Visualizing Geographic Variability in the Economic Outcomes of Industry Diversity in the United States

Aaron Pacheco
Indiana University

Kristian Braekkan
Region Nine Development Commission

Received: 03/15/2025
Accepted: 08/18/2025

Abstract

This study investigates the variability in association between industry diversity and economic activities related to economic performance, socioeconomic well-being, and innovation. While economic development literature has extensively examined the formation of industry clusters and their influence on economic outcomes, less is known about how industry diversity may mitigate the challenges faced by single-sector economies and what factors may hinder its relationship to its generally expected positive outcomes. This exploratory research, which examines various dimensions of economic diversity, uncovers potential geospatial differences or similarities across regions and their possible relationships with performance and resilience. The findings indicate that no strict assumptions regarding the relationship between economic diversity and economic performance, well-being, or innovation can be made. Instead, these relationships are complex and nuanced, appearing to be geographically contingent and shaped by interactions with local or regional economic conditions, including demographic and socioeconomic factors, business dynamics, and technological adaptation over time.

1 Introduction

Our study aims to identify patterns and heterogeneity in U.S. industry composition and explore how the association between industry diversity and different forms of positive economic activity varies across regions. The divide between rural and urban economies has long been a focal point for economic development professionals (Potts, 2022; Johnson and Lichter, 2019). Key differences, such as demographics, contrasting landscapes, development strategies, and political composition, are often considered when analyzing variability across regions. Over the last decades, rural communities in the United States (U.S.) have faced growing pressures from workforce shortages, deskilling, and challenges to maintaining local economic stability (Carr and Kefalas, 2011). To build resilience in rural U.S. communities, the first step is to examine the statistics associated with economic well-being. Unlike their urban counterparts, rural communities increasingly depend on dominant regional industries and anchor employers in often undiversified economies. This analysis examines how policymakers should be aware of underlying spatial relationships when using measures to steer public investment to drive meaningful change.

Structural factors such as industry diversity, business climates, and spatial spillovers play a pivotal role in shaping local economic outcomes, often surpassing demographic or socioeconomic predictors, particularly when viewed at the national scale (Arano and Srinivasan, 2021). Building upon existing literature emphasizing local contexts within national policy, scale and aggregation in economic development policy can hide important variations within regional landscapes. Arano and Srinivasan (2021) provide robust evidence that economic growth in the Midwest is spatially dependent and that specific drivers such as human capital levels, innovation intensity, and supportive business conditions matter at different phases of recovery or expansion.

We agree that location matters, and communities rarely grow in isolation, responding to and influencing their neighbors. However, while their study focused heavily on temporal elements by examining growth rates within clusters, we delve deeper into the spatial relationships within and between them, using industry diversity as a key marker to highlight associations across space.

In rural geographies, decades of ongoing rural-to-urban migration have negatively affected local economies, especially as domestic manufacturing has been vastly expanded in response to the COVID-19 pandemic and global supply chain disruptions (Previtali and Fagiani, 2015; Fitzgerald, 1993). The lack of skilled labor, combined with pressures from large anchor employers to boost production, has shifted workforce demographics toward an influx of international migrant labor who, within the large growing manufacturing sector, fill rapidly expanding deskilled and low-wage positions (Sisk and Donato, 2018; Reddy, 2006). This shift raises concerns about socioeconomic inequalities and economic stagnation. Unlike densely populated urban centers, rural areas struggle to diversify their local economies. Without addressing this challenge through targeted regional development, rural communities risk becoming increasingly reliant on single-industry economies, exacerbating their already precarious situations.

Single-sector economies are linked to various socioeconomic risks at both national and regional scales, including income inequality, unemployment, negative net migration, and reduced overall well-being (Hanna, 2019). Industry diversification—defined here as regional concentrations of related industries connected through local linkages and spillovers—offers a framework for understanding the interplay between location, value chains, and regional specialization patterns (Woerter, 2009; Forni and Paba, 2002). Diversification emerges from existing regional firms and industries when new development paths are forged by combining current competencies with previously unrelated knowledge (Audretsch et al., 2004). This fusion can lead to new competencies and innovations that existing firms exploit as they enter new markets, or it may enable the establishment of new firms in the region, contributing to uneven geographical development.

Moreover, diversification extends beyond the economic realm to include social impacts. Entrepreneurship, proprietorship, and innovation require a supportive ecosystem rich in resources conducive to nurturing new ideas and fostering social progress (Neumann, 2021). The exchange of ideas and business competition relies on relationships across regions and industries. Industry, therefore, plays a role as an employer and a contributor to local culture. Cultivating a positive culture, whether in business, social, or academic spheres, is crucial for driving positive societal change and, in turn, fostering socioeconomic progress (Capra and Jakobsen, 2017; Storsletten and Jakobsen, 2015).

The emphasis on association and scale becomes key to discussing how regional industry clusters may or may not follow national trends. National economic development efforts will likely fall short without recognizing regional economic behaviors. This is the focus of section 2, as we introduce industry clusters as the smallest unit of our study in economic geography. In section 3, we discuss our data and analysis methods, beginning with correlations to understand how economic activities relate to industry diversity and confirm the spatial clustering patterns present in the dataset. Section 4 will expand on our Hot Spot comparison analysis results and our visualization through geographically weighted regressions. We open the discussion in section 5 with our main points being how geographic differentials should be at the forefront of regional economic development and how such realizations can help guide communities toward utilizing industry diversity to improve economic resiliency.

For clarity throughout the text, italicized measures directly refer to the categories and variables within the dataset, while the same term is used without italics to refer to real-world economic activity. For example, *Industry Diversity* and *Latent Innovation* are the variables in our dataset that represent measurements of industry diversity and latent innovation activity throughout the country. We will introduce our variables further in Section 3. To avoid confusion, it is also important to differentiate three related concepts used in this study. *Industry diversity* refers to the breadth and evenness of industrial sectors within a regional economy. Industry clustering denotes the concentration of related industries in a given location, often linked through supply chains, labor markets, or knowledge spillovers; strong clustering can occur even in low-diversity economies. Cluster analysis, by contrast, is a statistical tool (e.g., Hot Spot Analysis, spatial autocorrelation) used to identify patterns of high or low values in geographic space. These are distinct: clustering in the economic sense describes a structural phenomenon, while cluster analysis is a method used to detect such patterns in the data.

2 Importance of Industry Clusters

Industry diversity and industrial clustering are fundamental concepts in economic geography, each shaping regional economic dynamics through distinct yet complementary mechanisms. Industry diversity refers to the variety and distribution of industries within a region, often associated with increased economic resilience and adaptability in the face of sector-specific shocks (Brown and Greenbaum, 2017). A diversified industrial structure can buffer regions against external disruptions by spreading risk across multiple sectors. In contrast, industrial clustering refers to the geographic concentration of interconnected firms and institutions operating within related industries (Kosfeld and Mitze, 2023; Delgado et al., 2010).

Recognizing the interplay between these two constructs is essential for understanding contemporary regional development strategies. Clusters may emerge within otherwise diversified economies, fostering localized synergies while maintaining system-wide adaptability (Boschma and Iammarino, 2009). This interrelation can support both resilience and specialization, enabling regions to leverage the benefits of economic variety alongside the efficiencies of co-location.

Our argument is not based on the generalization that economic prosperity is directly associated with demographic and socioeconomic measures, but instead, there exist broad shifts in the structural patterns of the economy that may override other inputs and ultimately steer cluster behavior outside of expectation (Martin et al., 2016). At a local to regional scale, business climates and industry dynamics shape and result from a broader economic ecosystem (Pilinkienė and Mačiulis, 2014). For instance, existing industry conditions can generate entrepreneurial opportunities by supplementing research and development, creating demand for services and materials, and driving demand for goods and services for the workforce and their families. Conversely, a robust entrepreneurial climate can attract larger employers to a community (Korez-Vide and Tominc, 2016). Thus, we look to measures of business climates and industry dynamics to understand the association between clusters with the resilience of local or regional economies and the prosperity of their residents.

Therefore, studies on cluster formations must consider the context and scale in which socioeconomic and demographic changes occur. Considering technological advancements, entrepreneurs and industries may not operate in the same environment where they sell their products or services. For example, an entrepreneur in a small rural town may have target customers nationwide or internationally. Nonetheless, industry clusters encompass a wide range of economic activities and form dominating spatial features, including local clusters where businesses produce for and sell to other local businesses or consumers (Porter, 2011). A deeper understanding of regional industry clusters is essential to grasp the diverse business environments across the national economy.

