Despite Improvement, the U.S. Care Economy Remains Geographically Unequal

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Abstract

The formal care economy including paid labor in health care, education, and daily living support is essential to individual well-being and national productivity. Yet access to these services remains geographically unequal across the United States. Here, we develop the Care Resource Equity Score (CaRES), a that integrates the Gini coefficient and Location Quotient to jointly quantify internal distribution and regional concentration of care employment. Using tract-level data from 2009 to 2021 across all U.S. counties, we apply CaRES to assess equity in three care sectors: health care, education, and daily living. We identify four typologies Equitable Coverage, Unequal Scarcity, Concentrated Access, and Even Desert and find that most counties exhibit either insufficient or unevenly distributed care resources. Rural counties disproportionately experience Even Deserts, whereas urban areas more often show localized inaccessibility despite resource abundance. Although spatial inequality has declined nationally, it is often accompanied by decreasing care employment levels. The CaRES framework enables a more comprehensive, scalable assessment of care access and offers actionable insights for targeting policy interventions.

Introduction

Across the globe, demographic, economic, and social transformations are reshaping how societies organize and provide care. Aging populations lead to increasing demand for health and eldercare [1]. Simultaneously, rising female labor force participation from 50% in 1980 to over 57% in the United States (U.S.) today has reduced the availability of unpaid caregivers within households [2]. The growing prevalence of dual-earner and single-parent households has further intensified reliance on formal care infrastructure [3,4]. These shifts have made the care economy once considered peripheral to mainstream economic policy a focal point of both academic and policy concern [5–7].

The formal care economy encompasses paid labor that supports the health, development, and daily living needs of individuals. This sector includes not only teachers, nurses, and home health aides but also food service workers and childcare providers whose labor enables the functioning of households and the broader workforce. Nearly 48 million adults in the U.S., approximately 18% of the labor force, are employed in care-related occupations, reflecting the sector's increasing importance to economic and social well-being [8].

Yet, despite its growing size and importance, the care economy remains under-recognized, undervalued, and unevenly accessible across communities [9,10]. Understanding where and how care is delivered and where it is lacking has thus become essential for ensuring economic inclusion, gender equity, and social resilience in an era of structural change. As part of the effort, scholars have defined the areas lacking services as "deserts"[11]. However, the lack of a standardized definition for "care deserts" complicates efforts to identify and compare these areas systematically. In the absence of a universal methodology, scholars have employed a range of tools to delineate care-scarce regions[12–15]. Among the most commonly used are the Gini coefficient, which measures internal inequality [16], and the Location Quotient (LQ), which captures regional concentration of services [17]. Some studies also used geographic proximity such as distance to the nearest facility to assess access[13]. However, each approach has notable limitations. The Gini coefficient reflects disparities in distribution but does not account for overall adequacy[18]. The LQ indicates whether services are concentrated or underrepresented but fails to capture how equitably they are distributed within a region[19,20]. Distance-based measures, while intuitive, are difficult to generalize across large study areas and require context-specific definitions of acceptable travel distances, which may vary by service type, infrastructure, and population needs [13,21].

Moreover, existing approaches often focus on either the adequacy or the equity of care resources, but rarely both, which can constrain our ability to fully characterize and compare care deserts. Some prior studies have applied multiple indices to mitigate individual limitations[19,22], no existing approach integrates these dimensions into a single, unified framework. Additionally, while a substantial body of research has applied these tools to identify underserved areas, such classifications may not always distinguish between different types of scarcity whether due to a lack of overall resources or to their uneven distribution within communities. This distinction is important for designing effective interventions tailored to specific local needs. Additionally, few studies have examined how they evolve over time, particularly across multiple sectors. Most existing research remains cross-sectional, leaving important questions about the persistence, mitigation, or expansion of care scarcity unanswered.

In this study, we introduce the Care Resource Equity Score (CaRES), a new framework that jointly captures both the supply and spatial distribution of formal care employment. Combining the Gini coefficient and LQ into a standardized metric, CaRES enables consistent comparisons across geographies, time, and sectors. Using data from 2009 to 2021 across all U.S. counties, we assess equity in three care domains health care, education, and daily living and identify persistent clusters of inequality using spatial analysis. By providing a standardized typology of care access, CaRES offers a new lens for understanding regional disparities in the care economy. In this study, we detail the development of the CaRES framework, analyze spatial and temporal trends in care provision, and identify regional clusters using Local Indicators of Spatial Association (LISA).

Methods

This paper calculates yearly CaRES measurements at the county level for 2009-2021, using census tract-level data. Due to data availability, some counties periodically drop out of the sample as different states change their reporting, resulting in the Census Bureau's inability to provide estimates for needed data to compute the score. During the years of this study, data availability for Mississippi ends after 2018, Alaska ends after 2016, and Massachusetts begins in 2011. We provide the score only for counties with full data availability within a year. We rely on two specific data measures at the census tract level to create this data: 1) Census tract level employment data in the care economy, and 2) Census tract level population data. We excluded the District of Columbia from the analysis, as it comprises only a single census tract, making it unsuitable for calculating the Gini coefficient required for this study's spatial inequality framework. We also exclude counties with too small population counts that are located in a single census tract, as these counties lack sufficient subunit variation to calculate the GINI.

We used census tract data to create county-level estimates because it provides the necessary sub-county variation for calculating measures like the Gini coefficient. While census blocks offer finer geographic detail, they are often too small for analyzing resource distribution due to ease of access across block boundaries. Census tracts, typically covering 1,000 to 8,000 people, strike a balance between geographic resolution and data availability, making them a common proxy for neighborhoods in research on spatial and demographic inequality.[11]

To gather employment data at the census tract level in the care economy, we utilized the Workplace Area Characteristics dataset from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics program, developed by the U.S. Census Bureau. This dataset utilizes both census and administrative data to provide yearly employment statistics at the census block level by North American Industry Classification System industry codes. The data itself comes from State unemployment insurance wage records, the Quarterly Census of Employment and Wages, Federal employment data from the Office of Personnel Management, various Census Bureau surveys and administrative data. Data from WAC covers most US states from 2002-2021 except for the cases listed above.

We split this data into three care economy categories based on industry codes. The WAC data utilizes 2-digit NAICS codes, which split jobs into broad categories. Among these, we pull out code 61, representing "Educational Services", code 62, representing "Health Care and Social Assistance", and code 72, representing "Accommodation and Food Services." These three groups represent the three distinct sectors of the Care Economy, as defined by the Care Board[8]. These sectors encompass a wide range of care activities that occur both in formal markets and at home, including childcare, caring for a sick family member, and household chores such as cooking or cleaning. These sectors are referred to as Educational Services, Health Care, and Daily Living to match naming conventions with prior work[8]. We computed separate CaRES scores for each of these three sectors.

The U.S. census tract population data is obtained from the five-year American Community Survey (ACS) [31]. The ACS five-year estimates represent aggregated data from five consecutive years of ACS responses. This aggregation allows for better statistical reliability and geographic granularity. We used this data to gather information at the census tract level for comparison with the WAC employment data.

The urban and rural spectra are associated with resource allocation and employment [13,32]. Therefore, we applied urban and rural classifications from the U.S. Department of Agriculture

(USDA)'s 2013 Rural-Urban Continuum Codes (RUCC), which provide county-level categories based on metropolitan influence and population size [33]. RUCC 2013 was selected to maintain consistency across our 2009–2021 study period and to match the geographic scale of GINI and LQ metrics. RUCC codes classify U.S. counties on a 9-point scale based on metropolitan influence and population size. A detailed description of the urban and rural classification scheme is provided in Table S1.

Care Resource Equity Score (CaRES) development
Gini coefficient

The Gini coefficient measures inequality in resource distribution, ranging from 0 (perfect equality) to 1 (maximum inequality) [16]. While often applied to income, we used it to assess how evenly care-related employment is distributed across census tracts within each county. Higher values indicate care jobs are concentrated in a few tracts, while lower values suggest more equitable distribution relative to population. We calculated annual Gini coefficients (2009–2021) for three sectors (Health Care, Educational Services, and Other Services) using population-weighted tract-level employment data. See supplemental materials for calculation details.

