Digital Development Convergence in the United States: A Spatial and Temporal Analysis from 2013 to 2023

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July 2025

Abstract

This study investigates the convergence of digital infrastructure across U.S. counties and states from 2013 to 2023, with a focus on whether regional disparities in digital access have narrowed over time. Using microdata from the Integrated Public Use Microdata Series (IPUMS USA), we construct a household-level digital access index based on device and internet connectivity variables. We apply both standard σ- and β-convergence models as well as a spatial lag β-convergence model to evaluate two key hypotheses: (1) initially disadvantaged regions have experienced faster digital growth, and (2) geographically proximate regions converge together through spatial spillovers. Our results provide strong evidence of both σ- and β-convergence at the county and state levels, indicating a general reduction in the digital divide. However, we find no robust support for spatial spillovers—regions do not appear to converge faster as a result of their neighbors' growth. This suggests that while local catch-up dynamics are at play, geographic diffusion of digital development may be limited by policy fragmentation, administrative boundaries, or infrastructure barriers.

Keywords: ICT Development, Spatial Economics, Convergence Analysis, Spatial and Temporal Statistical Analysis

1 Introduction

Digital infrastructure has become a critical enabler of economic participation, education, healthcare access, and public service delivery in the 21st century. While much of the early literature emphasized the role of broadband deployment in driving macroeconomic growth, recent studies have begun to focus on regional disparities in digital access and the implications for long-run development. Holt and Jamison (2009), for instance, argues that broadband infrastructure should be treated as a general-purpose technology whose deployment creates spillover benefits across sectors, similar to the historical role of electricity or transportation networks. Their analysis emphasizes the role of regulatory and institutional factors in shaping both the speed and equity of broadband diffusion across geographic regions.

This paper applies convergence analysis—a method traditionally used to study income or productivity growth—to the domain of digital infrastructure. Using household-level microdata from IPUMS USA (IPUMS USA, University of Minnesota (2023)), we construct a composite digital access index and apply both σ- and β-convergence models, along with a spatial lag β-convergence framework. This allows us to assess whether regions with initially poor digital access have experienced faster growth and whether proximity to more digitally advanced neighbors has any measurable effect. Through this empirical strategy, we aim to test two core hypotheses: that the digital divide is narrowing and that spatial spillovers play a role in shaping convergence dynamics.

Our study makes three main contributions. First, it quantitatively maps the trajectory of digital infrastructure development across the United States, providing evidence on both absolute and relative convergence. Second, it introduces spatial econometric modeling to assess geographic interdependence in digital growth—an aspect underexplored in the current literature. Third, it offers practical policy implications and highlights the importance of coordination across regions to address digital inequality.

2 Literature Review

2.1 Digital Infrastructures Development

Despite significant federal investments such as NTIA's "Internet for All" initiative, about 15% of U.S. households remained without high-speed internet in 2023 (National Telecommunications and Information Administration (NTIA), 2024). This phenomenon, called "digital divide"(Ragnedda and Muschert (2013)), which defined by the inequality of accessibility of digital technology, such as the Internet and computers. The persistence of this divide was already documented two decades ago in NTIA's foundational report "Falling Through the Net" (National Telecommunications and Information Administration (NTIA), 1999).

Digital infrastructures development and the digital divide have already became a critical and enduring research focus in the economic academic society. Empirical works such as Cohron (2015) use qualitative analysis and case studies to investigate the digital divide in the United States in the last 30 years; Malecki (2008) studies the spatial distribution of broadband providers across the United States; Smith and Johnson (2021) deployed a difference-in-difference model to analyzed the effectiveness of public program policies to mitigate the digital divide in the United States. Although these advanced literary measures analyzed the digital inequality across the United States, most of them focused on the policy analysis rather than the spatial-temporal growth differences between states and counties.

2.2 Convergence Analysis and Growth Models

This study draws on the economic convergence literature, which distinguishes between α-convergence Barro and Sala-i-Martin (1992), defined as a decline in the cross-sectional dispersion of a variable, and β-convergence, where initially disadvantaged units improve at a faster rate than more advanced counterparts. This econometric research framework inspired a wide range of studies on economic development and growth economics.

