra, as the country's second most economically productive island, contributed approximately 21.32% to Indonesia's national GDP in 2022 (BPS, 2023). Despite its natural resource endowments and proximity to major growth hubs such as Singapore and Java, the economic performance across Sumatra's provinces reveals uneven development. Provinces like Riau and North Sumatra exhibit robust economic activity, while others such as Aceh, Bengkulu, and Bangka Belitung continue to experience sluggish growth. Such disparities underline the critical need for policy frameworks that not only encourage investment but also address

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structural imbalances through innovation and technology.

In recent years, digital transformation has emerged as a key enabler of inclusive economic development. The increasing penetration of digital financial services—such as e-money, mobile banking, and peer-to-peer lending—has provided new opportunities for regions to overcome physical, institutional, and financial barriers (Simamora, 2021). Digital financial inclusion, in this context, refers not only to the physical availability of services but also to their effective usage by individuals and businesses across regions. According to Miranti et al. (2024), the integration of digital finance, fintech, and digital literacy has a strong positive relationship with regional economic performance, particularly when analyzed through spatial and heterogeneity-aware approaches. Their findings reveal that these factors can unlock latent growth potential in regions historically underserved by traditional banking systems.

Furthermore, the adoption of e-commerce platforms by businesses in non-metropolitan areas has opened new pathways for market access, reduced transaction costs, and created demand for digital infrastructure (Lisha et al., 2023). The proliferation of e-commerce, often supported by digital payments and fintech credit systems, has redefined local economic ecosystems (Pu et al., 2024). However, the extent to which these digital services contribute to economic outcomes remains contingent upon regional capacity to absorb, implement, and adapt to digital technologies. This includes the availability of supporting infrastructure, human capital readiness, and local policy responsiveness.

Understanding the spatial dimension of digital economic transformation is therefore essential. Regional development does not occur in isolation; rather, it is influenced by spatial interactions, diffusion effects, and geographic interdependencies. Theoretical and empirical studies (Anselin, 1988; Rey & Montouri, 1999) have emphasized the importance of spatial econometric modeling in capturing these dynamics. By integrating spatial lag and error components into regression analysis, researchers are better equipped to estimate the true impact of exogenous variables on regional performance, including those related to digitalization.

This study seeks to contribute to the growing body of literature on regional digital economics by focusing on the provinces of Sumatra between 2019 and 2022. Specifically, it investigates the spatial relationship between economic performance—proxied by GRDP growth—and key indicators of digital economic activity: fintech lending, e-money circulation, e-commerce penetration, and debit card usage. Unlike prior studies that often overlook spatial interactions, this research employs Spatial Autoregressive Models (SAR) to capture the complexity of interprovincial dependencies and potential spillover effects.

The relevance of this study is further heightened by the COVID-19 pandemic, which accelerated digital adoption across sectors while simultaneously exposing digital divides. By comparing spatial patterns in 2019 (pre-pandemic) and 2022 (post-pandemic recovery), the research offers timely insights into the resilience and responsiveness of regional economies to digital transition under structural shocks.

In sum, the objectives of this research are threefold:

1. To analyze the spatial distribution of digital economic activity across Sumatra;
2. To evaluate the spatial effects of digitalization indicators on regional economic performance; and
3. To propose spatially informed policy recommendations that promote equitable and sustainable economic growth through digital finance and commerce.

Through these efforts, the study aims to provide empirical evidence that supports more nuanced, localized, and spatially coherent strategies for Indonesia’s regional development in the digital era.

Literature Review

The advancement of digital technology has transformed the way societies access financial services and engage in commerce. The concept of digital financial inclusion refers to the availability and effective usage of formal financial services facilitated by technology. In this context, digital instruments such as fintech lending, e-money, debit cards, and e-commerce have emerged as important indicators of a region's digital economy readiness.