Demographic characteristics often correlate with socioeconomic outcomes. For instance, particular demographics may be disproportionately employed in low-wage career trajectories, resulting in lower net worth than their counterparts, which can stifle broader economic activity (Borowczyk-Martins et al., 2014). Moreover, educational attainment and access to technical assistance remain unequal across demographic and socioeconomic groups (Ragin and Fiss, 2016). Industrial employment in local economies is strongly tied to these conditions. Communities with high levels of industrial employment often experience lower levels of educational attainment, limiting opportunities for entrepreneurship, a key predictor of the socioeconomic conditions necessary to start a business (Byun et al., 2015).

The lack of industry diversification may pose challenges to economic resilience, though fostering resilience could provide the best opportunity to address these issues. Single-sector economies offer few opportunities for entrepreneurial success, as residents often rely on a small number of employers for survival (Toma et al., 2014). Supporting marginalized entrepreneurs, particularly those facing economic and social mobility barriers, could help alleviate local economic stagnation, inequities, and decline.

Diversification is frequently cited as necessary for economic stability, resilience, and risk management (Plummer et al., 2022; Woerter, 2009; Greve, 1994). This approach suggests that bolstering multiple sectors and spreading risk across various parts of the economy is a key aspect of maintaining a healthy economy. The study of rural economics, which often highlights the lack of industry diversification, suggests that there is significant room for improvement, as these communities face challenges such as income inequality, stagnant innovation, limited employment options, and restricted entrepreneurship opportunities. Our study

examines how different elements of a healthy economy are associated with industry diversity and how these relationships can vary between geographic clusters.

Clusters represent industry composition and local and regional culture. They are vital in assessing the diversity of economic drivers within a given economy, as they reveal the scope, geographical links, competition, and scale of local or regional industries. Firms and their supply chain networks, both within and across clusters, are shaped by four primary characteristics:

First, clusters consist of groups of related industries whose relationships unlock economies of scale. Clusters are not merely concentrations of economic activity within a narrow industry. They reflect "related variety," where dynamism emerges from complementary, rather than identical, capabilities and activities (Babkin et al., 2023).

Second, clusters are shaped by geographical proximity. They reflect the specific nature and density of local connections, such as access to a skilled labor pool, local knowledge spillovers, and opportunities for collaboration among local partners. While acknowledging the relevance of global value chains and knowledge networks, clusters offer unique competitive advantages by leveraging specific local circumstances (Hinzmann et al., 2019). Although global linkages can compensate for locally missing capabilities, they can often be replicated by competitors in other locations (Bergman and Feser, 2020).

Third, clusters are driven by the interplay of collaboration and competition among related activities in a given location. Co-location alone provides benefits such as knowledge spillovers and access to more specialized input markets. However, the dynamic power of co-location is greatly enhanced when co-located entities actively engage with one another. This engagement may take the form of collaboration, through joint research or training, or competition among rival firms, which pushes companies to adopt differentiated strategies and enhance productivity and innovation (Oman and Alisherovich, 2022).

Fourth, clusters are driven by the critical mass that a location achieves in related industries. When a cluster is small, possible linkages are also limited. As the cluster grows, however, the number of possible interactions grows more than proportionally. This results in an S-shaped growth path, with significantly higher performance and growth once a cluster reaches a specific size. Clusters naturally emerge as the benefits of co-location enhance firm growth in specific geographies and increase the attractiveness of certain locations for new businesses. The emergence of clusters is shaped by both firm decisions regarding investments and strategies, as well as government and institutional decisions regarding the cluster's business environment (Danesh Shakib, 2020).

Industry diversity can influence a region's ability to adapt, grow, and withstand economic shocks, but the nature of that influence depends on the kinds of industries present and how they relate to one another. In evolutionary economic geography, diversity is often separated into related and unrelated forms. Related diversity describes a mix of industries that are technologically or cognitively close enough to share ideas, skills, and infrastructure. This kind of diversity is associated with knowledge spillovers, recombination, and incremental innovation that can improve long-term adaptability (Boschma, 2015). Unrelated diversity, on the other hand, reflects industries that are much more distant in their capabilities. While less likely to exchange knowledge, unrelated industries can reduce vulnerability to sector-specific downturns by spreading risk across the economy (Content and Frenken, 2016; Frenken et al., 2007). Measuring these forms of diversity typically involves entropy-based decomposition, which separates within-group variety from between-group variety to capture both innovation potential and risk-spreading capacity.

Evidence from the U.S. shows that these forms of diversity matter differently depending on the setting and time horizon. In rural and intermediate counties, related diversity has been linked to higher chances of weathering crises, likely because it builds on the region's existing capabilities to adapt and reorganize after a shock (Grabner and Modica, 2022). Unrelated diversity in those same settings has shown weaker or inconsistent effects, suggesting that innovation potential, rather than pure risk-spreading, may be more critical in less complex economies. In contrast, studies of metropolitan areas following the Great Recession have found unrelated diversity to act as a stabilizing force, dampening short-term job losses and creating spatial spillovers that benefit nearby regions. Related diversity in those contexts sometimes slows immediate recovery by transmitting shocks through connected industries, even if it contributes to growth in the longer term (Chen et al., 2024). These differences highlight that strategies to strengthen regional resilience need to be tailored to local economic structures, existing industry linkages, and the type of diversity most likely to

produce desired outcomes.

Economic resilience does not depend on a single measure or model. Each geographic area has its own composition of variables that, when targeted by regional developers, may yield better outcomes than a national, one-size-fits-all approach to diversification and cluster formation (Angelopoulos et al., 2023). For example, while GDP per capita is commonly associated with economic well-being, its significance varies across geographies depending on local factors (Pacheco et al., 2021). Even if industry diversity were a universal solution to economic challenges, not all regions are equally positioned to adopt such an approach.

3 Data and Analysis

This study employs a correlational (associational) analytical framework to examine the relationships among key variables relevant to regional economic development. We explicitly acknowledge that the methods used do not establish causal relationships between the variables analyzed. Instead, our approach is designed to identify statistically significant associations that may reflect underlying dynamics relevant to policy formulation. The decision to adopt a non-causal analytical strategy reflects both the nature of the data and the goals of the research. Specifically, our intent is to inform the development of regional policy frameworks through empirically observed patterns, rather than to test specific causal hypotheses.

This correlational strategy is consistent with recent literature emphasizing the value of association-based evidence in the early stages of policy design and problem structuring, particularly in settings where controlled experiments or strong quasi-experimental designs are impractical (Manski, 2013; Morgan and Winship, 2010). In this sense, the statistical relationships presented here are not interpreted as policy "proof points," but as informative signals that can guide policymakers in identifying areas for further analysis, strategic planning, and potential pilot interventions.

By clearly delineating the scope and limits of our methodology, we aim to provide transparency and to facilitate appropriate interpretation of the findings. While we stop short of making prescriptive claims based on causality, the patterns we uncover contribute meaningfully to the evidence base on regional disparities and development strategies, providing a foundation for future causal research and adaptive policy experimentation.

First, as emphasized by Manski (2013), policy decision-making often proceeds under conditions of partial identification, where precise causal effects are unknown or unknowable due to data limitations or ethical constraints. In such settings, informative associations between variables, e.g., between infrastructure investment and employment growth, can help narrow the space of plausible hypotheses and identify promising directions for further investigation or pilot implementation.

Second, regional economic development is inherently multifaceted and context-specific, involving dynamic interactions across social, geographic, and institutional dimensions (Rodríguez-Pose, 2013). In this context, correlation analyses can reveal systematic patterns and spatial interdependencies that are useful for regional strategy formation, even in the absence of confirmed causal mechanisms. Our findings serve not as definitive prescriptions but as empirically grounded signals warranting attention from policymakers engaged in strategic planning and resource allocation.

Also, the policy recommendations we derive are explicitly framed as provisional and exploratory. They are meant to guide regional actors in identifying priority areas for intervention, experimentation, and further causal evaluation. This approach is consistent with the principle of "evidence-informed" rather than "evidence-determined" policymaking (Nutley et al., 2014), which emphasizes the integration of best-available evidence with local knowledge and judgment.

Finally, it is worth noting that several influential policy studies have historically relied on correlational data to motivate or justify significant policy shifts, with appropriate caution and qualification. For instance, regional disparities in educational attainment, public investment, and employment outcomes have often been documented through associative data, providing impetus for targeted place-based policies (Barca et al., 2012).