Location Quotients (LQs)

The Location Quotient (LQ) identifies whether a region is specialized in an industry relative to the national average [17]. We used LQ to determine if care-related jobs are disproportionately concentrated in certain counties. An LQ of 1.0 indicates average representation; values above 1.0 suggest specialization, while values below 1.0 indicate underrepresentation. This metric highlights local surpluses or shortages in care employment, supporting our analysis of resource equity (see supplemental materials for calculation details).

GINI and LQ Typology

Although both the Gini coefficient and LQ measure aspects of community resources, they capture different dimensions. LQ reflects the concentration of care jobs relative to the national average, while the Gini coefficient measures how evenly those jobs are distributed within a county. High Gini values (above 0.5) indicate significant inequality [34], whereas LQ values above 1 suggest a surplus of care jobs. Using thresholds of 0.5 for Gini and 1.0 for LQ, we developed a 2×2 typology to classify counties (Table 1). This framework identifies four categories: Equitable Coverage (high LQ, low Gini), where care jobs are both plentiful and accessible; Unequal Scarcity (low LQ, high Gini), where care jobs are few and unequally distributed; Care Deserts (low LQ, low Gini), where jobs are scarce but access is equally limited; and Unequal Access (high LQ, high Gini), where care jobs are concentrated in specific areas, limiting reach. This typology helps clarify the distinct policy challenges facing different types of communities.

Table 1 GINI – LQ Typology

Low GINI – High LQ (Equitable Coverage)	High Gini – High LQ (Concentrated Access)
Low Gini – Low LQ (Even Desert)	High GINI – Low LQ (Unequal Scarcity)

Care Resource Equity Score (CaRES)

While typologies are useful for categorizing locations, quantitative researchers also need a continuous measure to assess variation across counties. To evaluate spatial equity in care-related employment, we developed the Care Resource Equity Score (CaRES), calculated separately for three sectors: health care, educational services, and daily living services. CaRES combines two standardized metrics—the Gini coefficient (measuring spatial inequality) and the Location Quotient (LQ, measuring employment concentration)—using z-scores to place them on the same scale. The score is calculated by subtracting standardized LQ from standardized Gini, so higher CaRES values indicate counties with both fewer care jobs and greater inequality in their distribution. Lower scores reflect more equitable, resource-rich environments. This continuous measure highlights counties facing care access challenges due to both scarcity and uneven distribution. See Supplementary Materials for full calculation details.

Spatial Analysis

We used spatial analysis to examine clustering and outliers in care-related employment equity across U.S. counties from 2009 to 2021. A Queen contiguity spatial weights matrix defined neighboring counties. We calculated global Moran's I to assess overall spatial autocorrelation in CaRES scores, and Local Moran's I (LISA) to identify localized clusters [35]. LISA detects whether a county's CaRES is significantly similar to its neighbors, categorizing results as High–High (HH), Low–Low (LL), High–Low (HL), or Low–High (LH). HH clusters signal widespread inequity, while LL clusters suggest equitable care access. HL and LH identify outliers, and non-significant counties showed no spatial autocorrelation. To assess trends, we aggregated annual LISA results for each care sector, scaled cluster counts for visual comparison, and excluded non-significant cases. We also analyzed clustering across the rural–urban spectrum by linking LISA results with RUCC codes and calculating proportions of cluster types per RUCC category, scaled for standardized comparison.

Results

Using the typology classifications discussed above, we calculate the GINI and LQ for each U.S. county, using the available data, and plot them on a map. As shown in Fig.1, the bivariate maps illustrate distinct spatial typologies in care employment across U.S. counties. Each of the four typologies is represented on this map, with white representing the Even Deserts, dark green representing the Concentrated Access, light blue representing the Unequal Scarcity, and light green representing the Equitable coverage the colors between these categories representing counties that exist near the borders between these categories. The normatively desirable category of High LQ and Low GINI is particularly evident in parts of the Northeast, Upper Midwest, and coastal areas, suggesting more balanced and widespread access to healthcare, education, and other services in those regions. In contrast, the light blue color, representing the undesirable category of a low LQ and high GINI, is found throughout the Southeast, Rust Belt, and western counties.

The figure below illustrates the benefits of combining these scores to create the typologies. Regional concentrations and patterns exist in these typologies that would not be evident if the GINI and LQ results were examined separately. For example, both the Midwest and Southeast see low LQ scores, which is evidence of an undersupply of care jobs. However, once the GINI coefficient is also included, we see that while the Midwest has fewer resources, these resources tend to be more equitably distributed than in the Southeast. This distinction also works for counties with the same GINI but different LQ scores. For instance, both Florida and Texas have numerous counties with high levels of educational services inequality. However, for Florida, this is compounded by a low LQ score, indicating fewer jobs than would be expected, compared to Texas, which has above-average employment in many areas but continues to experience high Gini scores. The CaRES typology enables the classification of communities in a novel manner, distinguishing between these various factors.

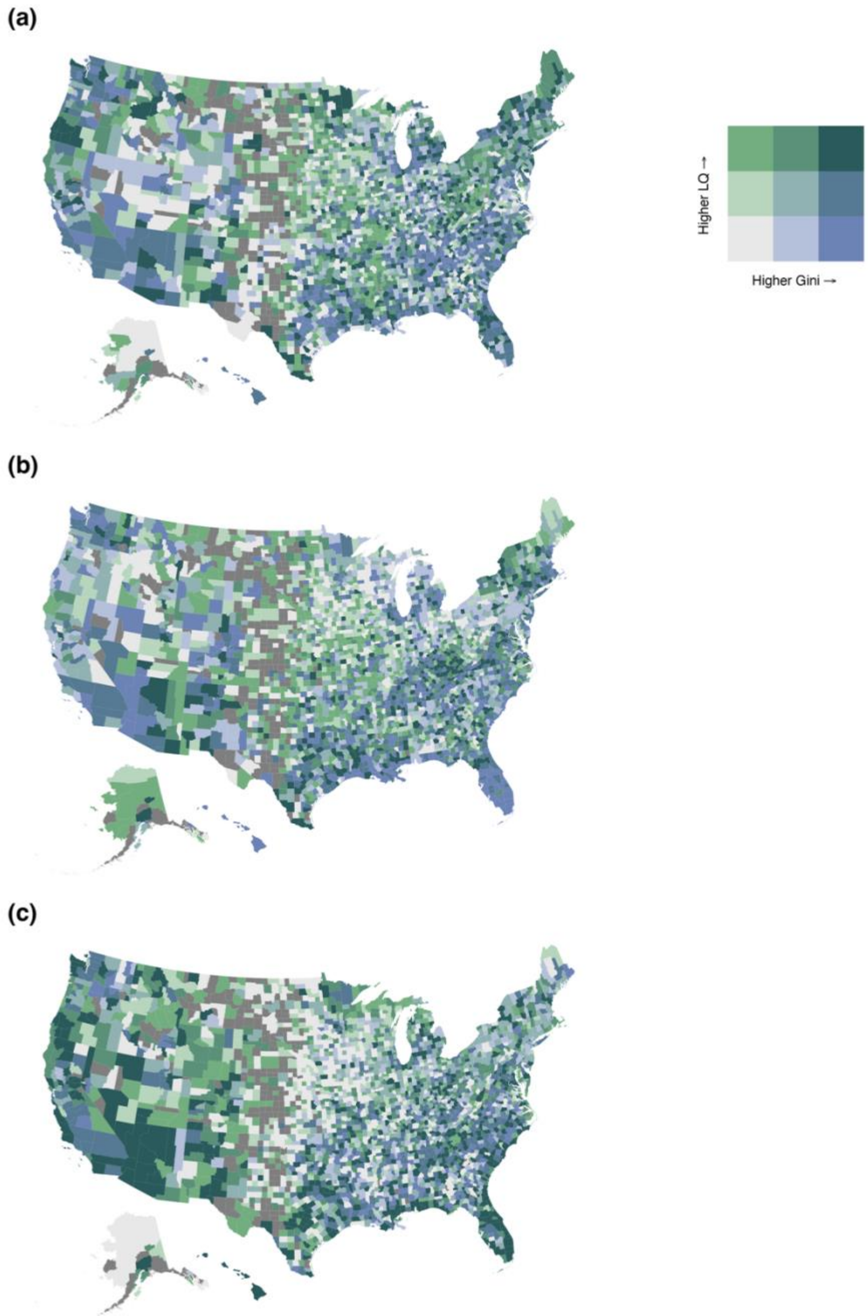

Figure 1 Multivariate choropleth maps displaying the spatial distribution of Gini coefficients and location quotients (LQ) at the county level across the United States for three service sectors: **(a)** Health Care, **(b)** Educational Services, and **(c)** Daily Living Services. The color scheme represents the intersection of inequality (Gini coefficient) and sectoral concentration (LQ), with darker shades indicating higher values of both metrics.