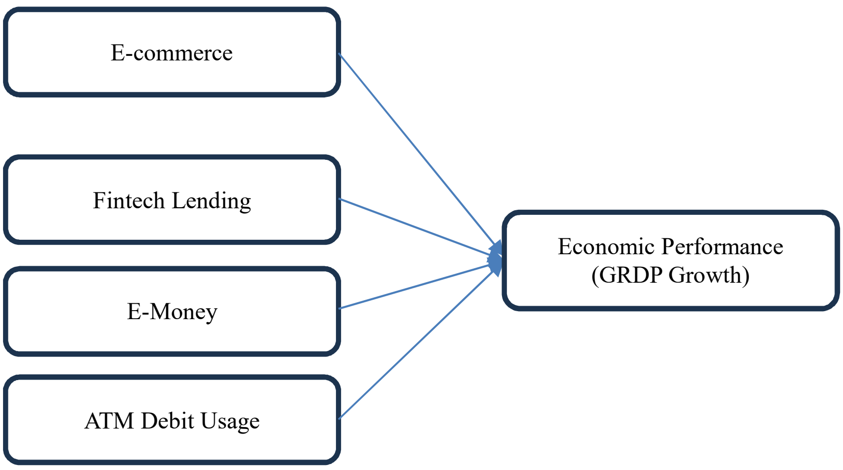
Miranti et al. (2024) conducted a spatial heterogeneity analysis across 154 districts in Sumatra and found that digitalization has an uneven impact on regional economies. The study reveals that the positive effects of digital financial inclusion and fintech lending are more pronounced in the central and northern regions of Sumatra, whereas southern regions continue to lag in digital adoption. These findings highlight the need for place-based interventions tailored to local development contexts.

Previous literature supports the economic significance of financial digitalization. Khera (2022), using cross-country regression models, found that enhancing digital financial inclusion can increase annual economic growth by up to 2.2 percentage points. Similarly, Le et al. (2019) noted that financial inclusion positively influences financial efficiency and stability, particularly through diversified banking assets, which in turn mitigate systemic risk. Fintech lending, in particular, plays a pivotal role in promoting inclusive economic development. Onaolapo (2015) and Narayan (2019) emphasized that fintech services foster financial inclusion in developing countries by easing access to credit for underserved populations. These services enable individuals and microenterprises to bypass conventional financial intermediaries, thereby reducing transaction barriers.

Additionally, e-commerce has significantly contributed to market expansion for micro, small, and medium enterprises (MSMEs). As discussed by Sudirman and Disemadi (2022), digital marketplaces allow businesses to reach broader consumer bases beyond local and regional boundaries, leading to greater contributions to regional GDP.

Nevertheless, the benefits of digitalization are not equally shared. Miranti et al. (2024) identified Aceh as a province that remains disadvantaged in terms of digital financial infrastructure and literacy, thereby limiting its economic gains from digitalization. This reinforces the importance of digital literacy as a prerequisite for maximizing the benefits of digital financial services.

Taken collectively, the literature underscores the multifaceted position of digitalization in shaping regional financial effects, at the same time as also emphasizing the want to cope with spatial inequality thru targeted digital regulations and investments.



Based at the conceptual framework performed on this observe, a ability speculation may be proposed as follows

Table 1

Hypothesis Study

Hypothesis	Information
Hypothesis 1	E-commerce has a positive effect on the performance of Economic Performance in Sumatra.
Hypothesis 2	Fintech Lending has a positive effect on the performance of Economic Performance in Sumatra.
Hypothesis 3	E-money has a positive effect on the performance of the performance of Economic Performance in Sumatra.
Hypothesis 4	ATM Debit Usage has a positive effect on the performance of regional economics in Sumatra.

Methodology

Data

This research uses economic performance as dependent variable which is proxied by GRDP growth at the provincial level with 2010 constant price as the base year. We use four economic digitalization components which are fintech lending, e-money, e-commerce, and debit card usage as independent variables. The observation unit is 10 provinces in Sumatra over the 2019-2022 period. For the sake of spatial analysis, we use year 2019 and 2022 for the spatial comparison, while we take year 2022 for cross-sectional spatial autoregressive analysis.

Table 2

Data Source

Variable	Description	Source	Unit
Economic Performance	GRDP growth per province (2010 constant price)	BPS-Statistics Indonesia	Percentage
Fintech Lending	Change in the distribution loan value from Fintech Lending	Financial Service Authority	Percentage Point
E-Money	Number of e-money cards activated	SPIP Bank Indonesia	Million Units
E-commerce	Percentage of businesses conducting electronic commerce	BPS-Statistics Indonesia	Percentage
Debit Card Usage	Debit Card transaction value	SPIP Bank Indonesia	Billion Rupiahs

Analysis Method

Exploratory Spatial Data Analysis. Exploratory spatial statistics analysis (ESDA) has drastically benefited from the integration of spatial statistical approaches into the geographic facts technology (GIS) environment. The practitioner now has access to a huge collection of spatial statistics evaluation software, which need to help to keep the level of fulfillment proven in this region in latest years. ESDA enables for the spatial context in which most spatially referenced events arise. These occurrences can not be considered as disjointed and geographically independent; in any other case, empirical consequences and, greater substantially, theoretical implications about cross-space social dynamics would be not noted.