3.1 Data Source

This study uses the most recent version of the Kelley School of Business Innovation Intelligence Index (II^3) at Indiana University, Bloomington. For continuity, readers familiar with earlier versions may note that the II^3 is the updated form of the Innovation Index (StatsAmerica, 2023). The dataset is designed explicitly for the U.S. Economic Development Administration (EDA) to assist economic developers with strategic planning, grant writing, and technical assistance. The 43 measures and indices used in the exploratory analysis are categorized into five types of economic activity, each identified by a unique 5-digit m-code. The categories are as follows: *Human Capital and Knowledge Creation* (m10###), *Business Dynamics* (m20###), *Business Profile* (m30###), *Employment and Productivity* (m40###), and *Economic Development* (m50###) (StatsAmerica, 2023). The first two digits indicate the category, while the last three specify the particular measure.

This dataset is designed to aid in economic development with comprehensive and actionable indices for regional competitiveness, economic resilience, and strategic planning (EDA.gov, 2023). Measures indicating adverse conditions, such as unemployment, income inequality, and poverty, are expressed inversely. This means that regardless of their original polarity, favorable outcomes are represented by higher or positive values, while lower or negative values indicate adverse conditions. For example, a low poverty rate results in a higher value in the index. While migration has been associated with adverse socioeconomic impacts in rural-to-urban brain drain, it is expressed as a neutral condition. As such, the original polarity of its measurement remains unchanged. Our key measure, *Industry Diversity* (m40192), from the *Employment and Productivity* category, was selected due to its prominence in regional planning rhetoric and the literature (Angelopoulos et al., 2023; Plummer et al., 2022; McAreavey, 2022; Greve, 1994). Industry diversity is a metric that reflects the concentration of industries within a single county and how evenly these industries are spread across different sectors (StatsAmerica, 2023). Our entire dataset was georeferenced through manual data cleanup in a comma-separated value (CSV) spreadsheet to correct formatting errors and matched by county identification numbers (GEOID) with spatial data provided by the U.S. Census Bureau. The spreadsheet was uploaded to GIS software using the semi-standardized GEOID labeling system.

3.2 Correlation and Cluster Identification

Using RStudio, we analyzed multiple linear regression with all variables and *Industry Diversity*. First, the variables were analyzed across the entire U.S., and then the dataset was narrowed to focus on the Midwest region. For clarity, we adopt the U.S. Census Bureau definition of the Midwest (Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin) (Counts, 2021). We report national and Midwest results side by side to highlight scale effects. The Midwest subset is treated as a distinct context for interpretation rather than as subordinate to the national results. Though we do not analyze in detail other regions, we do touch on regional observations in Section 5.1 as the nationwide analyses visualize regional patterns of interest.

The significance of the regression was measured using the RStudio linear model default, with 0.1 set as the lowest threshold for significance and 0 as the highest, along with two graduated steps in between. Unlike the correlation analysis, we used multiple regression across all categories to account for the nested and interrelated behavior of the variables at both geographic scales. *Business Dynamics* (m20###) and *Economic Development* (m50###) showed high significance at both the U.S. and Midwest levels, while *Business Profile* (m30###) was significant at the U.S. level but not necessarily at the Midwest level. Although *Employment and Productivity* (m40###) displayed underwhelming significance, we maintained an interest in the relationship between *Latent Innovation* and *Industry Diversity*, which showed strong significance at both geographic scopes. Significance at both the U.S. and Midwest levels provides insight into key relationships. However, measures with significance at only one level are also important for understanding differences between scales. Significance at the U.S. level but not the Midwest level suggests potential spatial clustering at the national level, with the Midwest as an outlier. Conversely, significance at the Midwest but not the U.S. level also suggests a deviation from the national trend.

The category with the least relevance to *Industry Diversity*, which was subsequently excluded from further analysis, was *Human Capital and Knowledge* Creation (m10###). Apart from the measures of

educational attainment, the significance was low. Multicollinearity was a concern given the correlation among many variables; however, because of the progressive structure of educational attainment levels, it was assumed that the significance among these variables resulted from their nested behavior. To confirm this, we conducted a standard linear regression and geographically weighted regression (described in subsequent sections) to examine the relationships between *Associate's Degree* (m10104), *Bachelor's Degree* (m10105), *Graduate Degree* (m10106), and *Industry Diversity* (m40192). As expected, the association levels increased as higher education levels advanced, reflecting the prerequisite structure of progressive education levels. Although the nesting of higher education measures and their ascending relationship with *Industry Diversity* was intriguing, we excluded this entire category from further analysis and recommend it for future research focused specifically on the relationship between higher education and industry diversity.

While including additional variables in future analysis will likely strengthen the impact of this research, we spotlighted one measure from each category of interest. Due to the high correlation between measures in *Business Dynamics* (m20###) and *Business Profile* (m30###) categories, *Proprietorship Rate* (m30182) was selected as a per capita representation of both entrepreneurship and business health. *Income Inequality* (m50992) was selected from *Economic Development* (m50###) because of its relationships with relative poverty and its clear association with disparity. Lastly, *Latent Innovation* (m40191), which was selected from *Employment and Productivity* (m40###), stood out for its unique negative correlation and strong significance with *Industry Diversity*. It remains the only variable in the study with high significance at both geographic levels.

To further investigate the spatial distribution of *Industry Diversity* across the U.S., we used spatial autocorrelation to determine whether the pattern was dispersed, random, or clustered. With clustering confirmed, we conducted Hot Spot analyses (Getis-Ord Gi*) to compare the spatial distribution of *Industry Diversity* with other variables, identifying areas where hot spots and cold spots overlapped or contrasted. Finally, to explore the spatial clustering patterns of relationships between *Industry Diversity* and other variables, we applied geographically weighted regressions (GWR) to generate local R-squared values, producing maps that visualize the strength of these relationships. These methods employ visual aids and tables to enhance future analysis and foster discussion on how the variability in the effectiveness of industry diversity influences regional economic development.

3.3 Modeling Framework

To enhance transparency and reproducibility, we present the basic equations for the statistical and spatial methods used in this study.

Ordinary Least Squares (OLS)
We first estimated global linear relationships between Industry Diversity and each economic outcome variable using the OLS model:

$$y_i = \alpha + \beta D_i + x_i'\gamma + \epsilon_i$$

where y_i is the outcome for county i (*Income Inequality*, *Proprietorship Rate*, or *Latent Innovation*), D_i is *Industry Diversity*, x_i is a vector of control variables, α is the intercept, β and γ are parameters to be estimated, and ϵ_i is the error term.

Geographically Weighted Regression (GWR)
To capture spatial heterogeneity, we estimated local coefficients using GWR:

$$y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)D_i + x_i'(u_i, v_i)\gamma + \epsilon_i$$

where (u_i, v_i) are the spatial coordinates of county i, and coefficients $\beta_k(u_i, v_i)$ vary across space according to an adaptive kernel weighting scheme. Bandwidth optimization for GWR used ArcGIS Pro's golden search method to minimize the corrected Akaike Information Criterion.

Global Moran's I

We measured spatial autocorrelation in *Industry Diversity* and other variables using Global Moran's I:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

where n is the number of counties, x_i is the value for county i, $\bar{x}$ is the mean, and w_{ij} are elements of the spatial weight matrix W.

Getis–Ord G_i^* (Hot Spot Analysis)
To identify statistically significant spatial clusters (hot and cold spots), we used the Getis–Ord G_i^* statistic:

$$G_i^* = \frac{\sum_j w_{ij} x_j - \bar{X} \sum_j w_{ij}}{S \sqrt{\frac{n \sum_j w_{ij}^2 - \left(\sum_j w_{ij}\right)^2}{n-1}}}$$

where $\bar{X}$ and S are the mean and standard deviation of x for all n counties. High positive G_i^* values indicate statistically significant hot spots, and high negative values indicate cold spots. Spatial weights w_{ij} were row-standardized and based on k-nearest neighbors, with k selected to balance statistical power and spatial sensitivity.

4 Results

4.1 Exploratory Analysis

Through bivariate correlation and regression analysis, we first compared measures of economic activity in association with industry diversity for the U.S. and at a regional level, selecting the Midwest as defined by the U.S. Census Bureau (Counts, 2021). The exploratory analysis contrasted U.S.-level measures with those at the regional level. Multicollinearity and inherent nested behaviors were expected among many of the measures, particularly those within the same categories. However, since we are not seeking causality, the levels of association between measures are just as significant in understanding how entire categories relate to industry diversity.

