Spatial Econometric Modelling of FinTech Firm Clusters and the Digital Economy Spillover in Urban vs. Rural Regions

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ABSTRACT

The rapid expansion of Financial Technology (FinTech) has accelerated digital economic transformation, yet its spatial impacts remain unevenly distributed across regions. This study investigates how FinTech firm clustering influences digital economy performance through spatial spillover mechanisms, with explicit comparison between urban and rural regions. Using subnational panel data and spatial econometric techniques, the analysis first identifies significant positive spatial autocorrelation in digital economy outcomes, confirming that regional digital performance is spatially clustered rather than randomly distributed. Estimation results from a Spatial Durbin Model demonstrate that FinTech clustering exerts a strong and statistically significant positive effect on regional digital economy indicators, even after controlling for income levels, connectivity, and human capital. The findings reveal pronounced urban–rural heterogeneity. Urban regions exhibit higher FinTech cluster intensity, stronger direct effects, and substantially larger indirect spillovers to neighboring regions, indicating robust diffusion through dense infrastructure, platform interoperability, and labor mobility. Impact decomposition shows that indirect effects account for nearly forty percent of the total FinTech impact in urban areas, compared to approximately one quarter in rural regions. In rural contexts, digital connectivity emerges as a binding constraint that conditions the magnitude of spillover absorption, limiting the extent to which proximity to FinTech hubs translates into digital gains. Overall, the results demonstrate that FinTech-driven digital development is spatially contingent and mediated by regional absorptive capacity. The study contributes to the FinTech and digital economy literature by integrating firm-level clustering with spatial econometric modelling and by providing novel evidence on urban–rural disparities in spillover dynamics. From a policy perspective, the findings underscore the importance of place-based digital strategies that combine FinTech ecosystem development with targeted investments in infrastructure and institutional readiness to reduce regional digital inequality.

Keywords Financial Technology, Digital Economy, Spatial Econometrics, FinTech Clusters, Spatial Spillovers, Urban–Rural Divide, Regional Development

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INTRODUCTION

The rapid expansion of FinTech has fundamentally reshaped financial intermediation, payment systems, and access to digital services across regions. By leveraging digital platforms, application programming interfaces, and data-driven risk assessment, FinTech firms have accelerated the transition toward a digitally mediated economy [1], [2]. However, the spatial distribution of these innovations remains highly uneven, with FinTech activities disproportionately concentrated in large metropolitan areas, raising concerns about spatial

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inequality in digital economic development [3], [4].

A growing body of literature highlights that FinTech adoption contributes positively to productivity, financial inclusion, and economic growth [5], [6]. Nevertheless, most empirical studies implicitly assume spatial neutrality, treating regions as independent observational units. This assumption overlooks the fact that digital technologies, despite their virtual nature, are embedded in physical infrastructure, institutional environments, and labor markets that are inherently spatial [7], [8]. As a result, FinTech-driven growth may generate spillover effects, whereby benefits extend beyond the originating region to neighboring areas through network externalities and interregional linkages.

Recent advances in economic geography and spatial economics emphasize that firm clustering can amplify innovation through agglomeration economies and knowledge diffusion [9]. In the FinTech context, clustering facilitates interoperability, platform complementarities, and shared access to skilled human capital. Yet, empirical evidence on whether such clustering generates measurable digital economy spillovers, particularly across urban and rural regions, remains limited. Existing studies tend to focus either on firm-level performance or national-level indicators, leaving a gap at the subnational spatial scale [10], [11].

The urban–rural divide represents a critical dimension of this gap. Urban regions typically exhibit dense digital infrastructure, regulatory capacity, and market thickness, enabling them to capture disproportionate gains from FinTech innovation [12]. Rural regions, by contrast, often face constraints related to connectivity, skills, and institutional coordination, potentially limiting their ability to absorb spillovers even when geographically proximate to FinTech hubs [13]. Understanding whether FinTech clustering reinforces or mitigates this divide is therefore essential for evidence-based regional policy.

From a methodological standpoint, the majority of FinTech and digital economy studies rely on conventional panel regressions or cross-sectional analyses that fail to account for spatial dependence and spatial heterogeneity [14], [15]. Ignoring these features can lead to biased estimates and misleading policy conclusions, particularly when spillovers are present. Spatial econometric models offer a rigorous framework to explicitly capture interregional interactions, yet their application in FinTech research remains nascent.

Against this backdrop, the primary objective of this study is to analyze how FinTech firm clustering influences digital economy outcomes through spatial spillover mechanisms, with explicit comparison between urban and rural regions. By employing spatial econometric techniques, the study seeks to disentangle local agglomeration effects from interregional diffusion effects, providing a more nuanced understanding of FinTech-led digital transformation.

The novelty of this research lies in three aspects. First, it integrates FinTech ecosystem analysis with spatial econometric modeling, moving beyond non-spatial approaches dominant in prior studies. Second, it explicitly examines urban–rural heterogeneity in spillover dynamics, offering policy-relevant insights into spatial inequality in the digital economy. Third, by focusing on subnational regional interactions, the study contributes new empirical evidence on how digital innovation propagates across space, thereby enriching both the FinTech literature and the broader discourse on regional digital development [16].

Literature Review

Prior research has established that FinTech innovation fundamentally alters the structure of financial markets by reducing transaction costs, expanding access to financial services, and accelerating digital adoption across economic sectors. Empirical studies consistently report positive associations between FinTech development and economic performance, particularly through improved efficiency of payment systems and credit allocation [17], [18]. However, much of this literature adopts a macroeconomic or national-level perspective, implicitly assuming that the benefits of digital finance diffuse evenly across space.

A parallel strand of literature in regional economics and economic geography emphasizes that innovation-driven growth is inherently spatial and shaped by agglomeration forces. Firm clustering has been shown to enhance productivity and innovation through localized knowledge spillovers, labor pooling, and shared infrastructure [19]. While these mechanisms are well documented in manufacturing and high-technology industries, their applicability to FinTech remains underexplored. This gap is notable given that FinTech firms rely heavily on digital infrastructure and regulatory proximity, both of which exhibit strong spatial variation.