Fig.2 illustrates the relationship between the Gini coefficient and the LQ for formal Care employment across U.S. states and counties from 2009 to 2021. Each scatterplot panel visualizes the counties' Gini coefficients on the x-axis, indicating spatial inequality in care job distribution, and the LQ on the y-axis, representing the relative concentration from 2009 to 2021. The red dashed horizontal line at LQ = 1 refers the national employment threshold, while the dotted vertical line at Gini = 0.5 marks the threshold for high spatial inequality.

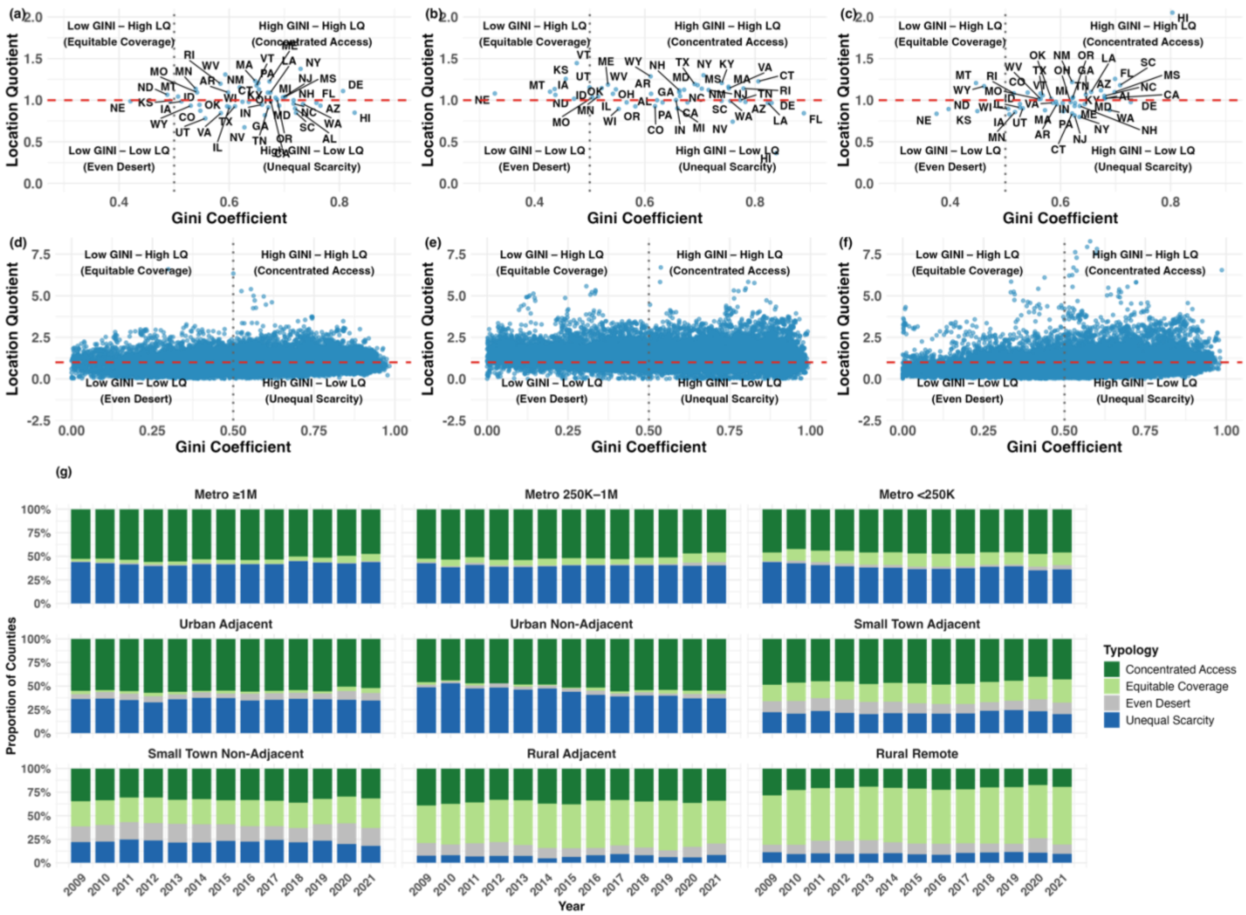

Figure 2 GINI – LQ Typology at state level and county level (a&d) health (b&e) education, (c&f) other services, (g) urbanicity level

Fig. 2a–c presents average state-level care employment typologies across three sectors: Health Care, Educational Services, and Daily Living Services from 2009 to 2021. Across all sectors, the most common patterns were unequal scarcity and concentrated access, indicating that care-related jobs tend to be either insufficient and unevenly distributed or spatially clustered in higher concentrations. Equitable coverage, where jobs are both plentiful and evenly dispersed, remained rare.

In the Healthcare sector (Fig. 2a), the majority of states fell into the "unequal scarcity " category. North Dakota, by contrast, was the only state that, on average, fell into the equitable coverage category, reflecting an abundance of care jobs relative to the population and being located proximal to where the people live. In Educational Services (Fig. 2b), concentrated access also dominated, although equitable coverage was more common than in other sectors. In Daily Living Services (Fig. 2c), which includes ancillary roles such as food service and janitorial work, unequal scarcity was again the most prevalent typology.

At the county level (Fig. 2d–f), the dominance of spatial inequality becomes more pronounced. In Health Care, a large share of counties experienced either concentrated access or unequal scarcity, while fewer than 9% demonstrated equitable conditions. A similar pattern emerged in Educational Services, where job concentration outpaced equitable distribution. In the Other Services sector, unequal scarcity was most common, and equitable coverage remained the rarest typology across all sectors (6%). Notably, even desert, a condition where jobs are limited but evenly spread, was frequently observed in rural counties.

Fig. 2g illustrates the distribution of GINI–LQ typologies across the urban–rural continuum. In metropolitan counties (≥1M, 250K–1M, and <250K), the most common classifications are concentrated access and unequal scarcity, indicating polarized care resource distribution. In contrast, concentrated access dominates small town areas both adjacent and non-adjacent to metro regions. Notably, equitable coverage is most prevalent in rural areas, particularly in rural adjacent and rural remote counties, suggesting a more balanced distribution of care services in these regions. Temporal dynamics of these typologies across urban classifications are further detailed in Supplementary Fig.1.

Temporal change of Gini coefficient and LQ

Fig.3 a,b&c presents temporal trends in the distribution and concentration of service sectors across U.S. counties from 2009 to 2021. Fig.3-a shows the average Gini coefficients for three service categories. Educational Services, Health Care, and Daily Living indicating the degree of inequality in their spatial distribution. All three sectors exhibited a general decline in inequality over time, with the daily living category showing the most pronounced drop after 2020. This suggests a trend toward more geographically even distribution of these services, particularly in the latter years of the study period.