The exploratory analysis began with a bivariate Pearson's correlation using a matrix of all 43 measures, including the explanatory measure, *Industry Diversity* (StatsAmerica, 2023). Unlike traditional quantitative studies that seek to establish causation, this study, situated within the social sciences, aims to use regression and correlation to only identify associations between variables. Following the relevance and significance guidelines for correlations in social science research described by Samuel and Okey (2015), we set a coefficient cutoff at +/- 0.5 to exclude weak correlations (i.e., those closer to 0). Any value above 0.5 (or below -0.5 for negative correlations) was retained for its relevant association, with particular attention given to those with strong correlations at +/- 0.8 (Samuel and Okey, 2015). Given the inherent correlation and nesting of many measures, a high degree of correlation was anticipated, especially within the same or similar categories, further suggesting substantial nesting among the different economic categories.

An important discovery from this analysis was that *Latent Innovation* (m40191) was the only variable with a relevant negative correlation coefficient within the specified range when compared with *Industry Diversity*. This finding marks *Latent Innovation* as a variable of particular interest, which may lead to opportunities for further study, as discussed in Section 5.1.

4.2 Cluster Analysis

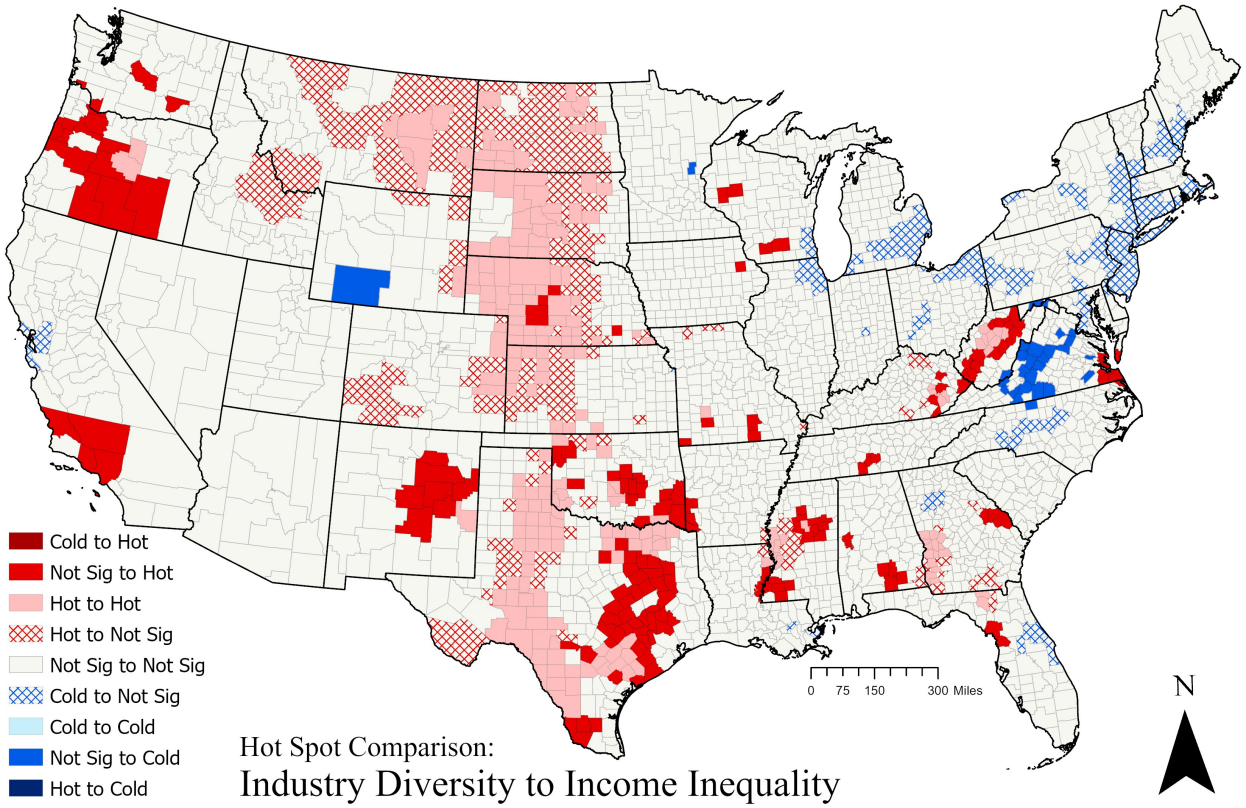
Using GIS, the first step of our cluster study was to confirm how the subject of this paper—industry diversity—is distributed across space. To do this, *Industry Diversity* was analyzed using spatial autocorrelation (Global Moran's I) to determine its distribution characteristics. Given the irregular shapes and sizes of counties across the U.S., the non-parametric algorithm K Nearest Neighbors was applied to the county-level dataset. The objective was to assess whether variations in *Industry Diversity* were evenly distributed

across the U.S. or exhibited spatial clustering patterns. The autocorrelation analysis using Global Moran's I returned an index of 0.226, a high Z-score (26.17), and a low P-value (0.0). These results confirmed our assumptions that the data exhibited significant spatial clustering, with a probability of less than 1% that the observed distribution was random. More importantly, this indicates that *Industry Diversity* is not constant and is influenced by different geographic phenomena across the country.

To qualitatively study the relationships of spatial clustering among variables in relation to *Industry Diversity*, a Hot Spot Analysis (Getis-Ord Gi*) was performed on the variables. The resulting raster layer products were then subjected to a Hot Spot Comparison Analysis to examine how the distribution of high values (Hot), low values (Cold), and insignificant values (Not Significant) compare across the variables. The maps in Figures 1-3 illustrate these results. Since these analyses do not represent the outcomes of correlation or regression, the clustering simply reflects the spatial density of high and low values for each variable pair. Even if density is high for a given pair, this does not imply causality. Instead, any strong visual association is only described by geographic proximity and excludes any quantified analysis.

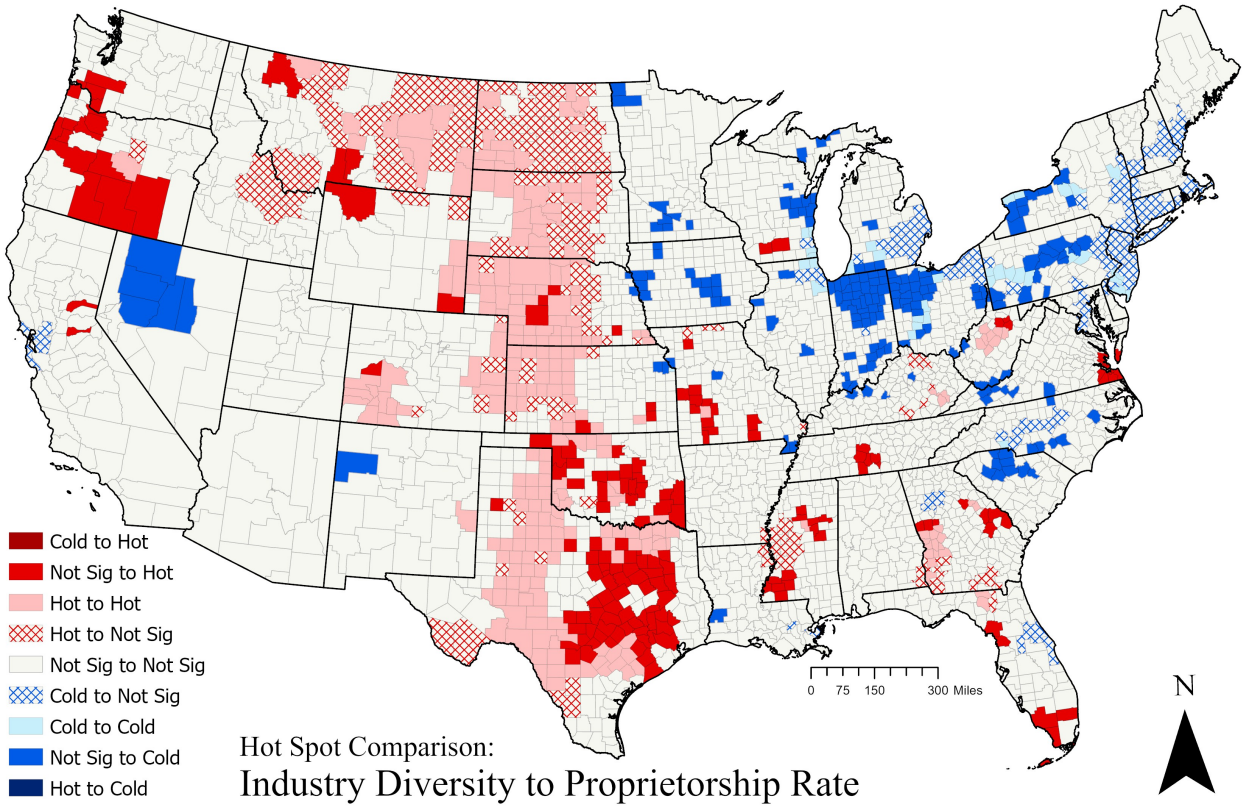
Examples of areas of interest in Figure 1 include the country's central region, where clusters of high industry diversity (hot spots) overlap with relatively favorable levels (a mix of hot spots and areas of no significance) of income inequality and proprietorship rates. Since income inequality and proprietorship rate were highly correlated in the exploratory analysis, there was some expectation that this correlation would be reflected in similarities in their geographic distribution. However, in the Mid-Atlantic region of the Eastern Seaboard (e.g., New York), high levels of industry diversity did not correspond with any significant spatial clustering of income inequality or the proprietorship rate.