Empirical study on economic growth convergence is a popular topic in economic development. Classic works include Barro and Sala-i-Martin (1992, 1991) on national income convergence; studies on U.S. state-level convergence (e.g., Baumol, 1986); and investigations into sectoral and regional convergence using panel and spatial econometric methods (e.g., Islam, 2003; Quah, 1996).

More recently, convergence research has been extended to digital domains, examining broadband infrastructure, internet penetration, and ICT diffusion. For example, Röller and Waverman (2001) estimates the impact of telecommunications infrastructure on cross-country growth, while Czernich et al.

(2011) quantifies how broadband adoption increases GDP per capita across OECD countries. However, none of these works examine how the overall digital infrastructures develop, leaving a research gap for this paper.

2.3 Spatial Statistics for Economics

Recent years have witnessed growing scholarly interest in the spatial interactions between economic and geographic characteristics, particularly how spatial proximity and diffusion influence regional development outcomes. The concept of spatial convergence refers to the process by which neighboring regions, through spatial spillover effects, experience a reduction in development disparities over time, often examined using spatial econometric models such as spatial lag or spatial error convergence models (Rey and Dev (2006)).

Kozonogova and Dubrovskaya (2021) investigates the spatial convergence of digital infrastructures at both local and global levels in the Russian Federation by using unconditional β-convergence. Li et al. (2022) estimate the spatial convergence of digital village development levels in China using the conditional β-convergence approach based on spatial panel modeling. Appalachian Regional Commission (2002) measure the digital development level in the Southeastern United States using an accounting-based evaluation of information and telecommunication infrastructure.

While these studies primarily focused on OECD countries and the regional U.S. data, they leave open the question of whether and how digital infrastructure development converges and its interactions between their spatial characteristics within the United States, which is one of the focuses of this study.

3 Dataset

3.1 Overview

In this study, we use microdata from the Integrated Public Use Microdata Series, United States of America (IPUMS USA), which provides nationally representative individual- and household-level data extracted from decennial U.S. censuses and the American Community Survey (ACS). The data include variables from the years 2013–2023, drawn primarily from ACS 1-year and 5-year samples, and reflect non-institutionalized households, excluding group quarters in most cases

3.2 Variable Description

The table below is a concise description of the interpretation for each variable in the given dataset.

3.3 Summary Statistics

The Table 2 below shows the summary statistics for all categorical variables.

3.4 Data Processing

To prepare the dataset for analysis, we first restrict the IPUMS USA microdata to the period from 2013 onward. We then perform several data cleaning steps, including filtering out group quarters and removing the original URBAN variable due to definitional inconsistencies. Core digital access variables are recoded into binary indicators: households are coded as 1 if they report access to a laptop or desktop (CILAPTOP), a smartphone (CISMRTPHN), a cellular data plan (CIDATAPLN), or broadband Internet (CIHISPEED), and 0 otherwise. Some missing values are imputed as 0 under conservative assumptions (e.g., lack of smartphone access). Finally, we compute a composite digital access index for each household by averaging the four binary indicators, reflecting the breadth of digital connectivity. Observations with missing values in any of these components are excluded from the final analytical sample.

For more detailed information about data transformation of CIHISPEED, we recode 10 and 20 as 1 to indicate access to broadband or satellite internet, and 0 if the household reports 0 (no access). Response 88 is treated as missing. For other variables(CILAPTOP, CISMRTPHN, CIDATAPLN), we recode 1 as 1 (has access) and 0 as 0 (no access). 8 is treated as missing. We classified 1, 0, 3 for METRO as Rural and others as URBAN.

A detailed data processing pipeline structure is shown in the Figure 1.