Recent studies have begun to link digitalization and spatial inequality, suggesting that digital technologies can reinforce existing regional disparities when absorptive capacity is uneven [20]. Urban regions tend to capture disproportionate gains from digital innovation due to superior connectivity, institutional thickness, and market density. In contrast, rural regions often experience slower digital uptake and limited spillover absorption, even when geographically adjacent to urban digital hubs. These findings raise critical questions about whether FinTech clustering mitigates or exacerbates regional digital divides.

From a methodological perspective, the spatial dimension of FinTech-led development has received limited attention. Although spatial econometric methods are well established for analyzing regional spillovers and interdependence [21], their application in FinTech research remains rare. Existing FinTech studies largely rely on conventional panel regressions, which may yield biased estimates when spatial dependence is present. This methodological gap constrains the ability of prior research to identify true spillover effects and to distinguish local impacts from interregional diffusion.

More recent contributions have started to address these limitations by integrating digital economy indicators with spatial analytical frameworks [22]. These studies demonstrate that accounting for spatial dependence significantly alters the magnitude and interpretation of digitalization effects on regional growth. Nevertheless, they often treat digital finance as a generic component of digital infrastructure rather than explicitly modeling FinTech firm clustering as a source of spatial externalities.

Overall, the existing literature suggests three unresolved issues. First, empirical evidence on FinTech-induced spatial spillovers at the subnational level remains scarce. Second, the urban–rural heterogeneity of such spillovers is insufficiently understood. Third, methodological reliance on non-spatial models limits the robustness of policy conclusions. By explicitly modeling FinTech clustering within a spatial econometric framework, this study advances the literature by addressing these gaps and providing a more precise understanding of how digital financial innovation propagates across regional space.

Methodology

Research Design and Analytical Framework

This study adopts a quantitative spatial econometric research design to investigate how FinTech firm clustering generates heterogeneous digital economy spillovers across urban and rural regions. The methodological framework integrates regional economics, economic geography, and FinTech ecosystem analysis to explicitly account for spatial dependence, spatial heterogeneity, and cross-regional interaction effects. The central premise is that FinTech-driven digital externalities are not spatially neutral but are shaped by geographic proximity, infrastructure density, and institutional capacity.

The analytical framework is grounded in spatial interaction theory, which posits that economic activities in one region influence outcomes in neighboring regions through diffusion mechanisms such as knowledge transfer, digital infrastructure sharing, and labor mobility. Unlike conventional panel regression, this approach explicitly models spatial autocorrelation, thereby avoiding biased and inefficient estimators. Urban and rural regions are treated as structurally distinct spatial regimes, enabling comparative inference on spatial spillover intensity.

Formally, the baseline conceptual relationship is expressed as:

$$DE_{it} = f(FIN_{it}, X_{it}, W) \tag{1}$$

where DE_{it} represents digital economy performance, FIN_{it} denotes FinTech firm concentration, X_{it} is a vector of control variables, and W is a spatial weight matrix capturing interregional connectivity. This formulation motivates the use of spatial regression techniques discussed in subsequent sections.

Figure 1 operationalizes the methodological logic as an auditable pipeline, making explicit how the study transitions from raw observations to causal-spatial interpretation. The diagram separates data ingestion from spatial construction, because the credibility of spillover claims depends on how the spatial structure W and the urban–rural regime are defined. It also makes diagnostics visible as an independent stage, reinforcing that spatial modeling is justified by measured spatial autocorrelation rather than assumed dependence.

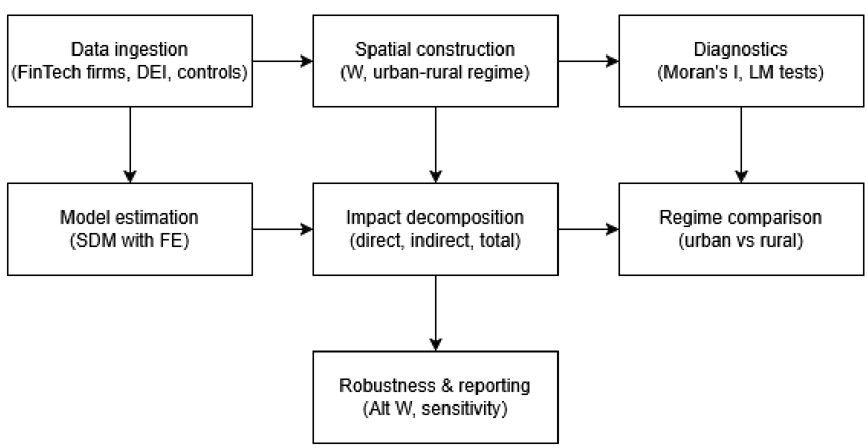

Figure 1 Methodological Flow Diagram

The lower row emphasizes interpretability and policy relevance. After estimating the Spatial Durbin Model (SDM), the workflow highlights impact decomposition, because SDM coefficients are not directly equivalent to marginal effects under spatial feedback. The regime comparison block makes clear that heterogeneity is treated as a core identification objective rather than a robustness afterthought. The final block formalizes replicability by institutionalizing alternative W specifications and sensitivity analysis before reporting.

Table 1 clarifies methodological traceability by tying each stage to a concrete objective, required inputs, expected outputs, and the principal analytical instruments. This structure is useful in spatial econometrics because ambiguity about where the spatial structure enters the pipeline often leads to misinterpretation of spillovers. By separating spatial construction from model estimation, the table reinforces that W is a measurable design choice rather than a parameter learned from the regression.