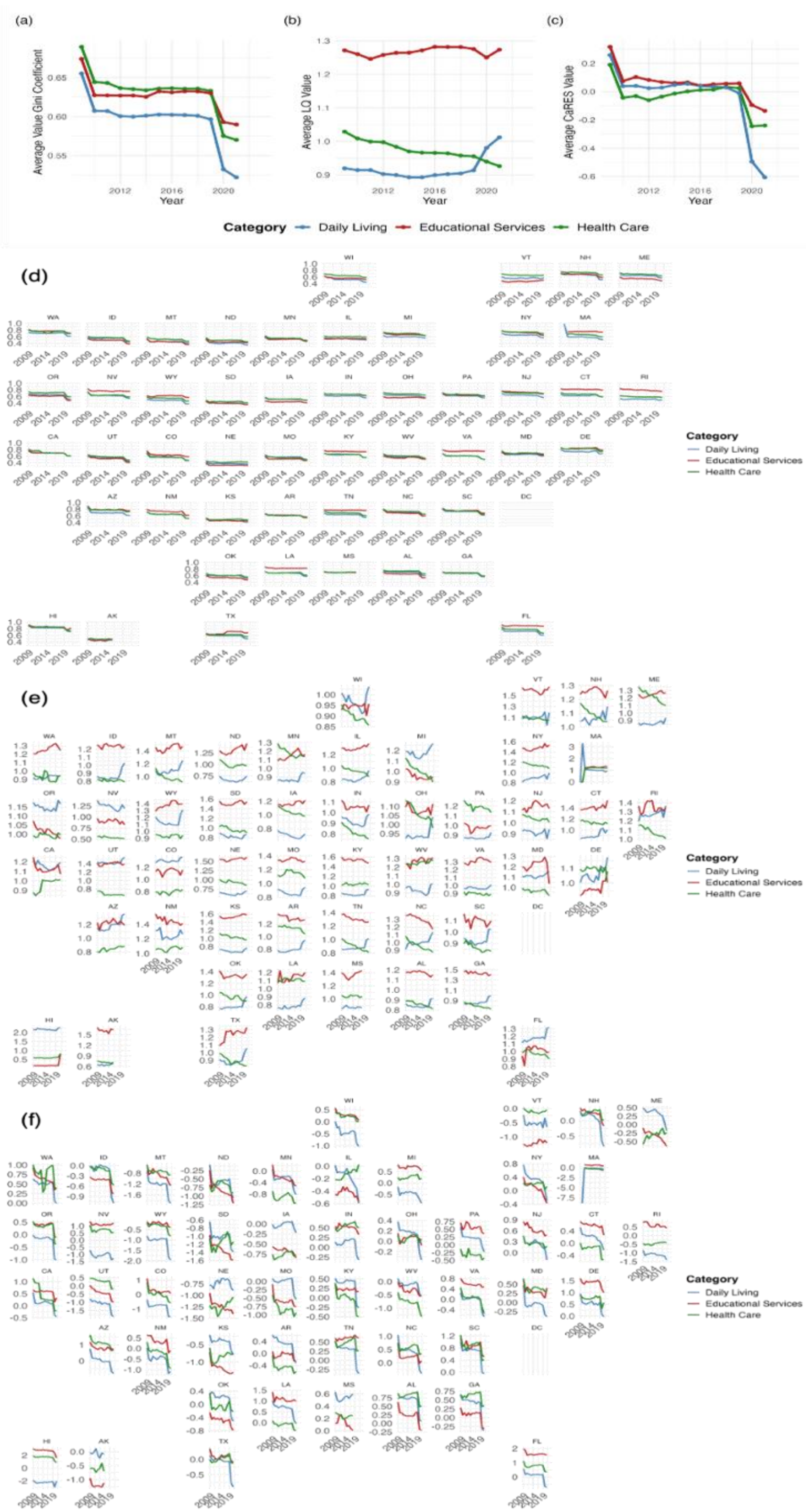

Figure 3: Temporal trends of Educational Services, Health Care, and Other Services access and across U.S. counties from 2009 to 2021. (a) average Gini coefficients (b) average LQ values (c) (d) average CaRES (e) Gini coefficients at state level (f) LQ state level average (g) CaRES state level average

Fig. 3-d&e provides a state-level view of the temporal dynamics of LQ and the Gini coefficient. Fig. 3-d shows that most states exhibit declining Gini coefficients over time across all three service categories, reinforcing the national-level trend toward reduced spatial inequality in care-related employment.

Fig.3-e highlights substantial variation in LQ trends by state and service category. For example, Educational Services remain highly concentrated in states such as Massachusetts and New York, while Health Care displays more moderate and, in some cases, declining LQ trends across states. The daily living category shows increasing divergence among states in recent years, with several states experiencing sharp rises in LQ post-2020.

Fig.3-f shows the state-level trends for the CaRES score in its entirety. A higher score in this category indicates a state with more formal care economy distributional problems. For many states, we see a steady decline in the CaRES scores across all three categories, indicating improvement in the formal economy distribution of employment. Interestingly, this measure also shows a variety of differences across states. As an example, Educational Services for some states are the most vulnerable category while for others are the best. There appears to be some potential regional patterns in these scores across the three categories, and future research can look at how state and regional policy trends impact a state’s formal care economy. A striking feature of the CaRES score is the widespread impact seen across numerous states in 2020, reflecting the magnitude of that year's disruptions (e.g., COVID-19). Due to current data availability, our post-pandemic analysis is limited to the year 2021, preventing a full assessment of how states have recovered. However, the CaRES score reveals notable patterns in how states responded most notably through an increased relative reliance on the formal care economy, particularly in sectors such as healthcare and daily living, which grew as a proportion of their overall economic activity.

Local Indicators of Spatial Association analysis

Moran’s I results, as shown in Fig.4, illustrate the spatial distribution of LISA clusters for the combined CaRES across three rolling five-year periods (from 2009–2013 to 2017–2021) across the three care economy sectors. Across time, a clear spatial pattern was found. HH clusters, representing significant vulnerabilities in care employment, remain persistent in parts of the Southeast and other historically underserved regions, while LL clusters, representing areas with adequate care employment, gradually expand across the Midwest, Northeast, and Western U.S. This shift points to a growing presence of spatial equity in certain regions, even as other areas remain concentrated in scarcity. These maps also show important differences based on the sector of care the first row of maps representing healthcare, the second representing educational services, and the third representing daily living.