Spatial Weighting Matrix

The addition of a spatial weight matrix is an important issue of spatial autocorrelation in growth analysis in the spatial evaluation framework. This means that awesome geographies have interaction, as seen by the dispersion of spatial relationships. The spatial weight matrix is analogous to the diploma of spatial connectedness among spatial gadgets. The spatial weight matrix, designated via W, expresses the diploma of spatial connectedness among a fixed of M gadgets. The degree of spatial connection between two items (i, j) in W is represented by wij. Based on its application, the primary diagonal element M of W is set to have a value of w_{ii} = 0 or a value of w_{ii} > 0. A common variation of W is the row-standardized spatial weight matrix, whose elements are denoted as:

$$w_{ij}^{std} = \frac{w_{ij}}{\sum_{j=1}^{M} w_{ij}} \quad (1)$$

Moran's I and Moran's Scatter Plot

The best-recognised records for measuring international spatial autocorrelation of a quantitative variable are Moran's I and Geary's C. They represent the diploma of linear courting between the price of a variable at one area and the spatially weighted average of surrounding values. If Moran's I is less than one, it suggests poor spatial autocorrelation. This would have implied a chess board pattern of spatial dissimilarity, which is uncommon with spatially referenced records. It is a good idea to run both statistics with different weight matrices over several years (if possible) to corroborate your findings. Moran's I indicator is formulated as follows:

$$I_x = \sum_i \quad \sum_j \quad w_{ij} \cdot (x_i - \mu) \cdot \frac{(x_j - \mu)}{\sum_i \quad (x_i - \mu)^2} \quad (2)$$

where w_{ij} represents the spatial data structure and is formed from a spatial weight matrix, x_i is the value of variable x at location-i, x_j is the value of the same variable at location-j, and μ is the data's cross-sectional average. Moran's I statistical inference can be performed by making normality assumptions or simulating reference distributions using random permutations (Anselin, 1995).

Local Indicator of Spatial Association

The Moran scatterplot compares the value of a commentary (on the horizontal axis) to the standardized spatial weighted common (common of the friends' values, additionally called spatial lag) on the vertical axis. whilst the variables are expressed in standardized shape (i.e., with mean zero and popular deviation equal to one), it's miles viable to look at each worldwide geographical affiliation (for the reason that slope of the line is the Moran's I coefficient) and neighborhood spatial affiliation (the scatterplot quadrant). Local spatial autocorrelation analysis substitutes for global dependence analysis via identifying unique geographical clusters and outliers. Specifically, the method established by Anselin (1995) can identify local spatial patterns such as hot spots (relatively high values), cold spots (relatively low values), and spatial outliers (high values surround low values and vice versa). A local version of Moran's I can be determined for each spatial unit specified as follows

$$I_i = \frac{(x_i - \mu)}{\sum (x_i - \mu)^2} \sum_j \quad w_{ij} \cdot \left(x_j - \mu\right) \quad (3)$$

1. Quadrant I (in the higher proper corner) shows observations with an excessive price (above common), which might be surrounded by means of observations with a high value. This quadrant is usually called HH (high-high

2. Quadrant II (on the top left nook) indicates observations with a low price surrounded by means of observations with excessive values. This quadrant is normally mentioned as LH (low-excessive).

3. In Quadrant III (backside left), observations with low values are flanked via other low-value observations, denoted as LL (low-low).

4. Quadrant IV (bottom right) displays observations with high values surrounded by low values.

Spatial Autoregressive Models. Spatial regression modeling makes use of a dataset that carries observations at spatial units such as international locations, counties, or even non-geographic devices consisting of social network nodes. For simplicity, these spatial devices are known as regions. The dataset in spatial regression modeling includes at least non-stop variables along with disorder incidence, agricultural yield, or crime fees, along with other variables which can be assumed to predict the selected final results. In spatial regression modeling, linear regression is used because the place to begin.