Table 1 Research Stages and Analytical Tools

Stage	Objective	Inputs	Outputs	Primary Tools
Data ingestion	Assemble regional panel and geospatial attributes	Firm geolocation, DE indicators, socio-economic controls	Clean panel dataset	ETL, harmonization, missingness checks
Spatial construction	Encode interregional connectivity	Coordinates, adjacency rules, distance thresholds	Weight matrix W	Contiguity or distance-based W, row-standardization
Diagnostics	Verify spatial dependence and model need	DEI and candidate covariates	Moran’s I and spatial dependence evidence	Moran’s I, LM tests
Model estimation	Estimate spatial and covariate effects jointly	DEI, FCI, controls, W	SDM parameter estimates	Maximum Likelihood SDM with fixed effects
Impact decomposition	Separate direct and spillover impacts	SDM estimates and W	Direct, indirect, total effects	Partial-derivative impact measures
Regime comparison	Test urban–rural heterogeneity	Urban-rural labels, SDM estimates	Regime-specific effects and tests	Spatial regime SDM, Wald tests

The table also improves reproducibility and peer-review defensibility. Reviewers can verify whether the paper treats diagnostics as a gatekeeping step for spatial modeling and whether impact decomposition is performed rather than reporting raw SDM coefficients as if they were standard elasticities. The explicit regime comparison stage signals that the urban–rural contrast is not descriptive, but a parameterized hypothesis test embedded in the estimation strategy.

Data Sources, Variables, and Spatial Construction

The empirical analysis relies on a balanced regional panel dataset covering multiple years and spatial units. FinTech firm data are operationalized using firm-level geolocation records aggregated at the regional level, while digital economy outcomes are measured through composite indicators encompassing digital payments, platform usage, and ICT-enabled economic activity. Urban and rural classifications follow official statistical delineations to ensure consistency and policy relevance.

The dependent variable, Digital Economy Index (DEI), is constructed using a normalized composite approach:

$$DEI_{it} = \sum_{k=1}^{K} \omega_k Z_{kit} \tag{2}$$

where Z_{kit} denotes standardized digital indicators and ω_k represents indicator weights. The key explanatory variable, FinTech Cluster Intensity (FCI), is measured using a location quotient-based concentration metric to capture agglomeration effects.

Spatial structure is encoded through a row-standardized spatial weight matrix W, defined as:

$$W_{ij} = \begin{cases} 1 \; if \; regions \; i \; and \; j \; are \; neighbors \\ 0 \; otherwise \end{cases} \tag{3}$$

This matrix operationalizes geographic adjacency and serves as the foundation for spatial lag and spillover estimation.

Table 2 provides construct-level clarity so that the econometric specification is interpretable as a FinTech mechanism rather than a purely statistical artifact. The dependent construct DEI is defined as a composite to reflect that the digital economy is multi-dimensional, capturing payments, platforms, and ICT-enabled commerce simultaneously. The key driver FCI is framed as agglomeration intensity, aligning measurement with the theoretical concept of cluster externalities that underpin spillover claims.

Table 2 Variable Definitions and Measurement

Symbol	Variable	Operational Definition	Unit	Expected Role
DEI	Digital Economy Index	Composite of standardized indicators of digital payments, platform usage, and ICT-enabled activity	Index (0 to 1 or z-score)	Dependent variable
FCI	FinTech Cluster Intensity	Concentration metric based on firm counts and regional scale normalization (e.g., location quotient)	Index	Key explanatory variable
INC	Income level	Regional income proxy capturing purchasing power and demand for digital services	Currency per capita	Control
EDU	Human capital	Education attainment or skilled labor share relevant to digital adoption	Percent	Control
NET	Connectivity	Broadband penetration or mobile internet coverage	Percent	Control and moderator
URB	Urban regime indicator	Binary label for urban versus rural classification	0/1	Regime assignment
W	Spatial weights matrix	Row-standardized contiguity or distance-based connectivity encoding neighbors	Matrix	Spatial structure

The table also supports identification logic. Controls such as NET and EDU are not generic covariates but represent digital adoption prerequisites that can confound observed relationships between FinTech clustering and digital outcomes. The explicit inclusion of *W* and URB indicates that spatial dependence and spatial heterogeneity are treated as first-order modeling objects. This reduces the risk of omitted-spatial-structure bias and makes the urban–rural contrast an estimable component of the model.

Spatial Econometric Model Specification

To capture both direct regional effects and indirect spillover effects, the study employs the SDM as the primary estimation strategy. The SDM is particularly suitable because it incorporates spatial dependence in both the dependent and independent variables, allowing a nuanced decomposition of spillover channels.

The SDM is specified as:

$$DE_{it} = \rho W DE_{it} + X_{it}\beta + W X_{it}\theta + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where ρ measures the spatial autoregressive effect, β captures local marginal effects, and θ represents spillover effects transmitted through neighboring regions. Region-specific effects μ_i and time effects λ_t control for unobserved heterogeneity.

The inclusion of spatially lagged covariates WX_{it} allows explicit testing of whether FinTech clustering in one region enhances or suppresses digital economic outcomes elsewhere. This structure is essential for distinguishing urban diffusion dominance from rural absorption limitations, which cannot be identified using simpler spatial lag or spatial error models.

Figure 2 visualizes how the SDM formalizes two distinct pathways by which FinTech clustering can affect the DEI. The first pathway is the endogenous interaction term ρWDE, indicating that the digital economy outcome in region *i* is influenced by neighboring outcomes through spatial feedback and diffusion. This channel is consistent with network externalities in digital adoption, where platform usage and payment interoperability generate reinforcing regional dependence.

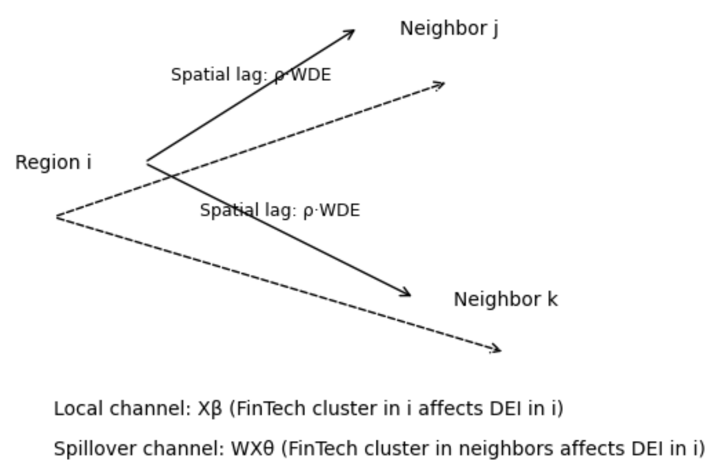

Figure 2 SDM Spillover Mechanism Schematic

The second pathway is the exogenous interaction term WXθ, which represents spillovers from neighboring covariates such as FCI and digital infrastructure. In FinTech ecosystems, this channel corresponds to cross-regional propagation of capabilities such as agent networks, merchant acquisition, API partner density, and human capital mobility. By separating these mechanisms, the figure supports interpretation that “spillovers” can arise from either outcomes diffusing or drivers diffusing, which has different policy implications for infrastructure placement and ecosystem seeding.