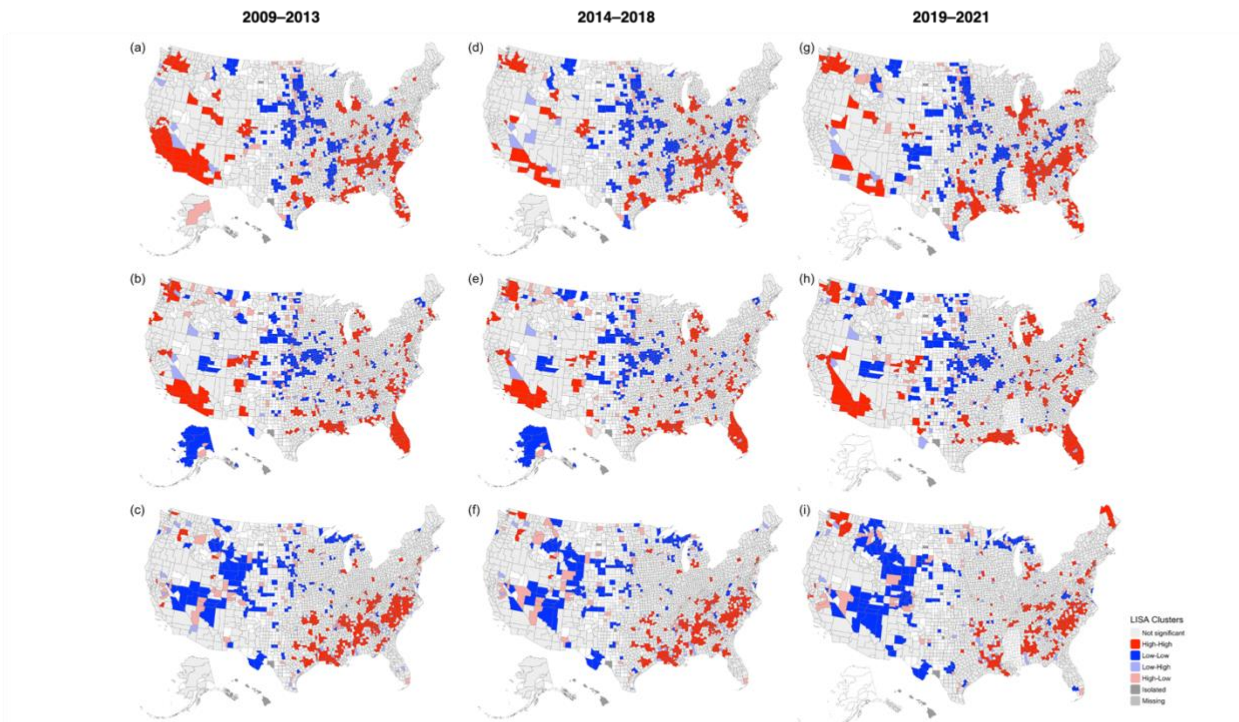

Figure 4. Local Indicators of Spatial Association (LISA) cluster maps for Care Resource Equity Score (CaRES) in U.S. counties. Panels show spatial clustering of CaRES for three formal care sectors (a, d, g) health care, (b, e, h) educational services, and (c, f, i) other services—across three time periods: 2009–2013 (a–c), 2014–2018 (d–f), and 2019–2021 (g–i).

Fig.5-a complements these spatial trends found in Fig.4 by summarizing the temporal dynamics of LISA clusters from 2009 to 2021 across three service categories. Each tile in these figures represents approximately 10 counties classified into one of the four significant LISA categories. The chart reveals that while HH clusters were dominant in early years, particularly in Health and Education, LL clusters (blue) steadily increased over time, especially in the Education and Daily Living sectors. Together, these figures illustrate the changes of the geography of care equity in the U.S., with some sectors and regions progressing toward greater balance while others remain entrenched in inequity.

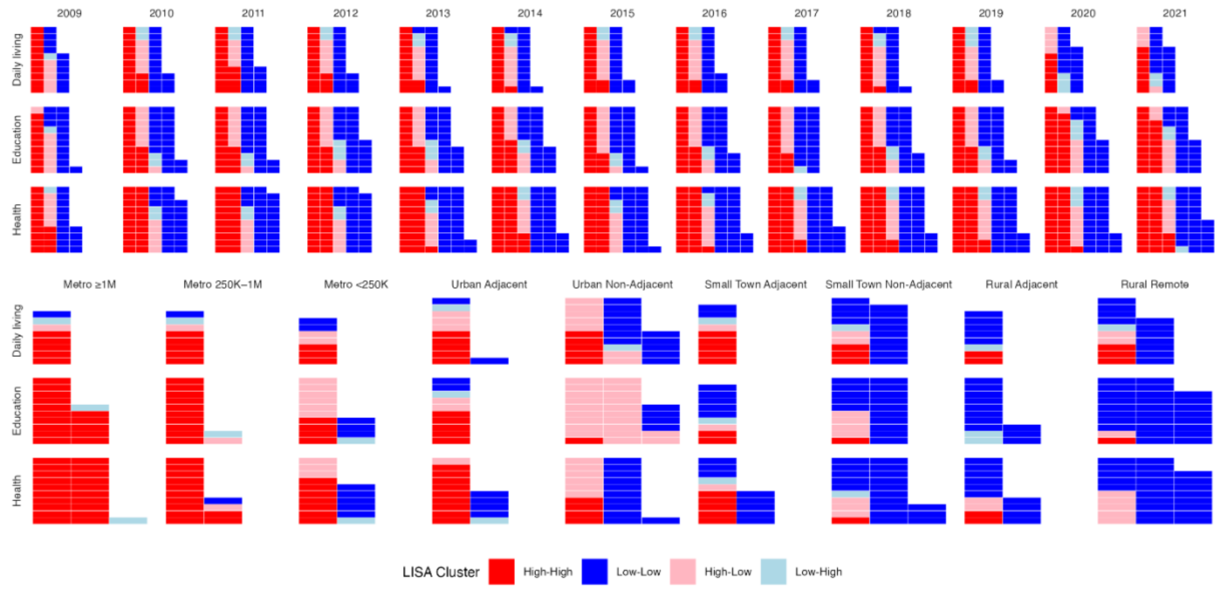

Figure 5. Local Indicators of Spatial Association (LISA) clusters by time and urbanicity from 2009 to 2021. (a) Temporal change in LISA clusters. Each tile represents approximately 10 U.S. counties within a given year and service category. (b) LISA clusters by urbanicity level based on RUCC classification. Each tile represents approximately 1% of counties within a given RUCC group.

Fig.5-b illustrates the spatial clustering patterns of care-related employment equity across different levels of urbanicity, as defined by the RUCC. For each RUCC level, the total number of counties is scaled to 100 tiles to enable proportional comparison across service categories and cluster types. Thus, a tile represents 1% of the counties in that RUCC group.

A clear spatial trend was found across service categories: as urbanicity decreases, the prevalence of LL clusters increases relative to HH clusters. In the case of Educational Services, HH clusters dominate the most urbanized counties (Metro ≥1M, Metro 250K–1M, and Metro <250K). However, a shift toward LL dominance becomes apparent starting with Urban Non-Adjacent counties. It continues across Small Town and Rural designations, particularly in Small Town Non-Adjacent and Rural Remote areas. Health Care showed a similar transition. While HH clusters remain prevalent in metro regions, LL clusters become more common beginning in Rural Adjacent counties and remain dominant across Rural Remote, Small Town Adjacent, and Small Town Non-Adjacent areas. For other services, HH clusters again dominate metropolitan and Urban Adjacent counties, but LL clusters exceeded HH clusters starting in Urban Non-Adjacent areas and strongly dominate in Small Town Non-Adjacent and Rural Remote regions. This trend indicates that the Formal Care Economy is a more significant share of the economies of non-urban areas and that these areas tend to have easier geographic access to the existing formal care infrastructure. It is important to remember that the CaRES score is a relative measure and is able to account for within unit population sizes meaning that these Rural communities might have far fewer formal jobs than their urban counterparts, but see a higher share of their employment in these positions as well as a more equitable distribution among the population. We discuss in the discussion section why this might be the case.

Discussion

This study introduced the CaRES and care resource typology, a novel metric designed to evaluate the geographic distribution of formal care labor in the U.S. By combining the Gini coefficient and the LQ, CaRES captures both the intensity of care-related employment relative to population size and its spatial concentration across counties. This dual-lens approach offers a comprehensive framework for identifying not just whether care jobs are abundant or scarce, but also how equitably they are distributed within regions. Unlike prior methodologies that rely on singular inequality or specialization metrics, CaRES enables systematic comparisons across time, place, and care sectors, and yields a typology that supports both academic inquiry and policy intervention. This contribution fills a critical gap in empirical care economy research, which often lacks tools that are both interpretable and analytically comprehensive.

Our results revealed pronounced and persistent spatial inequities in the distribution of care-related employment. Across all three sectors examined, typologies of Unequal Scarcity and Concentrated Access dominate, reflecting structural imbalances in both job availability and spatial allocation. In the Health Care sector, over 78% of counties fall into one of these two categories, suggesting widespread issues with both access and equity. Educational Services showed a similarly skewed pattern, with nearly 73% of counties classified as either over-concentrated or insufficiently served. The Daily Living sector, encompassing support and ancillary care roles, exhibited the highest share of Unequal Scarcity counties (44.1%), indicating significant gaps in foundational care infrastructure, particularly in economically vulnerable regions.

Our analysis also indicated interesting temporal trends in these measures. Nationally, the GINI coefficient is decreasing, indicating better national distribution of care resources. At face value, this suggests a positive trend, indicating that care resources within a community are becoming more evenly distributed across the population. However, in many states and sectors, the LQ score is decreasing, meaning that while these communities might have more equal distribution of resources, they have fewer resources to distribute. This reflects an increasing pattern of scarcity, rather than equal access. This pattern is further supported by our LISA results in both the health and education sectors, the number of HH clusters has increased since 2019, highlighting the increase of inequality and resource scarcity. Additionally, given the relative nature of the LQ score, we see signs that much of the growth in the Care Economy is concentrated in specific geographies, leaving other areas behind. Nationally, this appears to lead to an improvement in the data; however, at sub-national geographies, there is significant variance in outcomes. This trend aligns with prior literature that has shown a decrease in the supply of teachers and nurses in specific geographies, particularly rural areas [23–26].