Table 1: Summary of Key Discrete Variables in the IPUMS Dataset

Variable	**Description**	**Encoded Values**
`YEAR`	Census year	2013–2023 (four-digit year of enumeration)
`SAMPLE`	IPUMS sample identifier	6-digit code, e.g., 202301 (2023 ACS); 201903 (2015–2019 ACS 5-year)
`METRO`	Metropolitan status	0(Mixed/indeterminable); 1(Not in metro area); 2(In metro, central city); 3(In metro, non-central city); 4(In metro, city status mixed)
`URBAN`	Urban/rural classification	0(N/A); 1(Rural); 2(Urban)
`GQ`	Group quarters status	0(Vacant); 1(Household—1970 def.); 2(Household—1990 def.); 3(Institution); 4(Other GQ); 5(Household—2000 def.); 6(Fragment)
`CILAPTOP`	Access to laptop/desktop computer	0(N/A, GQ); 1(Yes); 2(No)
`CISMRTPHN`	Access to smartphone	0(N/A, GQ); 1(Yes); 2(No)
`CIDATAPLN`	Cellular data plan	0(N/A, GQ); 1(Yes); 2(No); 8(Suppressed for 2023)
`STATEICP`	State identifier	Encoded using ICPSR state codes (no further decoding required)

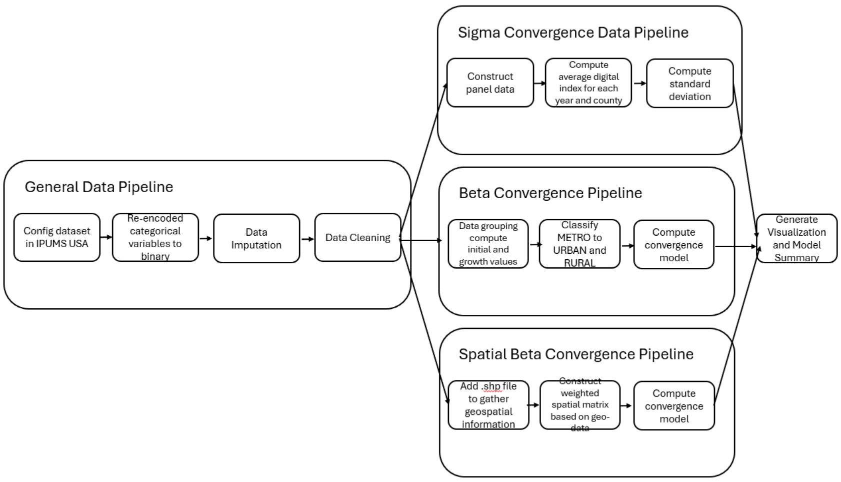

Figure 1: **A detailed view of the data processing pipeline we used in this paper.**

4 Methodology

In this paper, we used both standard convergence models, such as σ-convergence and *beta*-convergence, as well asthe spatial lag β-convergence model to evaluate our hypotheses: 1) regional digital amenity levels in the United States exhibit convergence over time; 2) the spatial structure matters: regions should exhibit similar catch-up effect with their neighbors.

4.1 Standard Convergence Models

To assess regional convergence in digital infrastructure across U.S. counties and states over time, we adopt two standard frameworks from the economic growth literature: σ-convergence and β-convergence. These models are commonly used to evaluate whether disparities in a given indicator (e.g., income, education, digital access) are diminishing over time across spatial units. In our case, we examine whether regions with initially low levels of digital access have experienced faster growth, thereby narrowing the digital divide.

Table 2: Distribution of Key Discrete Variables

Category	Level	Description	n	Proportion
Broadband Access	0	No access to broadband	746,098	0.1101
	10	Has broadband access	5,051,204	0.7451
	20	Satellite internet	981,146	0.1447
	88	Suppressed/missing	739	0.0001
Laptop Ownership	1	Has laptop/desktop	5,480,223	0.8084
	2	No laptop/desktop	941,829	0.1389
Smartphone Access	1	Has smartphone	5,992,345	0.8839
	2	No smartphone	429,707	0.0634
Mobile Data Plan	1	Has data plan	5,716,327	0.8432
	2	No data plan	316,023	0.0466
Metro Status	1	Not in metro area	710,369	0.1048
	2	In metro central city	759,632	0.1121
	3	In metro non-central city	1,934,710	0.2854
	4	Mixed city status	2,355,390	0.3474

4.1.1 σ-Convergence Model

The σ-convergence model is used to assess whether the overall dispersion in digital infrastructure across regions has decreased over time. It captures the extent to which inequalities in digital access persist or diminish by examining the standard deviation of digital index values across counties or states. This approach is particularly useful for tracking long-term equalization trends in access to technology and connectivity.