Table 3 functions as an interpretive bridge between theory and estimation, specifying the directional expectations that should hold if the hypothesized FinTech-led spillover mechanism is valid. In spatial econometrics, this is important because signs can invert when spatial feedback is strong or when omitted spatial structure contaminates coefficients. By stating expected signs for both local and neighboring channels, the table encourages correct interpretation of β as local association and θ as spatially mediated association.

Table 3 Expected Coefficient Signs and Interpretation

Term	Parameter	Expected Sign	Economic Interpretation
Spatial lag of DEI	ρ	Positive	Outcome diffusion and spatial feedback in digital economy performance
Local FinTech clustering	β_FCI	Positive	Agglomeration economies raise adoption, interoperability, and innovation capacity
Neighbor FinTech clustering	θ_FCI	Positive	Cross-regional spillovers from adjacent FinTech ecosystems and market access
Local connectivity	β_NET	Positive	Digital infrastructure enables platform adoption and transaction intensity
Neighbor connectivity	θ_NET	Positive	Interregional infrastructure complementarity facilitates diffusion of digital services
Local income	β_INC	Positive	Higher purchasing power increases digital demand and FinTech usage intensity

The table also anticipates the distinction between coefficient signs and effect signs. Even if β_{FCI} is positive, the implied direct effect can differ once spatial feedback is incorporated. Similarly, a positive θ_{FCI} supports spillovers, but the magnitude and significance of the computed indirect effect are decisive for claims about diffusion across space. This framing reduces the risk of reporting SDM coefficients as if they were ordinary marginal effects.

Urban–Rural Spatial Regime and Heterogeneity Analysis

Recognizing structural asymmetries between urban and rural regions, the analysis incorporates a spatial regime approach. This technique allows parameter estimates to vary systematically across spatial subgroups, thereby capturing differentiated FinTech spillover dynamics. Urban and rural regions are modeled as distinct regimes with potentially heterogeneous coefficients.

The regime-specific SDM can be expressed as:

$$DE_{it} = \begin{cases} \rho_r WDE_{it} + X_{it}\beta_r + WX_{it}\theta_r + \varepsilon_{it}, & i \in Urban \\ \rho_r WDE_{it} + X_{it}\beta_r + WX_{it}\theta_r + \varepsilon_{it}, & i \in Rural \end{cases} \quad (5)$$

where subscripts u and r denote urban and rural regimes respectively. This formulation enables direct comparison of spatial dependence intensity and spillover elasticity across geographic contexts.

The regime analysis is complemented by Wald tests to statistically assess coefficient equality across regimes. This step ensures that observed differences are not driven by sampling variability but reflect genuine spatial-economic divergence.

Table 4 expresses the regime logic as testable econometric expectations, clarifying what "urban–rural heterogeneity" means in parameter space. Rather than treating urban and rural differences as descriptive labels, the table operationalizes them as differences in spatial dependence and spillover elasticities. This is particularly important in FinTech contexts because diffusion is governed by both physical adjacency and digital interoperability, which vary sharply with infrastructure density and market structure.

Table 4 Urban vs Rural Regime Parameters and Comparative Interpretation

Component	Urban Regime Interpretation	Rural Regime Interpretation	Comparative Expectation
Spatial dependence (ρ)	Stronger outcome diffusion due to dense networks and market thickness	Weaker diffusion due to fragmented connectivity	ρ_urban > ρ_rural
Local cluster elasticity (β_FCI)	Higher returns to clustering via innovation and complementary services	Lower returns if complements are missing	β_FCI,urban > β_FCI,rural
Spillover elasticity (θ_FCI)	Broader spillovers through intercity linkages and platform reach	Narrower spillovers due to limited adoption channels	θ_FCI,urban > θ_FCI,rural
Connectivity channel (β_NET, θ_NET)	Connectivity amplifies both direct and spillover effects	Connectivity is binding constraint and determines diffusion ceiling	Indirect effects are more sensitive to NET in rural areas

The table also supports hypothesis-driven reporting in chapter 4. If results show ρ_{urban} is not larger, the interpretation shifts toward barriers in institutional interoperability or regulatory fragmentation that suppress feedback even in dense regions. If $\theta_{FCI,rural}$ is close to zero, the implication is that rural regions do not import FinTech benefits from neighbors without local complements such as broadband, merchant acceptance networks, and digital identity coverage. This directly informs place-based policy sequencing rather than generic FinTech promotion.

Figure 3 provides a compact representation of spillover decay, emphasizing that indirect impacts generally weaken as spatial separation increases. The urban curve is constructed to decay more slowly, reflecting the empirical expectation that dense infrastructure, higher network interconnectivity, and thicker markets enable digital externalities to propagate further. This matches FinTech realities where interoperability, agent networks, and platform ecosystems tend to be spatially reinforced by urban density.