Figure 1: Hot spot analysis comparing industry diversity with income equality.



The Hot Spot Comparison between industry diversity and latent innovation (Figure 3) revealed more contrasting results. In many rural counties across the western U.S., where there was little significant spatial clustering of industry diversity, there was a substantial spatial clustering of low latent innovation. Given the topography, with large swaths of sparsely populated or undeveloped public land, the natural resource-driven

Figure 2: Hot spot analysis comparing industry diversity with proprietorship rate.



and rural economies may cause adjacent counties to form extensive cold clusters.

Although Hot Spot Analysis enables a localized examination of spatial clustering across the U.S., it holds less significance for our regional focus on the Midwest. The smaller clusters in this region suggest that economic activity should be studied at a community or economic district level. We will dive deeper into the relevance of these findings in the results and discussion, sections 4 and 5, respectively.

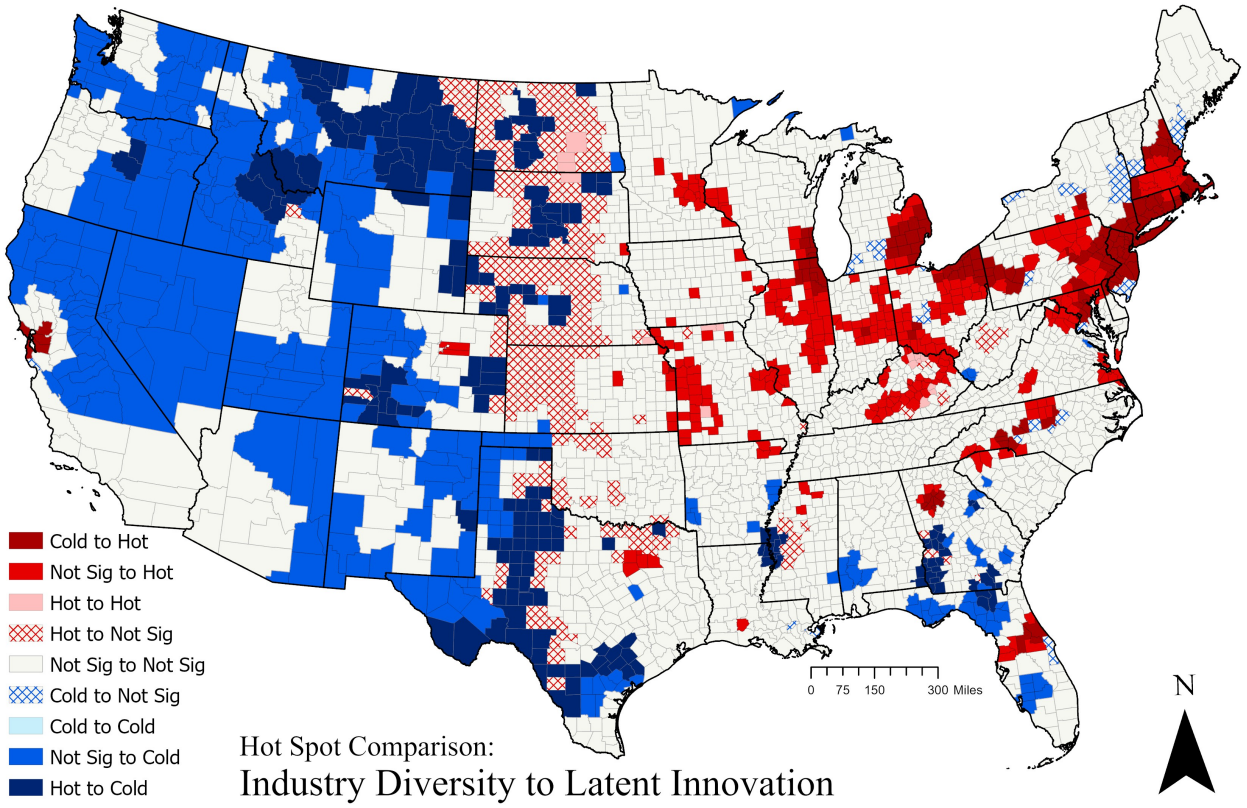
4.3 GWR

Geographically weighted regressions (GWR) were employed as our final level of analysis. Industry Diversity was used as the explanatory variable, while the highlighted measures—*Income Inequality*, *Proprietorship Rate*, and *Latent Innovation*—served as dependent variables. Considering multicollinearity and our goal of analyzing the association of different variables (not causality) with industry diversity, a separate GWR was performed for each measure (Price, 2023). An adaptive neighborhood type was utilized to account for variation in size, shape, and the number of neighbors for each county, and the Golden Search method offered by ArcGIS was used to fit an appropriate neighborhood selection. The local R-squared value was used to express the strength of the association between each variable and *Industry Diversity*. These R-squared values are represented in the maps and plots below (Figure 4-6) to indicate the association level between the dependent and explanatory variables.

In line with our previous parameters based on Samuel and Okey (2015), values of 0.5 or higher are considered relevant in determining an association between the measures. However, to assess significance within the local estimates, we focused on areas with values of 0.8 or higher and compared them to those without relevance. This contrast will guide the discussion on how areas where certain economic activities are highly associated with industry diversity differ from those where no association is observed.

Looking at *Income Inequality* (Figure 4), we identified the unusual feature of small geographic clusters

Figure 3: Hot spot analysis comparing industry diversity with latent innovation.