Let $x_{i,t}$ denote the digital index for region i at time t. Then σ-convergence is assessed by computing the cross-sectional standard deviation:

$$\sigma_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{i,t} - \bar{x}_t)^2}$$

where $\bar{x}_t$ is the mean digital index across all N regions at time t. A declining sequence of σ_t over years (e.g., 2013–2023) indicates convergence.

4.1.2 β-Convergence Model

The β-convergence model is employed to evaluate whether initially lagging regions are catching up over time in terms of digital infrastructure. Specifically, it tests whether areas with lower digital index levels in the base year tend to experience faster growth in subsequent years. This model is suitable for identifying conditional or absolute convergence dynamics and is widely used in regional development and growth economics.

Let $x_{i,2013}$ and $x_{i,2023}$ denote the digital index for region i in 2013 and 2023, respectively. We define the change in index as:

$$\Delta x_i = x_{i,2023} - x_{i,2013}$$

The β-convergence model is then:

$$\Delta x_i = \alpha + \beta x_{i,2013} + \varepsilon_i$$

where $\beta < 0$ indicates convergence: regions with lower initial digital access experienced higher growth. We estimate this model at both the county and state levels. Additionally, we extend the interpretation by examining whether convergence dynamics differ by urbanization, using the proportion of urban counties in each state as a contextual moderator.

4.2 Spatial Lag β-Convergence Model

To evaluate whether spatial dependence influences the convergence of digital infrastructure, we extend the baseline β-convergence model by incorporating a spatial lag term. This spatial lag β-convergence model allows us to test whether the growth of digital access in a given region is associated with the average growth of its geographically adjacent neighbors. The model accounts for potential spatial spillovers that may arise from shared infrastructure, regional planning, or market diffusion effects.

Formally, the model is specified as:

$$\Delta x_i = \alpha + \beta x_{i,0} + \rho \sum_{j=1}^{N} w_{ij} \Delta x_j + \varepsilon_i,$$

where Δx_i denotes the growth in digital index for region i over the study period (e.g., 2023–2013), $x_{i,0}$ is the initial digital index level in 2013, and w_{ij} are elements of a row-standardized spatial weights matrix W based on county-level contiguity. The term $\sum_j w_{ij} \Delta x_j$ represents the average growth in neighboring regions, and ρ captures the magnitude and direction of spatial dependence. A significantly positive ρ indicates that regions tend to converge in tandem with their neighbors, supporting the presence of spatial convergence.

In our empirical implementation, the spatial weights matrix is constructed using queen contiguity based on U.S. county shapefiles. We use a linear regression approach that includes the spatial lag term as an additional explanatory variable. This model enables us to directly test Hypothesis 2: whether geographically proximate regions exhibit similar convergence behavior.

5 Estimations

5.1 σ-Convergence Model Estimation(County-level)

The results of the σ-convergence analysis, presented in Table 3, reveal a general decline in the cross-sectional standard deviation of the digital index across counties from 2013 to 2023. The standard deviation decreased from 0.0617 in 2013 to 0.0286 in 2023, indicating that regional disparities in digital infrastructure have narrowed over the decade. Importantly, the standard deviation remains within a relatively low range throughout the observed period, suggesting that even at the starting point, differences in digital access across counties were moderate in scale. This low level of dispersion strengthens the evidence of convergence, as already modest inequalities continued to diminish over time.

While there are some short-term fluctuations—for example, an uptick in dispersion between 2013 and 2015, and a spike in 2020 possibly due to pandemic-related disruptions—the overall trend is downward. This supports the hypothesis of σ-convergence: regions with initially different levels of digital access are becoming more similar, and digital inequality across U.S. counties is gradually leveling out.