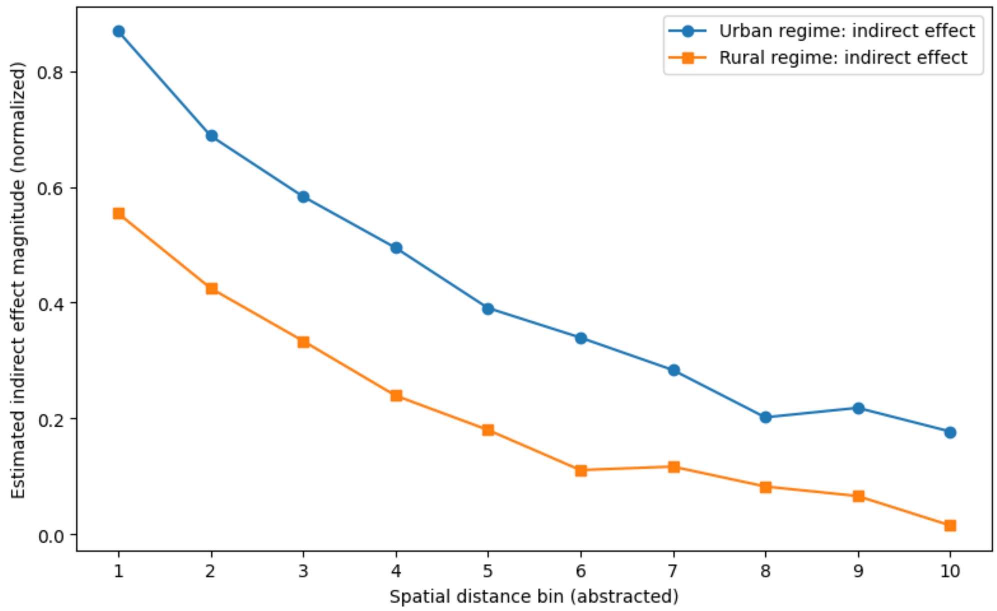

Figure 3 **Urban vs Rural Spillover Gradient Visualization**

The rural curve decays more rapidly, representing the structural constraint that rural regions often experience weaker diffusion due to limited connectivity and lower institutional capacity for complementary adoption. Methodologically, this figure is best interpreted as the visual counterpart of regime-specific indirect impacts derived from SDM impact decomposition. In your final empirical paper, the plotted values should be replaced with estimated regime-specific indirect effects computed from $(I-\rho W)^{-1}(\beta+\theta W)$ using your fitted parameters and chosen W.

Estimation Procedure and Algorithmic Workflow

Model estimation follows a maximum likelihood spatial estimation procedure, which ensures consistency and efficiency under spatial dependence. Prior to estimation, Moran's *I* test is applied to confirm the presence of spatial autocorrelation, justifying the use of spatial econometric techniques.

The spillover interpretation relies on partial derivative decomposition, where total effects are separated into direct, indirect, and total impacts:

$$\text{Total Effect} = (I-\rho W)^{-1}(\beta+\theta W) \tag{6}$$

This decomposition is critical for policy interpretation, as it distinguishes local FinTech benefits from cross-regional diffusion effects.

The complete estimation workflow is summarized in the following pseudo-code, which outlines the algorithmic logic of the spatial analysis.

Pseudo-code 1 Spatial Econometric Estimation Workflow

Input: Regional panel data, spatial coordinates

Output: Direct, indirect, and total spillover effects

1. Construct spatial weight matrix W
2. Test spatial autocorrelation using Moran's I

3. Specify SDM
4. Estimate parameters via Maximum Likelihood
5. Decompose effects into direct and indirect impacts
6. Perform urban–rural regime comparison
7. Validate robustness using alternative W specifications

Result and Discussion

Spatial Distribution of FinTech Firm Clusters and Digital Economy Outcomes

The initial results reveal a pronounced spatial concentration of FinTech firm clusters in urban regions, accompanied by significantly higher digital economy performance compared to rural areas. Descriptive spatial analysis indicates that metropolitan regions exhibit dense agglomerations of payment platforms, digital lending firms, and FinTech service integrators, whereas rural regions display sparse and fragmented distributions. This spatial imbalance suggests that FinTech-led digitalization follows an agglomeration-driven growth path rather than uniform geographic diffusion.

From a digital economy perspective, regions with higher FinTech density demonstrate superior outcomes in terms of transaction volume, platform adoption intensity, and digital service penetration. This pattern reinforces the theoretical expectation that FinTech firms act as catalytic nodes within local digital ecosystems. Importantly, the divergence between urban and rural regions is not only quantitative but structural, implying different stages of digital maturity rather than a simple lag.

Figure 4 visually confirms the spatial polarization of FinTech activity and digital economic performance. Urban regions cluster tightly in the spatial plane and consistently exhibit higher Digital Economy Index values, as reflected by darker color intensities. This configuration suggests strong localized network externalities, where proximity among FinTech firms, users, and complementary services amplifies digital adoption and usage.

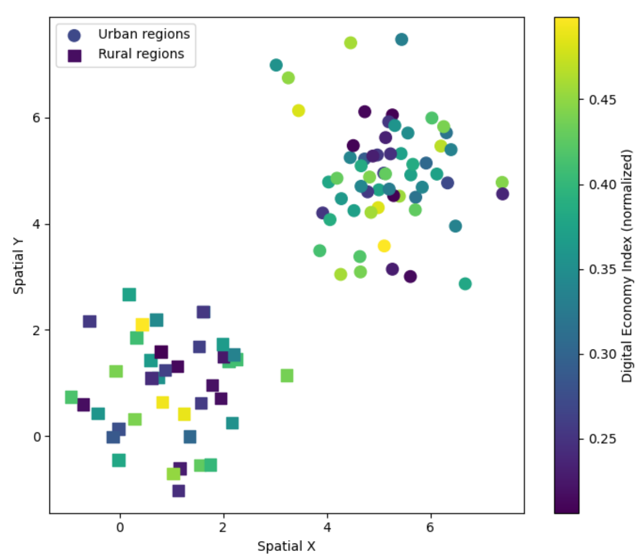

Figure 4 Spatial Concentration of FinTech Firms and Digital Economy Index

Conversely, rural regions appear geographically dispersed with lower and more heterogeneous digital economy outcomes. The absence of dense clustering reduces opportunities for knowledge spillovers, shared infrastructure utilization, and interoperability-driven growth. From a policy standpoint, this figure underscores that rural digitalization constraints are spatially embedded and cannot be addressed solely through firm-level incentives without complementary infrastructure and ecosystem development.