Large shifts in CaRES scores correlate with major economic events, notably the 2008 recession and the COVID-19 pandemic. In 2020, CaRES scores rose sharply, likely because care jobs were deemed essential and other sectors contracted. As a result, care jobs formed a larger share of total employment. While this temporarily boosted LQ scores, it remains unclear whether this shift reflects lasting structural change or a pandemic-specific anomaly. Future data will help determine if CaRES scores return to pre-pandemic levels or continue to rise.

Our results also offered valuable insights into the urban and rural spectrums. While rural areas generally have fewer care resources, access tends to be more evenly distributed, creating “even deserts.” In contrast, urban areas often have higher overall employment but face pronounced spatial concentration, limiting access for many residents. These findings echo prior studies on pharmacy, schools, and child care deserts and reflect broader patterns of suburbanization and infrastructure disparity.[13,15,24,25] We believe that patterns of urban development have significantly influenced the spatial distribution of resources. In particular, shifts in U.S. metropolitan structure namely, the decentralization of employment from central cities to suburban sub-centers have been associated with increased regional employment growth. Additionally, less regulations and constraints of greenfield development in suburbs or rural towns than infill construction in crowded cities, even if rural projects must extend roads and utilities to remote sites, it is often easier to develop new facilities[27]. As a result, rural areas, while seemingly more isolated, may offer more feasible opportunities for care facility expansion than inner-city areas constrained by cost, space, or zoning. This discussion is echoed in recent research by Pandey et al. (2025), who demonstrate that urbanization and economic development are frequently accompanied by rising infrastructure inequalities, particularly in rapidly growing or fragmented urban regions. Their work suggests that growth alone does not guarantee equitable infrastructure access, reinforcing the importance of spatial justice frameworks in evaluating care systems [28].

These results have significant policy implications. Within a community, individuals may have difficulty accessing formal care resources. However, these results suggest that not all causes of this difficulty are the same. For instance, in an even desert, care resources should be expanded in the existing locations. Across the board, increases in funding and employment in these communities should be seen, as the primary difficulty is a lack of resources. For areas with Concentrated Access, simply increasing employment will not solve the problem. Concerned policymakers in these areas need to focus on investment in ways to reach new communities. This could involve creating new infrastructure, such as building new schools, incentivizing businesses to open in underserved communities by providing subsidies to grocery stores[29], or increasing resources in remote operations, including home health aides or telehealth services[30]. Future research and policy considerations should specifically focus on correlations between areas with a high CaRES score and other measures of socio-economic vulnerability. Finally, areas in the unequal scarcity type should see the most attention as they need immediate action. Policymakers should prioritize these areas for improvement, as they are both under-resourced and unequal. For each of these reasons, it will likely be crucial to consult with locals and examine the local economy to understand why these problems exist and develop community-specific plans.

Together, these patterns suggest that while some regions serve as hubs of care employment, large swaths of the country remain either underserved or unequally provisioned. The typological framework of CaRES thus offers critical insights into the geography of care inequality, identifying not only where disparities exist but also the structural nature of those disparities. Future research on CaRES will involve continuing to produce these statistics for the coming years to understand how the Care Economy has recovered in the years following the pandemic. Research should also examine the application of this methodology to other care economy resources. This study has focused on employment as an important proxy for caregiving in the formal economy, but there are other opportunities as well. For example, this methodology could be used to understand the distribution of available childcare or eldercare slots in a society or the distribution of any other caregiving resource. The CaRES framework provides a method for comparing different resources.

While the CaRES framework offers numerous advantages, it also has limitations that should be considered in future research. We were unable to calculate the states (or regions) that have only one unit (e.g., DC) because GINI requires subunit variation. Additionally, a select few number of counties, most notably in rural and frontier areas, had too small populations to get reliable estimates of GINI coefficients and distribution. Moreover, our analysis is based on administrative boundaries, which limit consideration of service flows across these boundaries. For example, many large health care facilities, such as major hospitals, are located outside of a city boundary, which causes unequal distribution of employment. Future research can consider utilizing other boundaries, such as commuting zones, to analyze CaRES scores. Lastly, while generally considered accurate, this data has limitations. It can be challenging to assign jobs to specific workplace locations, especially for jobs that allow for work location flexibility or those that involve traveling to a client site (e.g., construction or home health aides).

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Ethical Approval
This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent
This article does not involve any human participants, and therefore, informed consent was not required.

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Author Contributions
Y.A. and J.B. jointly developed the research design. Y.A. led the data analysis and drafted the methodology and results sections. J.B. was responsible for data compilation and drafted the introduction and discussion sections. Y.A. and J.B. reviewed and revised the final version of the manuscript.

Competing Interests
The authors declare no competing interests.

Materials & Correspondence
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Data availability
This study uses publicly available datasets. The Workplace Area Characteristics (WAC) dataset, a component of the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) program, is accessible via the U.S. Census Bureau at https://lehd.ces.census.gov/data/. American Community Survey (ACS) microdata were obtained from the Integrated Public Use Microdata Series (IPUMS) at the University of Minnesota, available at https://ipums.org. The rural–urban classifications from the United States Department of Agriculture (USDA) are publicly available from the USDA Economic Research Service at https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/. The code used in this study is openly available at: https://github.com/YoonjungAhn/Care-Resource-Equity-Score-CaRESa

Tables
Table 1 GINI – LQ Typology

Low GINI – High LQ (Equitable Coverage)	High Gini – High LQ (Concentrated Access)
Low Gini – Low LQ (Even Desert)	High GINI – Low LQ (Unequal Scarcity)