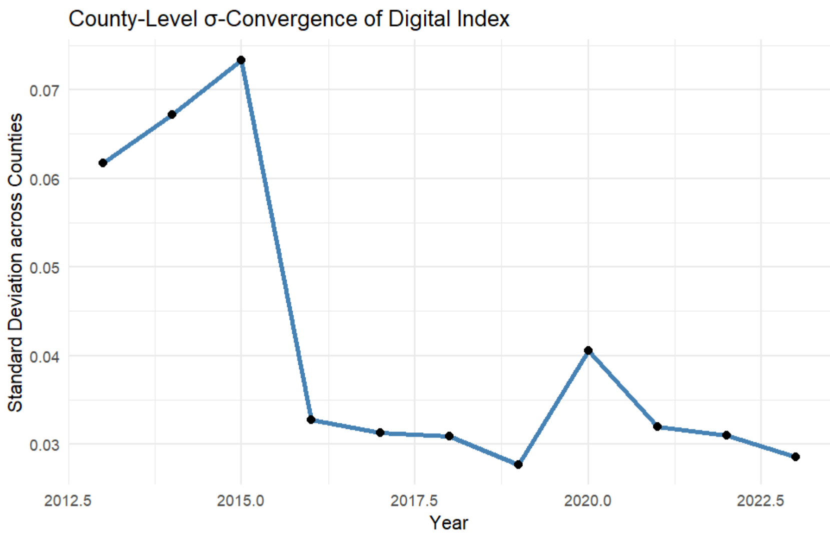

Figure 2: σ-**Convergence**. σ-convergence model of county-level digital index. a) The y-axis represents the standard deviation across counties; b) The x-axis represents the time.

Table 3: σ-Convergence Model Coefficients

Year	Standard Deviation
2013	0.0617
2014	0.0671
2015	0.0733
2016	0.0327
2017	0.0313
2018	0.0309
2019	0.0277
2020	0.0405
2021	0.0320
2022	0.0310
2023	0.0286

5.2 β-Convergence Model Estimation(County-level)

The β-convergence results at the county level, as shown in Table 4 and visualized in Figure 3, provide strong evidence of digital convergence across U.S. counties between 2013 and 2023. The regression model yields a significantly negative coefficient for the initial digital index ($\beta = -0.737$, $p < 2 \times 10^{-16}$), indicating that counties with lower starting levels of digital access experienced faster growth in subsequent years. This pattern is consistent with the theoretical expectation of absolute β-convergence, where lagging regions progressively catch up with more advanced ones.

The scatterplot in Figure 3 offers additional insights by distinguishing counties by region type. Urban counties (in red) and rural counties (in blue) both generally conform to the negative trend, suggesting that convergence dynamics are robust across regional classifications. However, urban counties tend to cluster at higher initial digital index values with smaller gains, while rural counties are more concentrated at the lower end of the initial distribution and tend to exhibit larger improvements. This visual pattern reinforces the notion that the convergence process is at least partly driven by rural catch-up, with counties that were previously underserved making significant strides in digital access over the decade. The consistent downward slope and narrow confidence band also reflect a well-fitted model with low residual dispersion ($R^2 = 0.806$).

Together, the regression results and urban-rural segmentation underscore that β-convergence in digital infrastructure is not only statistically strong but also spatially inclusive, benefiting both urban and rural counties—particularly those that were most disadvantaged in 2013.

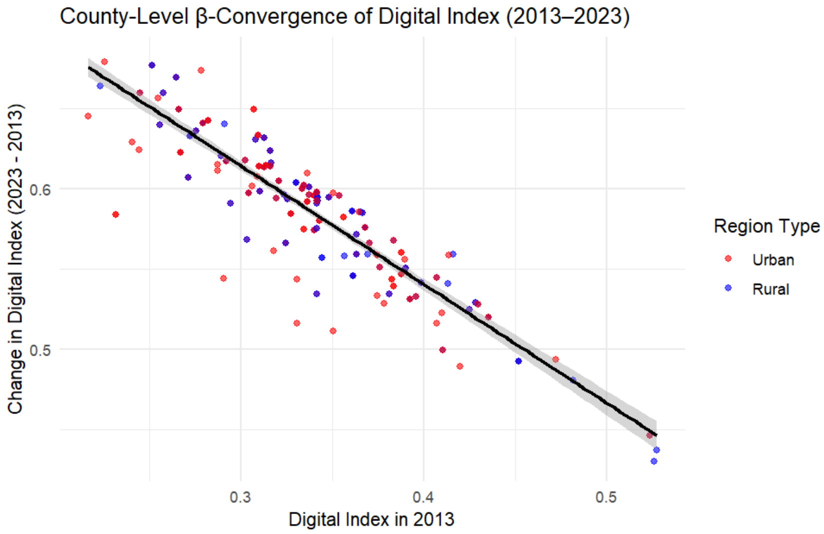

Figure 3: **β-Convergence(County-level)**. β-convergence model of county-level digital index. a) The y-axis represents the change in digital index from 2013 to 2023 across counties; b) The x-axis represents the digital index in 2013.