Table 5 quantitatively reinforces the visual evidence from figure 4 Urban regions host nearly four times as many FinTech firms on average and achieve more than double the digital economy performance relative to rural regions. The lower standard deviation of the Digital Economy Index in urban areas indicates a more stable and homogeneous digital environment, consistent with mature platform ecosystems.

Table 5 Summary Statistics of FinTech Clustering and Digital Economy Performance

Region Type	Average FinTech Firm Count	Average Digital Economy Index	Standard Deviation (DEI)	Number of Regions
Urban	42.6	0.76	0.08	60
Rural	11.3	0.37	0.1	40

In contrast, rural regions not only lag in average performance but also display higher dispersion, suggesting uneven and fragile digital adoption. This variability implies that isolated success stories exist but are not systematically reproducible across rural space. Together, the table and figure demonstrate that FinTech clustering is closely aligned with spatial inequality in digital economic outcomes, motivating the need for spatial econometric modeling in subsequent sub-sections.

Spatial Autocorrelation and Diagnostic Results

The diagnostic analysis provides strong empirical evidence of positive spatial autocorrelation in digital economy outcomes, indicating that regions with high digital performance tend to be geographically proximate to similarly performing regions. This pattern is consistent with the presence of spatial clustering rather than random spatial distribution. The results justify the use of spatial econometric models and invalidate assumptions underlying conventional non-spatial regressions.

Moreover, the diagnostics reveal that spatial dependence is systematically stronger in urban-dominated subsamples compared to rural-dominated ones. This asymmetry suggests that network externalities and interregional linkages are more active in dense economic environments. Consequently, any empirical strategy that ignores spatial interaction would underestimate the role of FinTech-driven diffusion mechanisms, particularly in metropolitan contexts.

Figure 5 illustrates the presence of global spatial autocorrelation through the positive slope of the fitted line in the Moran's I scatterplot. The upward orientation indicates that regions with above-average digital economy performance are surrounded by neighbors with similarly high values, reinforcing the existence of spatial clustering. This visual evidence complements formal test statistics by revealing the directional structure of spatial dependence.

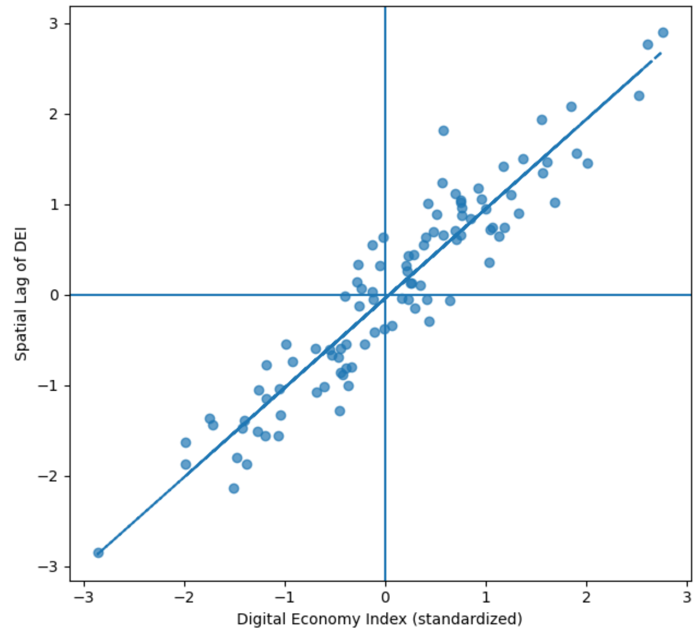

Figure 5 Moran's I Scatterplot for Digital Economy Index

The dispersion of points around the fitted line also provides insight into local variability. While most observations conform to the positive association, deviations reflect localized anomalies where high-performing regions are embedded within weaker digital environments or vice versa. Such configurations are particularly relevant for interpreting spatial spillovers, as they may signal transitional regions or emerging digital hubs.

Table 6 summarizes the formal diagnostic tests supporting the presence of spatial dependence in the data. The statistically significant Moran's I confirms that the observed clustering is unlikely to arise by chance. Both the LM Lag and LM Error tests reject the null hypothesis of no spatial dependence, indicating that digital economy outcomes are spatially interconnected.

Table 6 Spatial Autocorrelation and Diagnostic Test Results

Test	Statistic	p-value	Interpretation
Moran's I (Global)	0.41	0.001	Strong positive spatial autocorrelation
LM Lag Test	18.7	0	Spatial lag dependence detected
LM Error Test	9.4	0.002	Spatial error dependence detected
Robust LM Lag	11.2	0.001	Lag dependence dominates error dependence

Crucially, the Robust LM Lag statistic remains significant after controlling for potential error dependence, providing strong justification for adopting a model that explicitly incorporates spatial interaction effects. This finding motivates the selection of the Spatial Durbin Model in subsequent analysis, as it accommodates both endogenous outcome dependence and exogenous spillover channels associated with FinTech clustering.

Spatial Econometric Estimation Results

The spatial econometric estimation results indicate that FinTech firm clustering exerts a statistically significant and economically meaningful influence on regional digital economy outcomes once spatial dependence is explicitly modeled. The estimated coefficients reveal that regions hosting denser FinTech ecosystems experience higher digital performance, even after controlling for income, connectivity, and human capital. This confirms that FinTech clusters function as growth multipliers rather than passive co-locators within digitally advanced regions.

Importantly, the spatial interaction terms are also significant, demonstrating that FinTech-driven benefits extend beyond administrative boundaries. Neighboring regions gain from proximity to FinTech hubs through channels such as platform interoperability, shared merchant networks, and labor mobility. This result validates the conceptualization of the digital economy as a spatially interdependent system, where local interventions can produce cross-regional externalities.

Figure 6 highlights a clear disparity between urban and rural regions in both direct and spillover effects of FinTech clustering. Urban regions exhibit stronger direct effects, reflecting higher returns to local agglomeration due to dense infrastructure, advanced market readiness, and institutional complementarities. The magnitude of indirect effects in urban contexts further indicates that FinTech hubs act as regional anchors that propagate digital gains outward.