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,j} + \cdots + \beta_k x_{i,k} + \epsilon_i \tag{4}$$

$i =$ region (observation unit), numbered from 1 to N
$y_i =$ dependent variable in region-i
$x_{i,1} =$ independent variable-1 in region-i
$x_{i,j} =$ independent variable-j in region-i
$x_{i,k} =$ independent variable-k in region-i
$\epsilon_i =$ error in region-i

Referring to the research of Rey and Montouri (1999) and Fingleton (1999), linear regression is changed right into a spatial regression model to include the spatial structured outcomes among regions. The reason of inclusive of spatial dependency is to offer instinct and knowledge that interactions among geographically adjacent regions can affect the final results of the whole regional device. If the interplay isn't always accommodated in the spatial version, and the spatial dependency is disregarded within the shape of residuals (errors), then the resulting estimate can be biased (deceptive). Spatial dependency that is not calculated or considered can purpose biased or inefficient estimates in version estimation. Extending equation (1) of OLS linear regression in the form of a cross-section spatial regression model, the resulting equation is as follows:

Spatial lag model (SLM):

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,j} + \cdots + \beta_k x_{i,k} + \rho \mathrm{W} y_i + \epsilon_i \tag{5}$$

W is the spatial weighting matrix and ρW_y is the spatial lag of the dependent variable.

Meanwhile, spatial autocorrelation may also occur in disruption or error structure in estimation. In spatial analysis, this model is called the spatial error model (SEM). In detail, Anselin (1988) has described the error structure in the spatial error regression model:

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,j} + \cdots + \beta_k x_{i,k} + (\mathbf{I} - \lambda \mathbf{W})^{-1} \epsilon_i \tag{6}$$

Results and Discussion

Moran's I Scatterplot

Based on the effects of the global Spatial Autocorrelation take a look at seen through the Moran's I statistic (See determine 1.), it become concluded that spatial dependency (spatial linkage) all through 2019-2022 period drastically came about between provinces in Sumatra. Which means that the level of monetary overall performance that's proxied through GRPD boom in a province is associated with the level of monetary overall performance in regions which can be geographically close. The Moran's I statistical fee in 2019 and 2022 shows a negative coefficient, which implies that the increase in the level of financial performance in a single province is correlated with the lower within the stage of economic overall performance inside the nearest provinces. Although the Moran's I statistic value does not show a strong correlation in 2019 and 2022 period (-0,209 in 2019 and -0.208 in 2022), this parameter is significant (p-value < 0.05), thus the spatial interaction can not be directly overlooked.

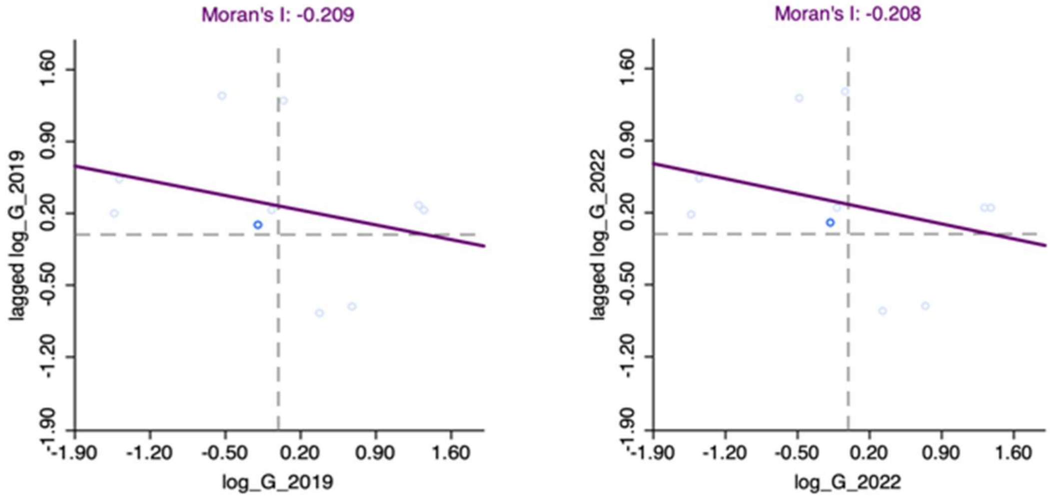


Figure 1. Moran's I Scatterplot of Economic Performance across provinces in Sumatera, 2019 and 2022.