Table 4: β-Convergence Model Coefficients

Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> $\|t\|$)**
(Intercept)	0.835132	0.007696	108.51	<2e-16 ***
Digital Index (2013)	-0.736670	0.022489	-32.76	<2e-16 ***
Residual Summary				
Min	1Q	Median	3Q	Max
-0.0808	-0.0093	0.0046	0.0117	0.0433
Model Summary				
Residual Std. Error	0.01977 (on 259 df)			
Multiple R^2	0.8056			
Adjusted R^2	0.8048			
F-statistic	1073 on 1 and 259 df, p < 2.2e-16			

Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

5.3 β-Convergence Model Estimation(State-level)

The state-level β-convergence model (Table 5) demonstrates a strong negative relationship between states' initial digital index in 2013 and their growth in digital access over the following decade. The estimated coefficient for the 2013 index is $\beta = -0.829$, highly significant at $p < 2 \times 10^{-16}$, indicating that states with initially lower digital development experienced larger gains between 2013 and 2023. The high explanatory power ($R^2 = 0.87$) and low residual error reflect a robust and systematic convergence process across U.S. states.

Figure 4 visualizes this convergence pattern, with each state labeled and shaded by its urban county share. While most states conform to the downward-sloping regression line, there is notable variation in initial values and growth trajectories. For instance, some states with relatively low urban shares, such as West Virginia, South Dakota, and Montana, appear in the upper-left region of the plot—indicating low starting values but high growth, consistent with a catch-up dynamic.

However, an interesting subset of states—such as Vermont, New Hampshire, and Maine—display both low urban shares and relatively high initial digital index values. This suggests that urbanization alone does not fully determine digital development, especially in smaller, compact states where geographic scale, historical infrastructure investment, or policy prioritization may compensate for the lack of metropolitan counties. These states may benefit from more uniformly distributed broadband policies or stronger public investment in rural areas.

The bar chart in Figure 5 reinforces this observation, showing that states like Vermont and New Hampshire rank among the lowest in urban county share, yet maintain competitive digital access metrics. Overall, the joint interpretation of convergence trends and urbanization gradients suggests that while urban density is a facilitating factor, it is not a necessary condition for strong digital growth or early adoption. Policy context, state capacity, and regional coordination also play a critical role in shaping convergence outcomes.

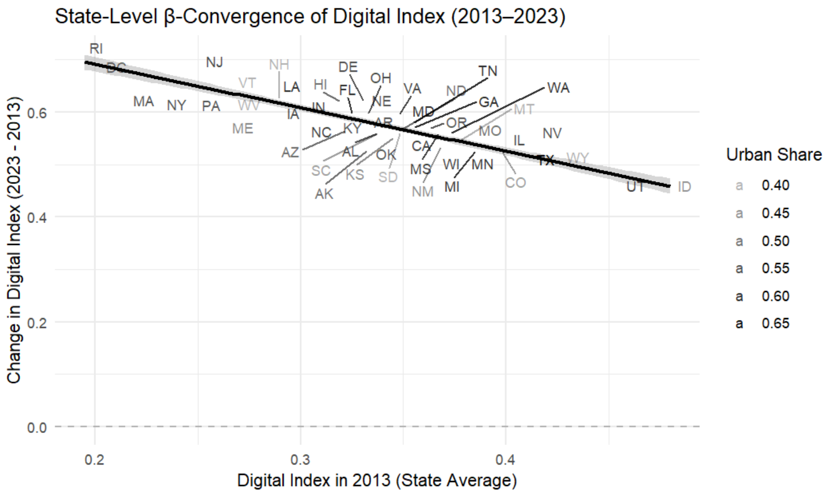

Figure 4: β**-Convergence(State-level)**. β-convergence model of state-level digital index. a) The y-axis represents the change in digital index from 2013 to 2023 across counties; b) The x-axis represents the digital index in 2013; c) The opacity of the state name encodes the urban share in each state.