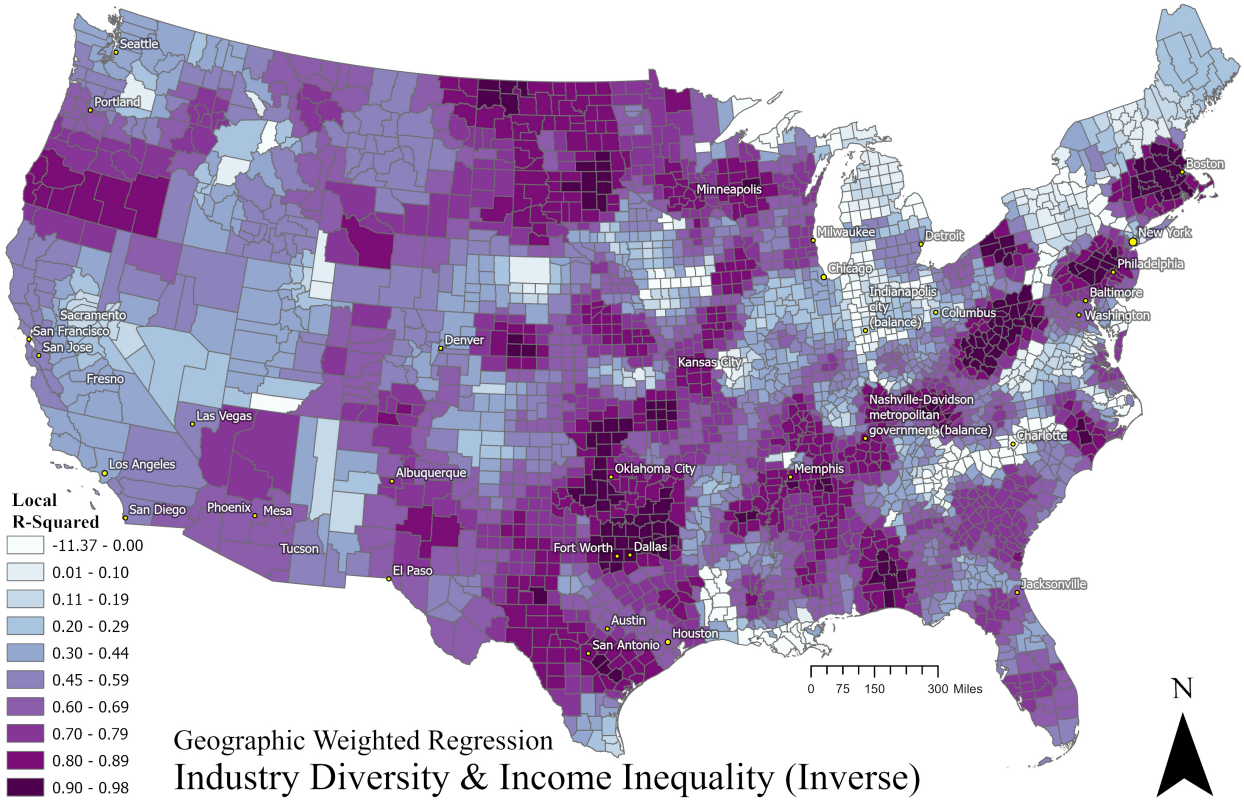


with negative R-squared values, though these are not widespread. Negative R-squared values indicate a poor fit and, for this study, are treated similarly to very low values or simply 0 (Chicco et al., 2021; Cameron and Windmeijer, 1996). For both *Income Inequality* and *Proprietorship Rate* (Figure 5), clusters with high R-squared values are concentrated in much of the Midwest, along a broad zone following the Mississippi River, large portions of Texas, and heavy concentrations throughout Appalachia. For *Latent Innovation*, the negative polarity observed in the exploratory correlation analysis also appeared in the GWR plot (Figure 6). A few strong geographic clusters with high R-squared values are found in Florida, and scattered patches are found nationwide. More intriguingly, *Latent Innovation* exhibits the weakest association in areas where the other variables are strongly associated with *Industry Diversity*, particularly in the central U.S. from the Mississippi Delta to the Midwest, producing only several small clusters with negative R-squared values.

The GWR results also show clear regional differences. For *Income Inequality* and *Proprietorship Rate*, the strongest links with *Industry Diversity* are in much of the Midwest, central U.S., near the Mississippi corridor, across large parts of Texas, and throughout Appalachia. These are the places where industry diversity seems most closely tied to more equal incomes or higher rates of local business ownership. For *Latent Innovation*, the map looks quite different with strong negative relationships with *Industry Diversity* appearing in Florida and a few metropolitan areas. At the same time, the central U.S., from the Mississippi Delta through the Midwest, shows much weaker links, even in places where the other two outcomes are strong. In the Northeast, *Industry Diversity* is generally high, but its link to these economic measures is less consistent, echoing the differences seen in the hot spot maps.

The national hot spot and GWR results show that the link between industry diversity and economic outcomes differs across U.S. Census regions. In the Midwest, higher diversity often goes hand-in-hand with stronger proprietorship rates and more balanced incomes, but this is not consistent everywhere. For example, much of Michigan, down along the Indiana–Ohio border, does not follow the broader regional trend. This variation highlights that these relationships are place-based and that geography, at both broad and local

Figure 4: US map of R-squared values for GWR results for industry diversity with income inequality using Jenks Natural Breaks map symbology.



scales, can reveal important nuances. In the South, especially in Appalachia, industry diversity is strongly tied to both proprietorship and income equality. At the same time, in the West, rural areas tend to combine low diversity with lower innovation. Together, these contrasts make clear that the Midwest's patterns are not replicated nationwide and underscore the need for region-specific economic development strategies.

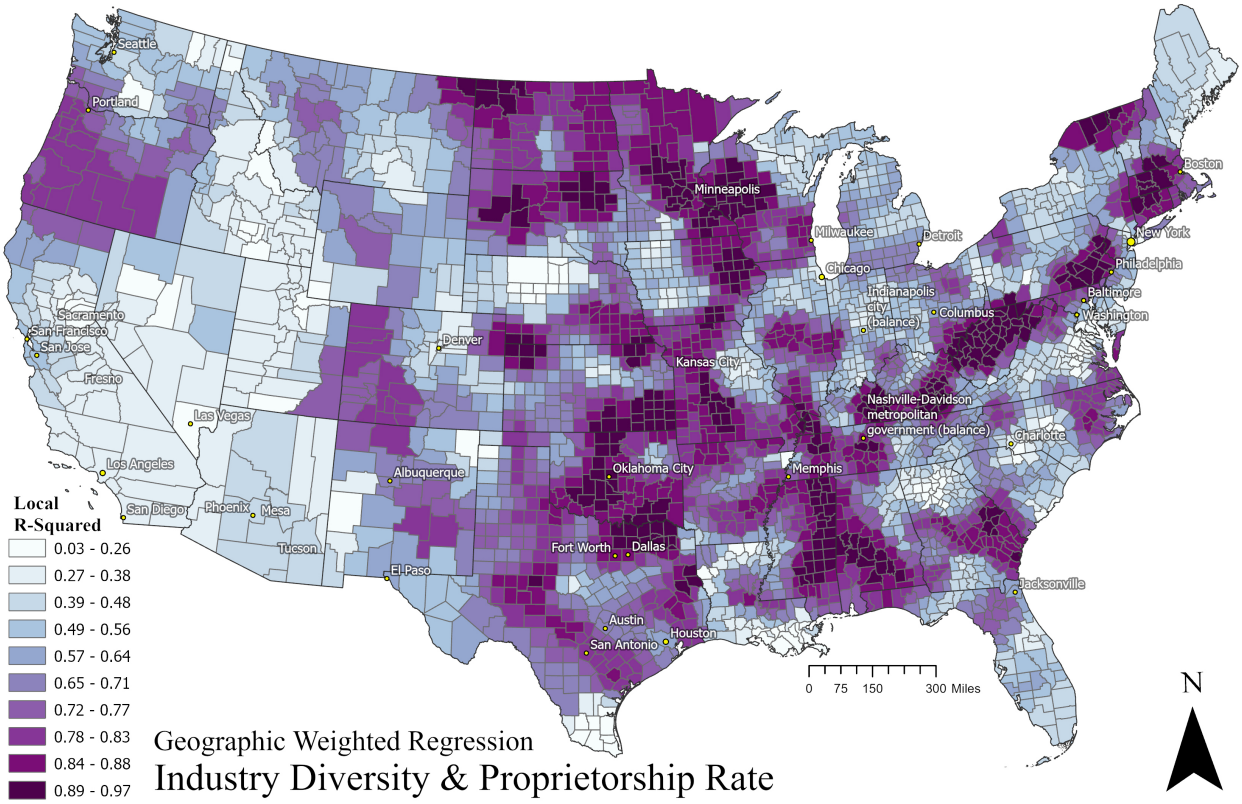
5 Discussion

5.1 Geographic Differentials and Impact on Regional Economic Development

Correlations and linear regressions used in initial exploratory analyses confirmed what literature in our field had long already assumed: a one-size-fits-all approach to economic development policy from a national perspective is severely limiting (Austin et al., 2018). As noted in our methodology, these implications are drawn from statistically significant associations rather than confirmed causal effects and should be interpreted as exploratory signals to inform, not determine, regional development strategies. The differences in significance levels between multiple U.S. and regional regressions provide the first clue that geographic variables are obscured in the national data. The Hot Spot and GWR maps illustrate the broader picture, demonstrating that tailored regional solutions would be far more effective for economic development than a uniform national approach. These findings, which go beyond the preexisting assumptions of the economic development community, call for a more local and comprehensive consideration of regional planning.

Of the three variables analyzed, Latent Innovation produced the most intriguing results and behaved contrary to the other variables. The activity of latent innovation, which involves the sharing of knowledge and processes among industries, was initially expected to benefit from a diverse pool of firms. However, what was anticipated to be a high and positive relationship between industry diversity and innovation instead revealed

Figure 5: US map of R-squared values for GWR results for industry diversity with proprietorship rate using Jenks Natural Breaks map symbology.