Spatial Distribution of Economic Performance and Its Determinant in Sumatra

Based on the development of economic overall performance 10 provinces in Sumatra for the 2019-2022 duration, the spatial distribution of NTL development may be visible in determine 1. In 2019, there are two types of spatial clusters formed, which are spatial clusters with high concentration (high-high clusters) and spatial outliers I low-high). On this look at, spatial clusters and spatial outliers are identified in the spatial distribution of monetary overall performance throughout provinces in 2019. Purple-colored area, which is low-high cluster, contain areas/districts that share low levels of economic performance and is surrounded by high levels of economic performance, which is Aceh Province. Meanwhile, Lampung has the high performance of economy in 2019 and is surrounded by high-performed of economy cluster. In 2022, there is no shifting pattern in the case of Lampung, while Kepulauan Riau has degraded into low-performer economy surrounded by high-performer provinces.

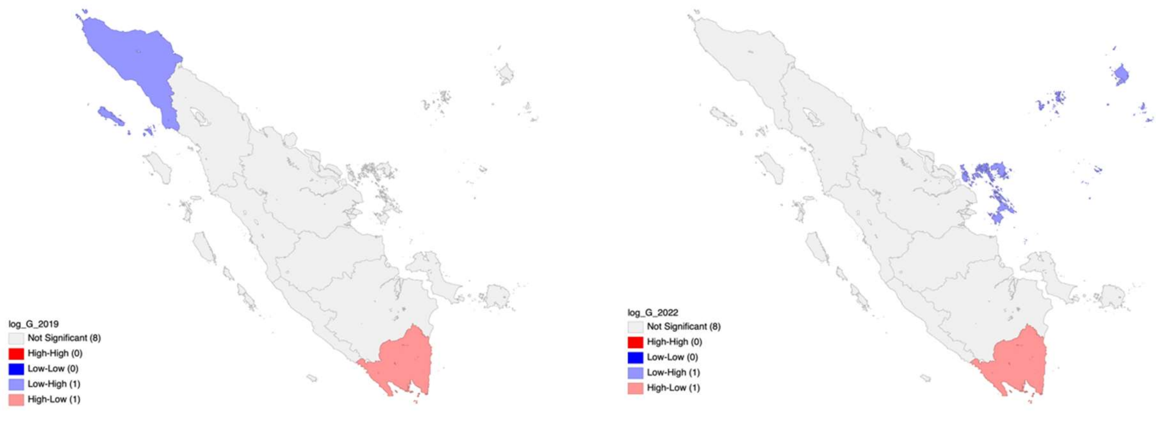


Figure 1. Local Indicators of Spatial Autocorrelation from GDP Growth, 2019 and 2022.

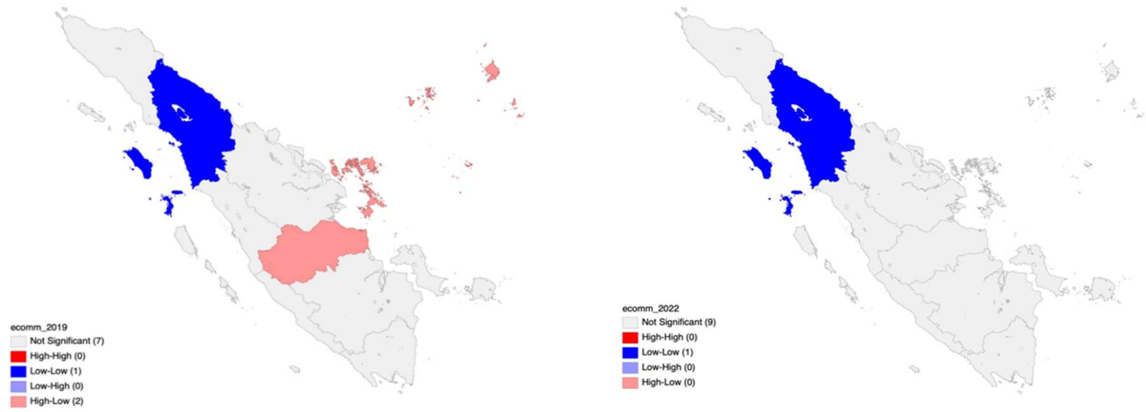


Figure 2. Local Indicators of Spatial Autocorrelation from E-Commerce, 2019 and 2022.