Table 5: State-Level β-Convergence Model Coefficients

Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> $\|t\|$)**
(Intercept)	0.85702	0.01589	53.93	<2e-16 ***
Digital Index (2013)	-0.82900	0.04624	-17.93	<2e-16 ***
Residual Summary				
Min	1Q	Median	3Q	Max
-0.0535	-0.0131	-0.0007	0.0111	0.0410
Model Summary				
Residual Std. Error	0.01838 (on 48 df)			
Multiple R^2	0.8701			
Adjusted R^2	0.8674			
F-statistic	321.4 on 1 and 48 df, p < 2.2e-16			

Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

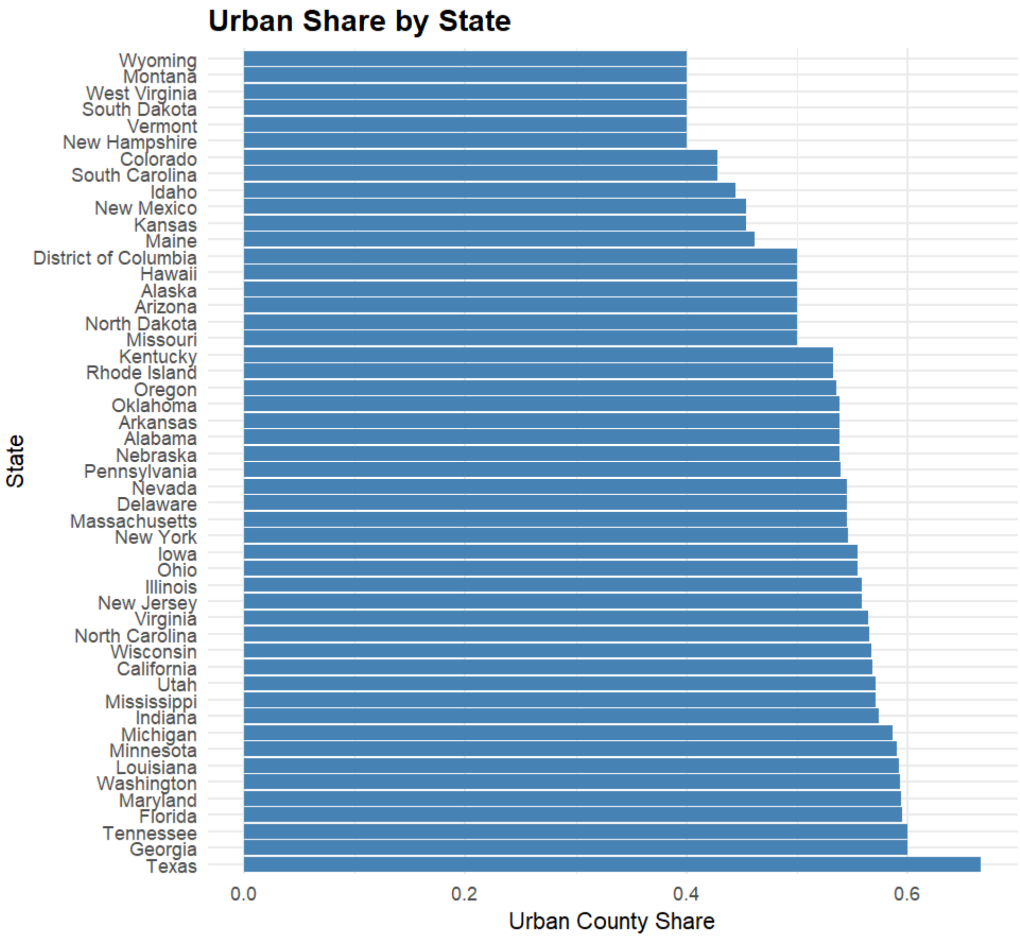

Figure 5: **Urban Shares**. β-convergence model of state-level digital index. a) The y-axis represents the change in digital index from 2013 to 2023 across counties; b) The x-axis represents the digital index in 2013; c) The opacity of the state name encodes the urban share in each state.