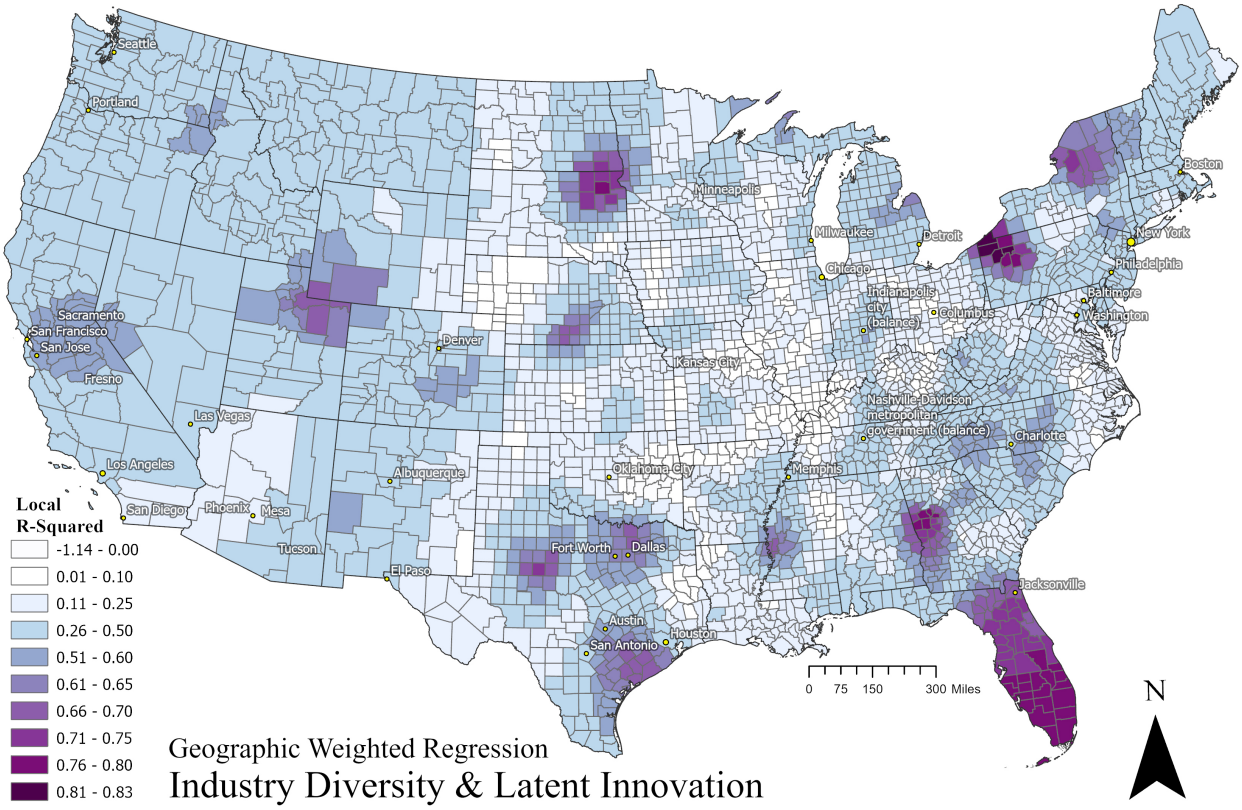


unexpected conditions. The Hot Spot Comparison showed a negative correlation in mismatch clusters across the U.S. In many areas with high industry diversity (and population density), latent innovation activity was low. These findings, which have significant implications for economic development strategies, suggest that latent innovation is driven by strong clusters of same-sector firms, which can compensate for low diversification through collaboration or shared resources. However, when industry diversity is introduced, it appears to dilute the clustering effect, and firms within one sector may have less to offer those in unrelated sectors.

Industry clustering has its advantages (Woerter, 2009), but it is conceptually distinct from industry diversity. Clustering refers to the spatial concentration of related industries that benefit from shared suppliers, specialized labor pools, and knowledge networks, whereas diversity captures the variety and evenness of industries present in a local economy, regardless of whether they are related. A county can be highly clustered but low in diversity if dominated by a single strong sector, or highly diverse but not strongly clustered if its industries are unrelated and geographically dispersed. Low diversity is not inherently detrimental to economic prosperity. In some regions where industry diversity shows little to no association with measures like income inequality, other structures, such as social programs or government regulations, may offset the adverse effects of low diversity (Martin and Sunley, 2006). The key takeaway is that regional approaches to economic development must account for geographic variations rather than a uniform national strategy.

Industry clustering can foster innovation and growth within a sector (Danesh Shakib, 2020; Hinzmann et al., 2019). While this might seem directly associated with industry diversity, the clustering and shared economic activity are more likely products of sectoral composition and geographic density. Highly urbanized areas, such as Silicon Valley, may exhibit a wide range of industry types, yet the dominance of the high-tech sector gives the region a low overall diversity score (StatsAmerica, 2023). Low diversity does not necessarily indicate an unhealthy economy. However, in distressed areas suffering from low diversity, examining their adverse conditions and their relationship to industry diversity could provide insights into relief. The cor-

Figure 6: US map of R-squared values for GWR results for industry diversity with latent innovation using Jenks Natural Breaks map symbology.



relation between variables within the same category suggests that supporting one variable could positively impact others. Since these variables often overlap in their association with *Industry Diversity*, efforts to increase diversity in regions where this association is strong could benefit targeted economic programming.

It is crucial to note that the R-squared value suggests the degree of association between industry diversity and the activities described by the dependent variables. This association (or lack thereof) is key to informing any development action. Increasing diversification alone may not yield the desired benefits if no strong association exists. The relationship between industry diversity and other economic measures is embedded in the local economy's structures and wide networks. One place of concern is when industry diversity conflicts with the interests of industry leaders who serve as key agents in the regional economy. Large enterprises or anchor employers can exert pressure on trends and policies, potentially suppressing the effects of industry diversity and stifling the flow of economic activity. Moreover, short-term reforms that stimulate economic growth can indeed offer an immediate, measurable boost to growth (Callais, 2022), yet as with industry diversity, these benefits may be transitory if underlying spatial and structural challenges remain unaddressed. It is essential first to recognize conditions that hinder the association of industry diversity before reaping the benefits of its development.

Our results contribute to the evolutionary economic geography literature by showing that the influence of industry diversity on economic outcomes is not uniform across space but is shaped by region-specific contexts. While theories of related variety (Frenken et al., 2007) and structural resilience emphasize the benefits of diverse but related industry structures, our findings suggest that these benefits are contingent: in some regions, diversity aligns strongly with proprietorship or income equality, while in others, the relationship is weak or even absent. This place-contingent pattern supports calls for a more geographically nuanced application of related variety theory and underscores the need to integrate spatial heterogeneity into frameworks of regional resilience.

5.2 Towards a Better Understanding of Industry Diversification and Economic Resilience

The findings from this exploratory study suggest that scholars interested in economic development and resilience must pay close attention to systematic changes in economic geography and sectoral composition over time. The observed differentials indicate that some economies successfully shift to higher value-added activities within existing industries or transition to higher value-added industries to compete in a broader set of sectors, while others experience a narrowing—or extension—of industry composition, favoring specialization (Isaksen et al., 2019). Specifically, the study contributes to the theoretical discourse on regional economic resilience by advancing a more integrated perspective that bridges the insights of industrial diversity, clustering, and evolutionary economic geography. Our findings highlight that resilience is not solely a function of diversity or specialization, but rather the result of their nuanced interaction. Specifically, we show that regions combining related industry clusters with broader sectoral diversity tend to demonstrate adaptive capacity. This supports and extends the notion of related variety (Frenken et al., 2007), suggesting that resilience is enhanced not just through diversification, but through diversification that builds on existing regional competencies and allows for recombination of knowledge across closely aligned sectors.

In doing so, our analysis refines existing theories of industry diversity by emphasizing the structural configuration and cognitive proximity of industries, rather than simply counting the number of sectors present. This distinction aligns with recent work by Chen et al. (2024) and Grabner and Modica (2022) who argue that the development benefits of industry diversity are conditional on its relatedness and the institutional capacity to leverage it. Our empirical patterns thus contribute to a more dynamic theory of regional resilience, one that recognizes the importance of industrial path dependencies and the evolutionary trajectories that shape the economic geography of places over time.

Furthermore, this study challenges conventional dichotomies that frame clustering and diversity as opposing forces. Instead, our findings reveal how clustered specialization and inter-industry diversity can coexist and reinforce one another when embedded in supportive institutional and innovative systems. This synthesis offers a more holistic understanding of regional development, encouraging future theoretical and empirical work to consider how structural variety, spatial concentration, and evolutionary logic collectively shape regional outcomes. In this way, the paper not only describes spatial-economic patterns but also provides a theoretical lens through which to interpret them.