Moving to e-commerce variable, there are also two types of clusters generated, which are spatial cluster and spatial outlier. In 2019, Sumatera Utara shared the low-performance of e-commerce businesses, surrounded by low performer provinces too. However, there were two provinces with the high performance of e-commerce businesses, which are Jambi and Kepulauan Riau, but surrounded by low performer clusters. In 2022, it was only Sumatra Utara which stood persistent pattern becoming low-performer in terms of e-commerce businesses.

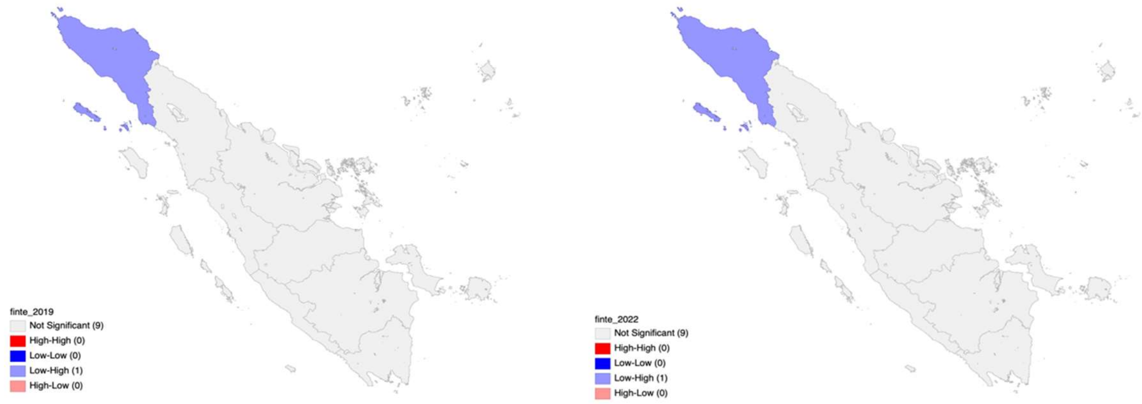


Figure 3. Local Indicators of Spatial Autocorrelation from Fintech, 2019 and 2022.

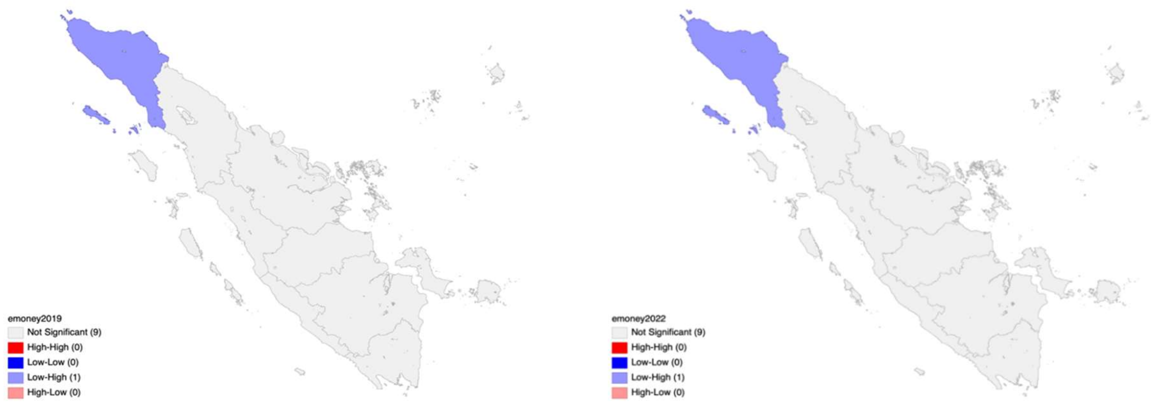


Figure 4. Local Indicators of Spatial Autocorrelation from E-money, 2019 and 2022.