Figures

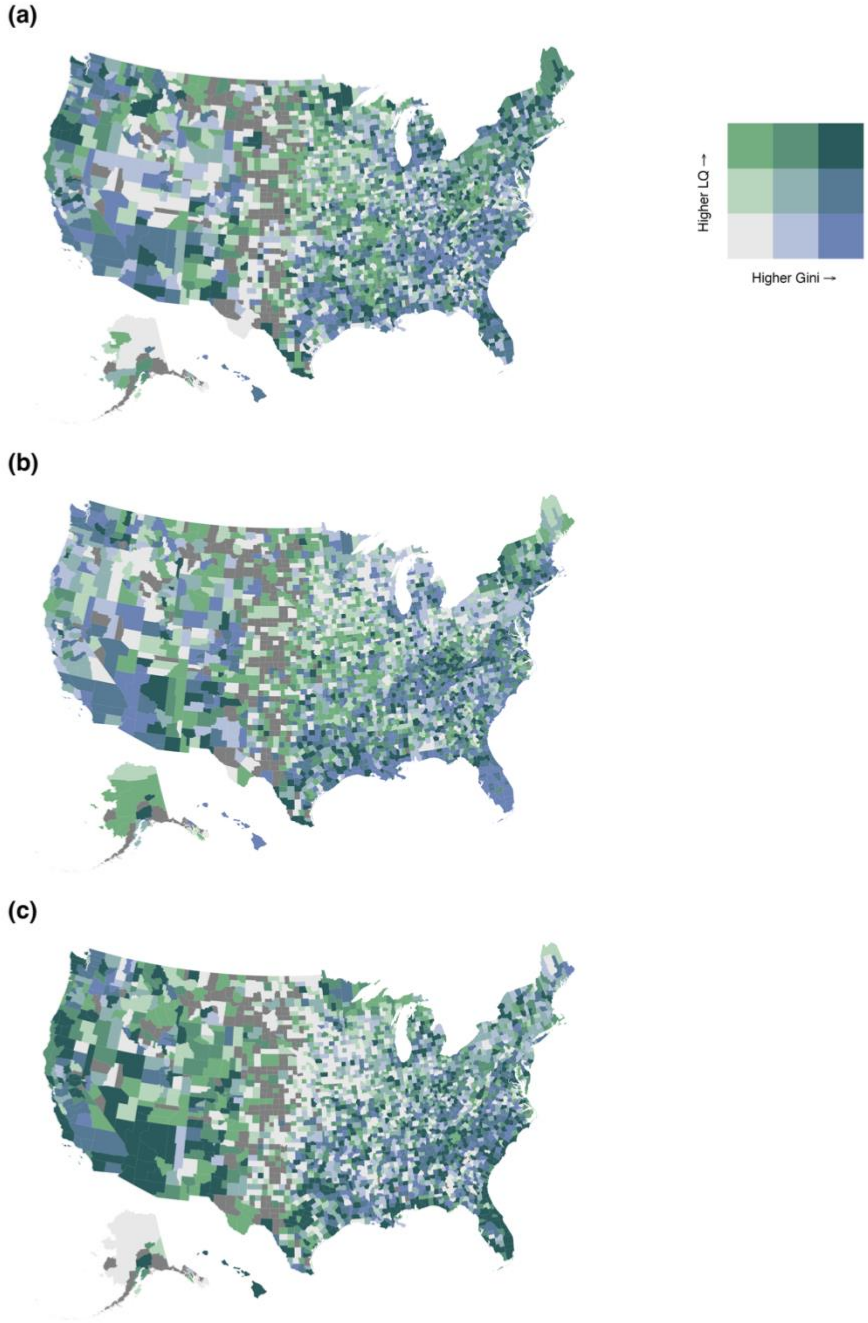

Figure 5 Multivariate choropleth maps displaying the spatial distribution of Gini coefficients and location quotients (LQ) at the county level across the United States for three service sectors: **(a)** Health Care, **(b)** Educational Services, and **(c)** Daily Living Services. The color scheme represents the intersection of inequality (Gini coefficient) and sectoral concentration (LQ), with darker shades indicating higher values of both metrics.

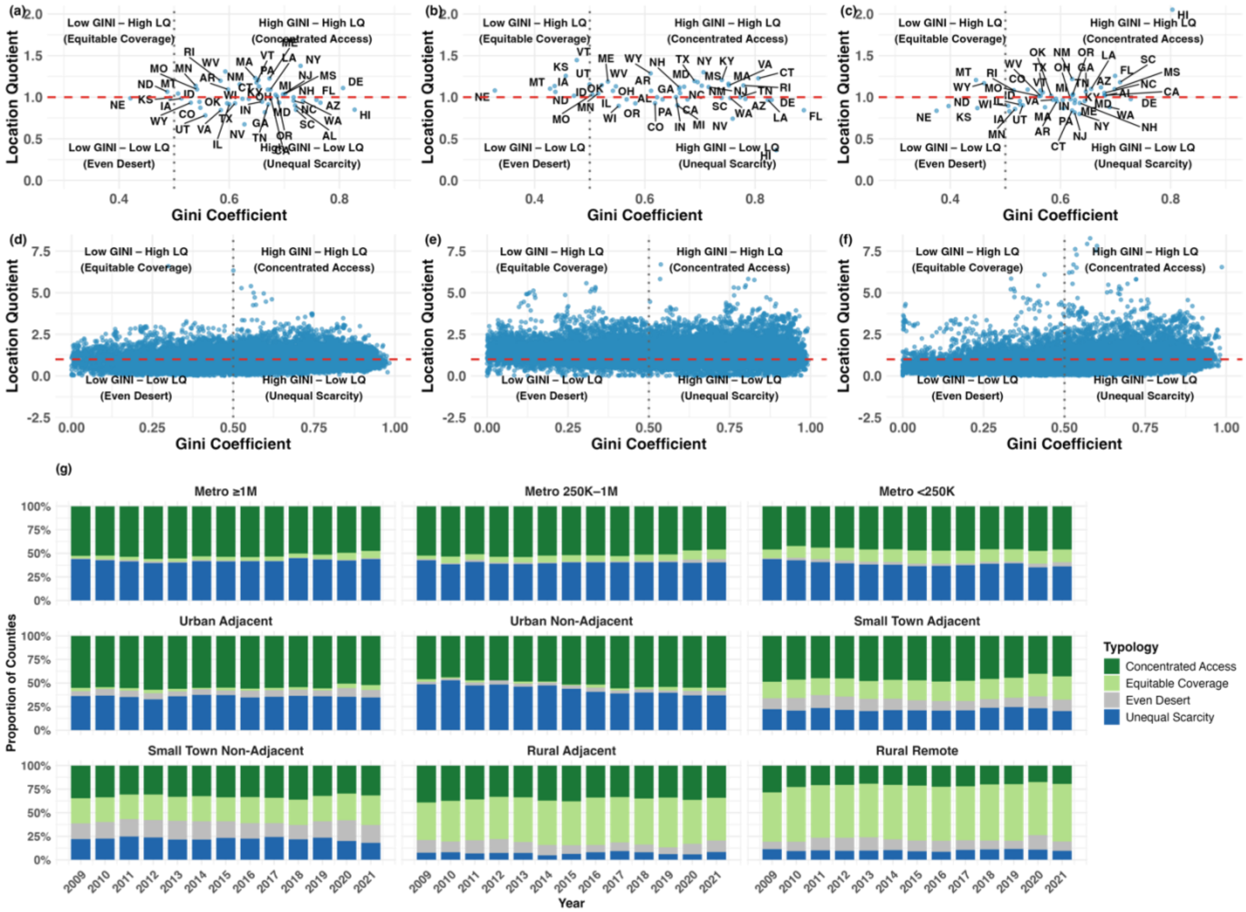

Figure 6 GINI – LQ Typology at state level and county level (a&d) health (b&e) edication, (c&f) other services, (g) urbanicity level