5.4 Spatial Lag β-Convergence Model Estimation(County-level)

Table 6 presents the results of a county-level β-convergence model that includes a spatial lag term to capture potential spatial spillover effects. The coefficient on the initial digital index in 2013 is significantly negative ($\beta = -0.7675$, $p < 0.001$), confirming strong evidence of β-convergence: counties with lower starting levels of digital infrastructure experienced faster growth between 2013 and 2023.

However, the spatial lag term, representing the average growth of neighboring counties, is not statistically significant ($\rho = 0.0090$, $p = 0.107$). This indicates that spatial spillover effects are not robustly detected in this model, and thus, Hypothesis 2 — which posits that geographically proximate counties tend to exhibit similar convergence behavior — is not supported.

Table 6: County-Level β-Convergence Model with Spatial Lag Term

Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> $\|t\|$)**
(Intercept)	0.8423	0.0039	215.216	<2e-16 ***
Digital Index (2013)	-0.7675	0.0065	-118.194	<2e-16 ***
Spatial Lag of Change	0.0090	0.0056	1.612	0.107
Residual Summary				
Min	1Q	Median	3Q	Max
-0.0866	-0.0086	0.0031	0.0106	0.0395
Model Summary				
Residual Std. Error	0.01585 (on 2796 df)			
Multiple R^2	0.8332			
Adjusted R^2	0.8331			
F-statistic	6985 on 2 and 2796 df, $p < 2.2\text{e-}16$			

Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

6 Results

Our empirical findings demonstrate strong evidence of β-convergence across U.S. counties from 2013 to 2023. Counties with lower initial digital index values experienced significantly faster growth, as reflected by the large and statistically significant negative coefficient on the 2013 digital index. The σ-convergence analysis further supports this pattern, showing a steady decline in the cross-sectional dispersion of digital access. Together, these results suggest a nationwide trend toward closing the digital divide over the past decade.

However, our spatial lag β-convergence model does not provide strong support for Hypothesis 2. The spatial lag term, representing the average digital growth of neighboring counties, is statistically insignificant. This implies that while local catch-up dynamics are evident, spatial spillover effects—i.e., the tendency for digital growth to diffuse through geographic proximity—are not robustly detected. The lack of significance may be due to the influence of administrative boundaries, non-geographic drivers of digital development, or limitations in the contiguity-based spatial weights used.

7 Discussions

7.1 Policy Implications

The confirmed presence of both σ-convergence and β-convergence suggests that federal and state-level policies promoting digital equity have been at least partially effective, particularly in enabling lagging regions to catch up.

However, the absence of spatial spillovers highlights a missed opportunity: infrastructure investment and digital policy may not be effectively diffused beyond county lines. Both the state and the federal governments should place greater emphasis on improving the transportation infrastructure and the network infrastructure to reduce the spatial gap between urban and rural regions. Policymakers should also consider fostering regional collaboration and cross-jurisdictional planning to amplify the effects of digital development and address fragmentation in rural connectivity efforts.

7.2 Generalization, Limitations, and Future Works

While the results provide strong evidence of convergence, they are subject to certain limitations. First, this analysis is based only on a small fraction of the national data since IPUMS USA only provided microdata, which has a limitation on data coverage. Second, the spatial structure is modeled using static contiguity, which may not fully capture the functional geography of digital infrastructure. Third, many counties that we investigated in the dataset have many missing values and incomplete records, which might also lead to statistical bias in our analyses. Future work could incorporate dynamic spatial models, examine multi-level structures (e.g., counties nested within states), or explore convergence mechanisms in relation to socio-economic outcomes such as education, health, or employment. These directions would enhance the generalizability and policy relevance of digital convergence research.

8 Reproducibility Statement

All R files involved in this paper can be accessed through Digital-Drifting GitHub Repository . IPUMS USA datasets are private datasets, but all experiments can be reproduced by following the data and programming configurations that are specified in the README.md file.

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