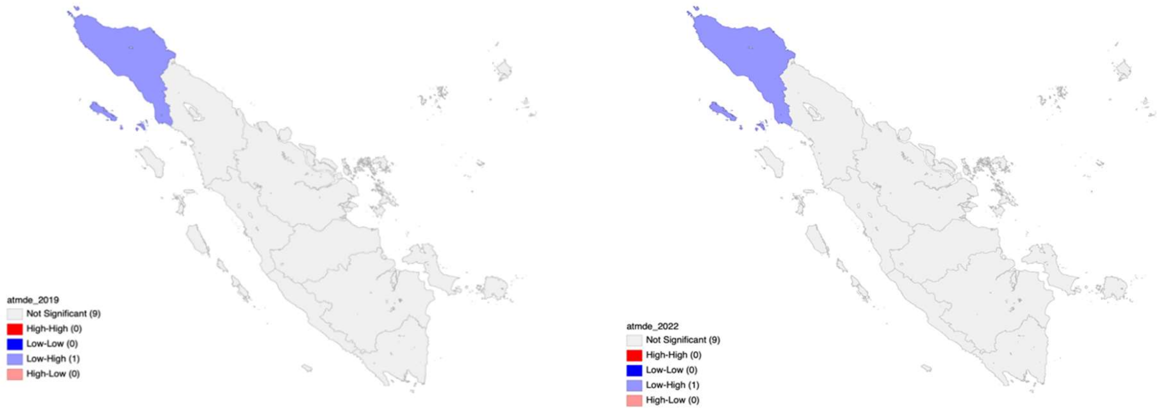


Figure 5. Local Indicators of Spatial Autocorrelation from Debit Card Usage, 2019 and 2022.

Regardless fintech, e-money, and Debit Card Usage, there is similar pattern among those three variables. It is quite surprising remembering that fintech, e-money, and debit card usage are the variables which boost financial inclusion and financial activities among consumers. Besides that, it is also closely related to economic digitalization which has been massively spreading over the regions. However, spatial distributions show that Aceh Province is less benefited from the financial digitalization. It is seen from the mapping that it is only Aceh Province shared the outlier pattern on those variables (fintech, e-money, and Debit Card Usage). Purple-shaded area indicates that this province shared the low performance in terms of fintech, e-money, and debit card usage activities, while surrounded by the high-performing Provinces. The pattern was also persistent during 2019-2022 period.

Spatial Autoregressive Models

Based on Table 3, we can see the estimation results of Spatial Lag Model and Spatial Error Model of economic digitalization variables on economic performance across Sumatra. Of three models proposed, Spatial Error Model is the best fit model which although there is no significant spatial lag in terms of Spatial Lag Model, lambda in the Spatial Error Model implies unobserved spatial autocorrelation in the residuals. The negative lambda coefficient is -0.90 in spatial error model indicates that the increasing economic performance in a province will reduce the economic performance in the neighboring regions. It has indication that there is still underlying issue in coordinating spatially regional economic policies considering geographic spillovers**.** This suggests that there is spatial interaction across provinces in Sumatra and the need to observe spatial effect is encouraged. Taking into details of each variable, e-money shows negative effect on economic performance both in spatial lag and error model, possibly due to substitution effects or financial access issues in certain provinces. Moving to other variables, Fintech and debit card usage contribute positively to economic performance when we involve spatial interaction. While debit card usage shows positive effect on economic performance in each province for both spatial lag and spatial error model, fintech is only significant in leveraging economies on spatial error models.

Table 3

Spatial Autoregressive Model of Economic Performance and Its Determinant, 2022

Variable	OLS Model	Spatial lag	Spatial Error

				Model			Model
	Coefficient	Std. Error	t/z-Statistic	Coefficient	Std. Error	z-value	Coef
	(Probability)			(Probability)			(Prob)
CONSTANT	5.310 (0.00004)**	0.384	13.807	4.260 (0.006)**	1.240	3.434	5.08 (0.00)
Ecommerce	-0.013 (0.487)	0.017	-0.748	-0.014 (0.225)	0.011	-1.213	-0.00 (0.46)
Fintech	0.001 (0.295)	0.001	1.168	0.002 (0.061)	0.000	1.872	0.00* (0.05)
E-money	-0.131 (0.202)	0.089	-1.469	-0.143 (0.024)*	0.063	-2.247	-0.20*** (0.00)
ATM Debit	0.004 (0.175)	0.002	1.579	0.003* (0.025)	0.000	2.230	6.881*** (0.00)
W_log_Growth	—	—	—	0.186 (0.379)	0.212	0.878	—
LAMBDA	—	—	—	—	—	—	-0.90*** (0.00)

Conclusion and Policy Recommendation

This study highlights the importance of spatial factors in understanding regional economic performance in Sumatra. The comparison between OLS, Spatial Lag, and Spatial Error models declares that ignoring spatial dependence can lead to the inaccuracy of true effects of digital financial and economic services. The Spatial Error Model comes as the best-suited to be applied in this research with a significant lambda coefficient ($\lambda = -0.90$, $p < 0.01$), confirming the presence of spatial autocorrelation in the residuals.