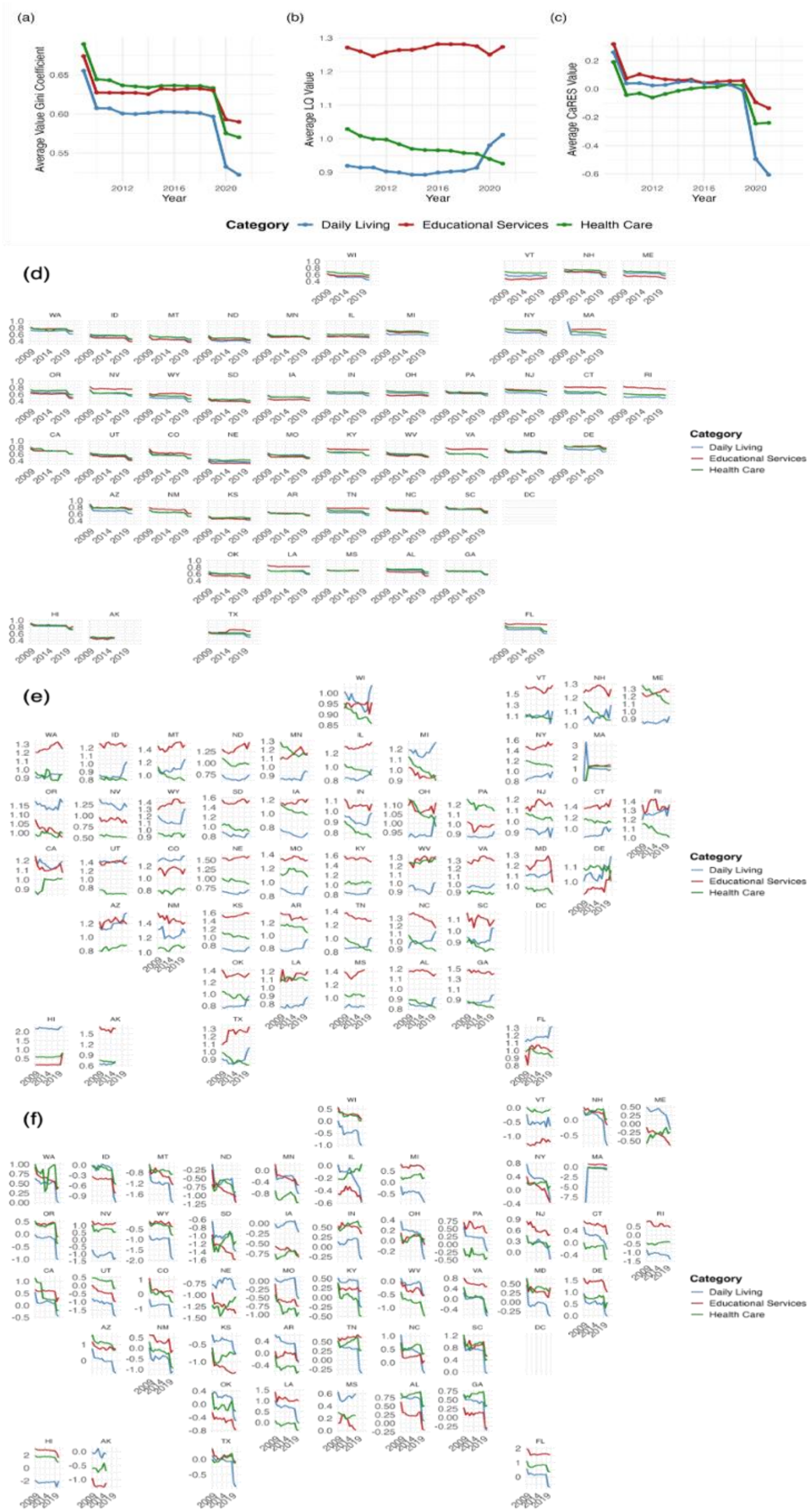

Figure.7 Temporal trends of Educational Services, Health Care, and Other Services access and across U.S. counties from 2009 to 2021. (a) average Gini coefficients (b) average LQ values (c) (d) average CaRES (e) Gini coefficients at state level (f) LQ state level average (g) CaRES state level average

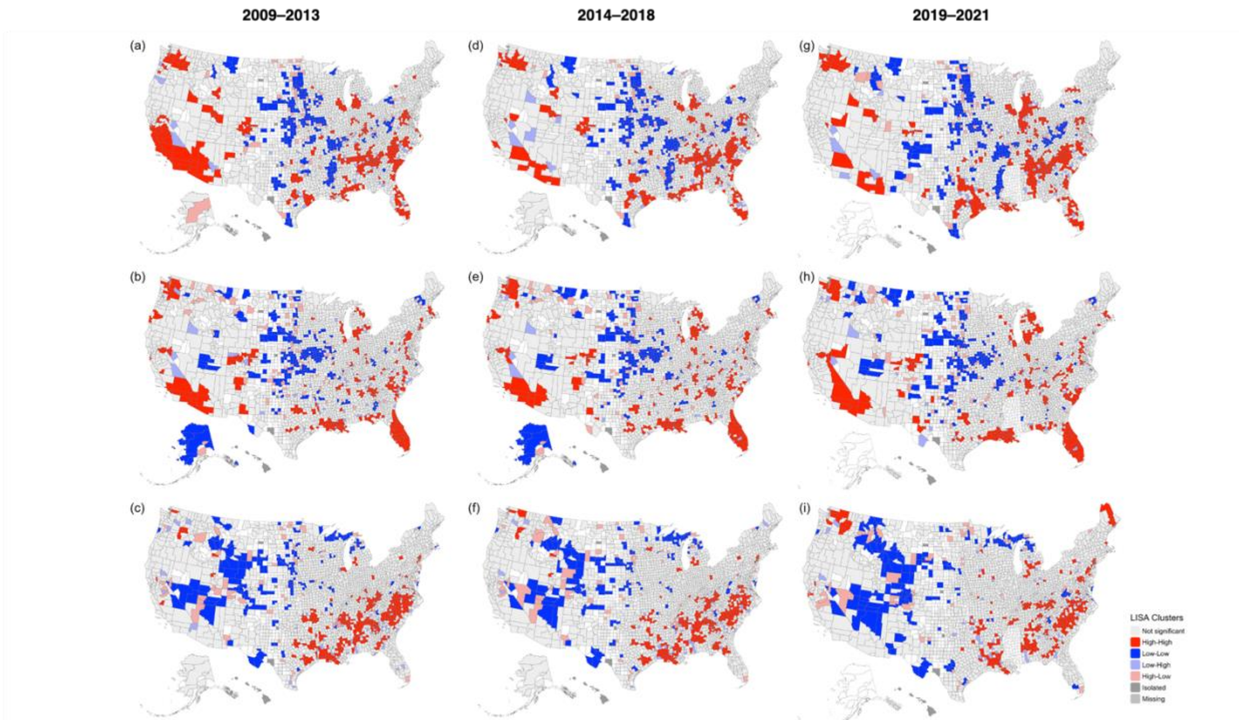

Figure 8. Local Indicators of Spatial Association (LISA) cluster maps for Care Resource Equity Score (CaRES) in U.S. counties. Panels show spatial clustering of CaRES for three formal care sectors (a, d, g) health care, (b, e, h) educational services, and (c, f, i) other services—across three time periods: 2009–2013 (a–c), 2014–2018 (d–f), and 2019–2021 (g–i).

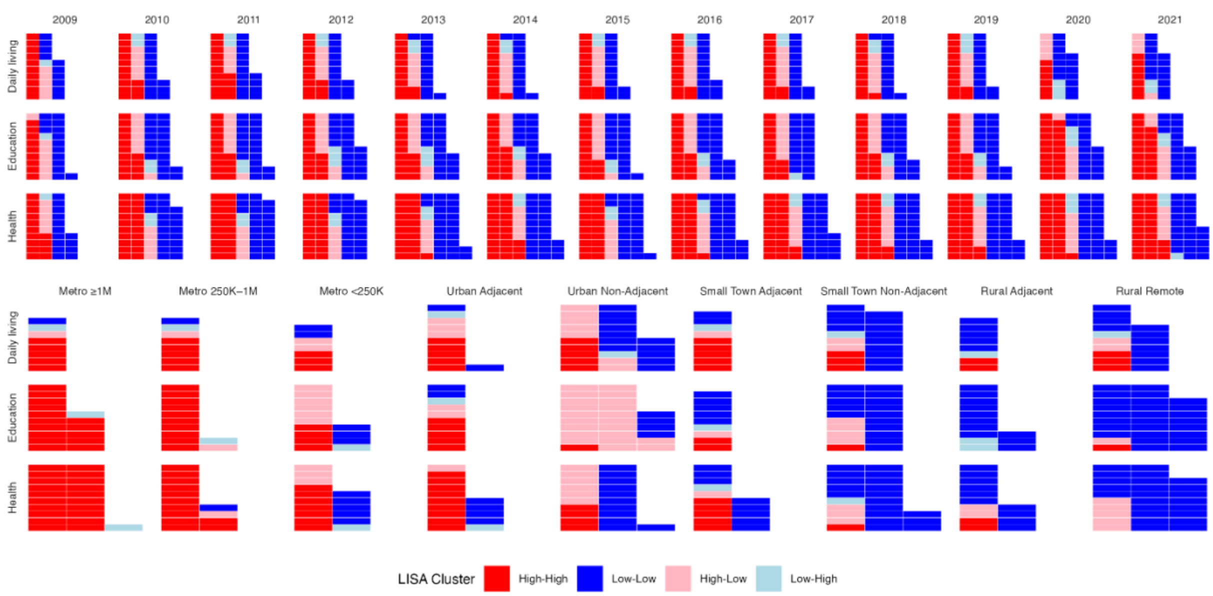

Figure 5. Local Indicators of Spatial Association (LISA) clusters by time and urbanicity from 2009 to 2021. (a) Temporal change in LISA clusters. Each tile represents approximately 10 U.S. counties within a given year and service category. (b) LISA clusters by urbanicity level based on RUCC classification. Each tile represents approximately 1% of counties within a given RUCC group.