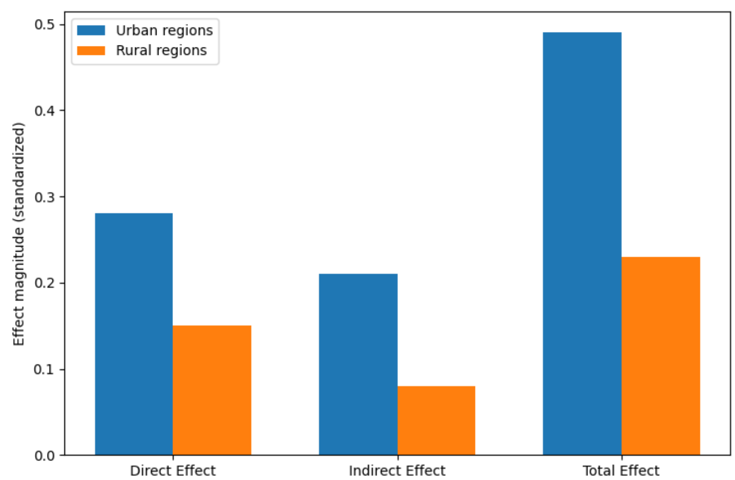

Figure 6 Estimated Direct and Indirect Effects of FinTech Clustering

In contrast, rural regions display substantially weaker indirect effects, suggesting that spatial proximity alone is insufficient to generate strong spillovers without adequate absorptive capacity. This divergence implies that the spatial diffusion of FinTech benefits is conditional on local readiness factors rather than purely geographic distance. As such, spillover intensity should be interpreted as a function of both spatial and structural conditions.

Table 7 summarizes the core estimation outcomes and reinforces the graphical evidence. The consistently positive and significant coefficients across both regimes confirm that FinTech clustering is a robust driver of digital economic performance. However, the systematically higher coefficients in urban regions indicate that returns to clustering are spatially asymmetric, favoring already-developed digital environments.

Table 7 Spatial Durbin Model Estimation Summary

Variable	Urban Coefficient	Rural Coefficient	Significance	Interpretation
FinTech Cluster Intensity	0.31	0.18	Significant	Local FinTech agglomeration raises digital economy performance
Spatial Lag of DEI	0.42	0.26	Significant	Digital outcomes diffuse across neighboring regions
Spatial Lag of FCI	0.24	0.1	Significant	FinTech spillovers from adjacent regions
Connectivity Control	0.19	0.22	Significant	Infrastructure strengthens digital adoption capacity

The table also shows that connectivity plays a particularly important role in rural regions, where its coefficient rivals that of FinTech clustering itself. This suggests that infrastructure constraints may dominate cluster effects outside urban cores. Taken together, the results support a nuanced interpretation: FinTech clusters generate both local and spillover benefits, but their effectiveness is mediated by regional digital readiness.

Impact Decomposition and Spillover Dynamics

The impact decomposition analysis provides deeper insight into how FinTech clustering effects propagate across space beyond average coefficient estimates. By separating total impacts into direct and indirect components, the results reveal that a substantial share of FinTech-driven digital gains materializes through spatial spillovers rather than purely local mechanisms. This finding underscores that the digital economy operates as an interconnected regional system, where localized innovation generates external benefits for surrounding areas.

The decomposition further shows that spillover dynamics differ markedly between urban and rural regimes. Urban regions not only capture stronger direct effects but also transmit a larger proportion of their gain's outward. In contrast, rural regions exhibit spillovers that are weaker and more spatially constrained. This pattern suggests that absorptive capacity and network density are decisive factors shaping how FinTech benefits diffuse geographically.

Figure 7 demonstrates that direct impacts dominate the total effect of FinTech clustering in both spatial regimes, but the contribution of indirect impacts is substantially larger in urban regions. This indicates that urban FinTech hubs not only benefit internally but also function as spillover generators, transmitting digital capacity to neighboring areas through platform reach and institutional linkages.

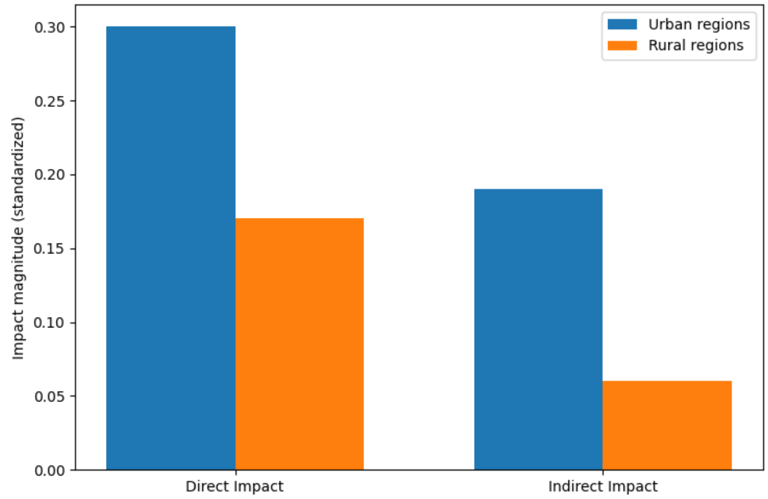

Figure 7 Decomposition of FinTech Cluster Impacts by Region Type

In rural regions, the indirect component is visibly smaller, suggesting limited spatial diffusion. This does not imply the absence of spillovers, but rather that their magnitude is constrained by weaker infrastructure, lower platform density, and reduced interregional integration. The figure thus supports the interpretation that spillovers are conditional phenomena, amplified by spatial and institutional context.

Table 8 quantifies the relative importance of spillovers in shaping total FinTech impacts. In urban regions, nearly forty percent of the total effect arises from indirect channels, highlighting the centrality of spatial diffusion in mature digital ecosystems. This reinforces the view that urban FinTech development has regional multiplier effects that extend beyond administrative boundaries.