To sum up, despite of significance of economic digitalization variables like fintech, debit card usage, and e-money, spatial spill-over across province is a factor that can increase regional economy at the province level. The results suggest that the spatially coordinated policy needs to be encouraged to boost equal economic across provinces in Sumatra. Besides that, several targeted policies need to consider, such as promote regional fintech ecosystems, strengthening digital banking infrastructure, adjust and promote e-money services within and inter-provinces. For the upcoming research, it is better to analyze the effect of digital finance and economy on regional economic performance at the smaller level, i.e. district level in Sumatra. In addition, the use of infrastructure and local regional policy is also worth to examine.

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Appendices

Appendix 1. Estimation Result of OLS Model

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SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  SUMATRA
Dependent Variable  :  log_G_2022  Number of Observations:   10
Mean dependent var  :       5.502  Number of Variables   :    5
S.D. dependent var  :    0.342748  Degrees of Freedom    :    5

R-squared           :    0.815491  F-statistic           :     5.52473
Adjusted R-squared  :    0.667883  Prob(F-statistic)     :   0.0444362
Sum squared residual:    0.216754  Log likelihood        :      4.9685
Sigma-square        :   0.0433508  Akaike info criterion :   0.0629984
S.E. of regression  :    0.208209  Schwarz criterion     :     1.57592
Sigma-square ML     :   0.0216754
S.E of regression ML:    0.147226

-----------------------------------------------------------------------------
       Variable      Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------------
          CONSTANT       5.31066        0.38462        13.8076     0.00004
        ecomm_2022    -0.0127499      0.0170287      -0.748731     0.48772
        finte_2022   0.000178519    0.000152769        1.16855     0.29526
           e-money     -0.131474      0.0894774       -1.46935     0.20168
        atmde_2022    4.1583e-06     2.6321e-06        1.57984     0.17498
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Appendix 2. Estimation Result of SAR Model

```
SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : SUMATRA
Spatial Weight      : SUMATRA
Dependent Variable  :  log_G_2022  Number of Observations:   10
Mean dependent var  :       5.502  Number of Variables   :    6
S.D. dependent var  :    0.342748  Degrees of Freedom    :    4
Lag coeff.   (Rho)  :    0.186472

R-squared           :    0.830774  Log likelihood        :     5.34124
Sq. Correlation     : -            Akaike info criterion :     1.31752
Sigma-square        :     0.01988  Schwarz criterion     :     3.13303
S.E of regression   :    0.140997

-----------------------------------------------------------------------------
       Variable      Coefficient      Std.Error        z-value   Probability
-----------------------------------------------------------------------------
      W_log_G_2022      0.186472       0.212199        0.87876     0.37953
          CONSTANT       4.26094         1.2407         3.4343     0.00059
        ecomm_2022    -0.0140239       0.011559       -1.21325     0.22504
        finte_2022   0.000226058    0.000120744        1.87221     0.06118
           e-money     -0.143091      0.0636919       -2.24661     0.02467
        atmde_2022   3.98413e-06    1.78631e-06        2.23037     0.02572
-----------------------------------------------------------------------------
```

Appendix 3. Estimation Results of SEM Model

```
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SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : SUMATRA
Spatial Weight      : SUMATRA
Dependent Variable  :  log_G_2022  Number of Observations:   10
Mean dependent var  :    5.502000  Number of Variables   :    5
S.D. dependent var  :    0.342748  Degrees of Freedom    :    5
Lag coeff. (Lambda) :   -0.903528

R-squared           :    0.909790  R-squared (BUSE)      : -
Sq. Correlation     : -            Log likelihood        :    7.199853
Sigma-square        :   0.0105975  Akaike info criterion :    -4.39971
S.E of regression   :    0.102944  Schwarz criterion     :    -2.88678

-----------------------------------------------------------------------------
       Variable       Coefficient     Std.Error       z-value    Probability
-----------------------------------------------------------------------------
        CONSTANT          5.08621      0.241303        21.0781       0.00000
      ecomm_2022    -0.00756111     0.0102849      -0.735168       0.46224
      finte_2022    0.000174917   9.29727e-05        1.88138       0.05992
         e-money        -0.20219     0.0342452       -5.90419       0.00000
      atmde_2022     6.88113e-06   1.21502e-06        5.66338       0.00000
          LAMBDA       -0.903528      0.233818       -3.86424       0.00011
-----------------------------------------------------------------------------
```