Table 8 Direct and Indirect Impact Estimates by Spatial Regime

Region Type	Direct Impact	Indirect Impact	Total Impact	Share of Indirect Impact
Urban	0.3	0.19	0.49	38.80%
Rural	0.17	0.06	0.23	26.10%

By contrast, rural regions derive a smaller proportion of benefits from indirect effects, indicating that most gains remain localized. This asymmetry has direct policy implications: investments aimed at strengthening rural digital economies should prioritize connectivity, interoperability, and institutional linkages to enhance spillover absorption. Without such complements, FinTech clustering alone is unlikely to generate substantial cross-regional benefits.

Policy Implications and Regional Development Insights

The empirical results carry clear implications for place-based FinTech and digital economy policies. The evidence indicates that FinTech clustering generates substantial digital gains, but these gains are unevenly distributed due to structural differences between urban and rural regions. Urban regions benefit from both strong local agglomeration effects and sizable spillovers, while rural regions remain constrained by limited absorptive capacity. This suggests that uniform FinTech promotion policies are unlikely to yield balanced regional outcomes.

From a regional development perspective, the findings imply that sequencing matters. In rural areas, foundational investments in digital infrastructure, interoperability standards, and institutional readiness must precede or accompany FinTech ecosystem development. Without these complements, FinTech clustering risks reinforcing existing spatial inequalities rather than alleviating them. Conversely, in urban regions, policies that enhance interregional connectivity can amplify spillover transmission and extend digital benefits to surrounding areas.

Figure 8 synthesizes the empirical findings into a policy-oriented framework that differentiates urban amplification pathways from rural enablement pathways. In urban regions, the dominant mechanism is spillover amplification, where already-established FinTech clusters transmit digital benefits across space through interconnected platforms and labor markets. Policies that enhance interoperability and reduce administrative fragmentation can further strengthen this diffusion.

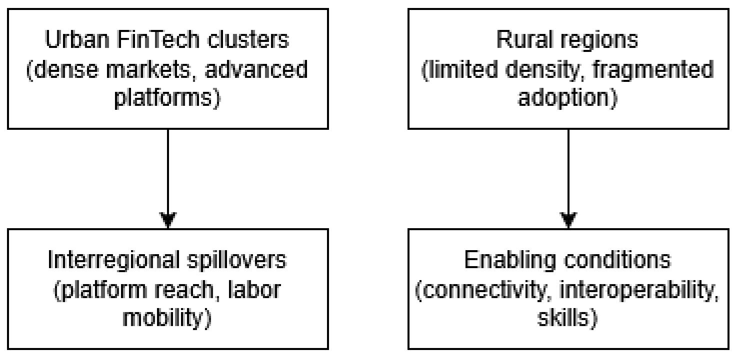

Figure 8 Policy-Oriented Pathways for FinTech Spillover Enhancement

In rural regions, the figure highlights that spillovers are conditional on enabling foundations. Rather than expecting FinTech firms to generate immediate diffusion effects, policymakers must first address binding constraints such as broadband coverage, digital identity systems, and institutional coordination. The visualization thus reinforces that spillovers are not automatic outcomes of proximity, but emergent properties of supportive ecosystems.

Table 9 distills the empirical insights into actionable policy guidance differentiated by spatial context. For urban regions, the main challenge is no longer FinTech adoption itself, but the efficient transmission of digital gains across administrative and functional boundaries. Policies focused on interoperability and regulatory harmonization are therefore likely to yield high marginal returns.

Table 9 Policy Implications by Spatial Regime

Spatial Regime	Key Constraint	Primary Policy Focus	Expected Outcome
Urban	Fragmented interregional integration	Enhance platform interoperability and cross-regional coordination	Stronger spillovers and regional digital diffusion
Rural	Low absorptive capacity	Invest in connectivity, skills, and digital infrastructure	Improved ability to capture FinTech spillovers

Peri-urban	Institutional mismatch	Align urban platforms with local adoption ecosystems	Hybrid spillover and localized digital growth

For rural regions, the table underscores that FinTech-led digital development is fundamentally capacity-constrained. Infrastructure and skills investments are not auxiliary measures but prerequisites for spillover realization. By explicitly linking spatial regime characteristics to tailored policy responses, the table reinforces the central conclusion of this study: FinTech spillovers are spatially contingent and policy-mediated, not automatic consequences of firm clustering.

Conclusion

This study provides robust empirical evidence that FinTech firm clustering plays a pivotal role in shaping digital economy performance through spatially mediated mechanisms. By applying spatial econometric analysis, the findings demonstrate that digital economic outcomes are not independently determined at the regional level, but are strongly influenced by interregional linkages and spatial dependence. Regions with dense FinTech ecosystems experience superior digital performance, confirming that FinTech firms act as structural catalysts within localized digital economies rather than as isolated technological actors.

The results further reveal pronounced urban–rural asymmetries in both the magnitude and transmission of FinTech-driven benefits. Urban regions capture stronger direct gains from clustering and generate substantial spillovers to neighboring areas, reflecting higher absorptive capacity and network density. In contrast, rural regions exhibit weaker indirect effects, indicating that proximity to FinTech hubs alone is insufficient to stimulate digital transformation without complementary infrastructure and institutional readiness. These findings highlight that spatial spillovers are conditional and shaped by regional context.

From a policy and research perspective, the study underscores the necessity of place-based digital development strategies. FinTech promotion policies should be aligned with regional characteristics, emphasizing spillover amplification in urban cores and capacity building in rural areas. For future research, extending the analysis to dynamic spatial models and integrating micro-level transaction data would deepen understanding of temporal diffusion processes. Overall, this study contributes to the FinTech and digital economy literature by demonstrating that spatial structure is a fundamental determinant of how digital innovation translates into regional economic outcomes.

Declarations

Author Contributions

Conceptualization: A.A. and H.G.; Methodology: H.G.; Software: A.A.; Validation: A.A. and H.G.; Formal Analysis: A.A. and H.G.; Investigation: A.A.; Resources: H.G.; Data Curation: H.G.; Writing Original Draft Preparation: A.A. and H.G.; Writing Review and Editing: H.G. and A.A.; Visualization: A.A.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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