This process of enhanced industry specialization, or extension, consists of "incremental product and process innovations in existing industries and along prevailing technological paths" (Isaksen et al., 2019). These developments consolidate industrial activities through stepwise innovations over time (Neffke et al., 2011). Path upgrading, defined as "major intra-path changes that shift an existing regional industrial path in a new direction" (Grillitsch, 2017), occurs through the integration of new technologies or significant organizational changes, such as the development of more advanced functions, more specialized skills, or niche markets in mature industries. Consequently, such developments strengthen certain regional industries, often at the expense of others, due to limited regional resources. This, in turn, can explain the inconsistent developments observed across geographic markets, as demonstrated in this study (Isaksen et al., 2019).

From a practical standpoint, the findings of this study raise important questions about workforce development needs and opportunities in regional economies. Industry diversity reflects the availability of employment options in a community. While a highly specialized local economy may attract workers based on concentrated demand for specific skills, low industry diversity in rural areas often leads to labor-intensive production, with downward pressure on wages, which can harm regional resilience (Ross and Bateman, 2017).

From an economic development perspective, one of the most critical goals of economic resilience is ensuring that people find meaningful work that allows them to support themselves, their families, and their overall well-being. Work provides economic freedom and independence and fosters community and social cohesion. Changing demographic patterns necessitate that rural communities adapt not only to shifts in business and industry composition but also to transformations in employment markets, such as new growth sectors like the green and silver economies, which influence local economies (Thurlow et al., 2019). Failure to adapt to these changes undermines efforts to build economic competitiveness and community resilience.

While local development needs vary greatly in terms of economic competitiveness, common challenges include attracting young people and encouraging entrepreneurs to settle in declining areas (Vazzana and

Rudi-Polloshka, 2019). Many local and regional economies have historically developed around strong industry clusters rooted in agriculture and related manufacturing sectors, such as food processing and other primary and secondary industries. As a result, specialization—or extension—often became the outcome (Al-Abdulmunem et al., 2021). Anchor employers, in particular, were key drivers of regional employment. However, since the 1970s, global competition, consolidation of operations, and other structural changes in national and state economies have contributed to rural population decline (Watkins and Seidelman, 2019). Additionally, the failure to adapt to technological changes has negatively impacted traditionally resource-based industries, leaving many communities struggling to reinvent themselves, leading to low product and employment diversity (Jablonski et al., 2021). The findings of this study suggest that the legacy of resource-based economies, anchor employers, and single-sector economies has been addressed unevenly across the U.S. While some regions have successfully diversified across geographic and regional clusters, others have struggled, facing negative outcomes in terms of demographics, socioeconomic factors, business dynamics, and economic competitiveness.

For the economic development literature, and particularly from a policy perspective, future studies should focus on market relevance in regional economies. Maintaining market relevance is crucial to successful regeneration strategies. Restructuring strategies in response to demographic, socioeconomic, and industry changes must first consider the consequences of these changes to identify conditions conducive to new development opportunities. Regeneration strategies, therefore, need to clarify the current state of industry diversity while integrating economic, socio-educational, and local policies to consolidate innovation, entrepreneurship, and human capital efforts. If the goal is to improve social and economic conditions, achieve environmental improvement, and bolster economic resilience, understanding the outcomes associated with industry diversity should be the first step.

6 Conclusions

Industry diversity is often recognized as a positive attribute of a healthy and resilient regional economy. However, simply injecting diversity to counter single-sector dependencies will not be a panacea for reviving rural communities or resolving rural-to-urban disparities. Such claims would be implausible in large cities, obscured by the complexities of urban systems. However, in rural areas of the U.S., where low population density and high relative productive output coexist, the complexities dissipate, revealing important social and economic relationships between industries and the local communities that depend on them. In this context, addressing clustering as a key spatial component highlights scale as the determining factor for the relevance of these relationships. Our comparison of national versus Midwest-level relationships suggests that spatial resolution is essential. The variability expressed in the regression and correlation results between these two scales, combined with spatial autocorrelation, confirmed that varying levels of industry diversity are clustered across the country.

Measuring smaller, rolling neighborhoods across the country produces maps at the county level of resolution. One limitation of this analysis is the inclusion of very small counties, some with populations under 1,000 residents. In such areas, economic and demographic measures can be more volatile from year to year, and a small number of establishments may heavily influence industry composition. While these counties are important for understanding the full geographic diversity of the United States, their small scale warrants caution in interpreting results. Future research could explore sensitivity analyses excluding very small counties or aggregating them to larger functional regions, such as commuting zones or core-based statistical areas (CBSAs), to assess the robustness of the observed patterns. Data visualization through geographically weighted regression and Hot Spot analyses allows the study to be applied to regional development efforts. By observing the varying associations between industry diversity and selected measures (income inequality, proprietorship rate, and latent innovation), it becomes clear that phenomena often generalized under national statistics could greatly benefit from increased spatial resolution. This would enable a more effective course of action for specific regions. For example, the association between diversification and income inequality may be weak in areas where diversification is low and income inequality is high.

For such communities, it is essential to study the factors that hinder the impact of diversity on the economy, such as resource dependency or adverse policy. Addressing these barriers is crucial before fully

benefiting from a diverse economy. This does not negate the positive effects of diversification; rather, it suggests that those effects may be obscured or suppressed by more pressing issues. To maximize the impact of local economic development, a regional approach tailored to the unique local conditions is recommended.

While there have long been calls for higher-resolution analyses in economic development, rather than focusing strictly on rigid causal relationships, exploring associations between different social and economic characteristics can reveal the mechanisms driving regional economies. Visualizing clusters of high and low industry diversity is informative, but studying the associations between various measures of industry diversity uncovers key drivers of the local economy and how it responds to crises and interventions.

Our findings show that the relationships between industry diversity and economic outcomes vary widely across Census regions, with distinct patterns in the Midwest, Northeast, South, and West. This study draws on national and Midwest regional analyses as a detailed case to keep the scope focused. Nevertheless, the national-level results make clear that these patterns are far from uniform nationwide. Such variation calls for economic development strategies tailored to regional contexts rather than a one-size-fits-all approach. Sustainable growth and equitable prosperity across the United States depend on recognizing and addressing each locality's unique mix of industries, cultural dynamics, and socioeconomic conditions.

Acknowledgments

The questions motivating this research grew out of ongoing conversations with regional stakeholders, particularly those engaged with the Region Nine Development Commission (RNDC) in Minnesota, whose practical concerns informed and inspired the study's policy relevance. The interpretations and conclusions presented here are solely those of the authors and do not represent the views of RNDC. We are especially grateful to Professor Scott Robeson for his generous guidance throughout this project. He provided careful readings of drafts and invaluable recommendations, particularly in strengthening our spatial statistics and academic contributions.

References

Al-Abdulmunem, M., Drake, R. E., and Carpenter-Song, E. (2021). Evidence-Based Supported Employment in the Rural United States: Challenges and Adaptations. *Psychiatric Services*, 72(6):712–715.

Angelopoulos, S., de Silva, A., Navon, Y., Sinclair, S., and Yanotti, M. (2023). Economic Resilience in a Pandemic: Did COVID-19 Policy Effects Override Industry Diversity Impacts in Australia? *Economic Papers: A journal of applied economics and policy*, 42(2):153–171. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1759-3441.12384.

Arano, K. and Srinivasan, A. K. (2021). Local Economies and Economic Growth, Does Location Matter? A Spatial Analysis in the Great Lakes Region. *Journal of Regional Analysis & Policy*, 51(1):79–93. Publisher: Mid-Continent Regional Science Association.

Audretsch, D. B., Houweling, P., and Thurik, A. R. (2004). Industry Evolution: Diversity, Selection and the Role of Learning. *International Small Business Journal: Researching Entrepreneurship*, 22(4):331–348.

Austin, B., Glaeser, E., and Summers, L. (2018). Saving the heartland: Place-based policies in 21st Century America. *Brookings Papers on Economic Activity*, (Spring):151–255.

Babkin, A., Shkarupeta, E., Tashenova, L., Malevskaia-Malevich, E., and Shchegoleva, T. (2023). Framework for assessing the sustainability of ESG performance in industrial cluster ecosystems in a circular economy. *Journal of Open Innovation: Technology, Market, and Complexity*, 9(2):100071.

Barca, F., McCann, P., and Rodríguez-Pose, A. (2012). The Case For Regioal Development Intervention: Place-Based versus Place-Neutral Approaches. *Journal of Regional Science*, 52(1):134–152.

Bergman, E. M. and Feser, E. J. (2020). Industrial and Regional Clusters: Concepts and Comparative Applications, 2nd ed.

Borowczyk-Martins, D., Bradley, J., and Tarasonis, L. (2014). Racial Discrimination in the U.S. Labor Market: Employment and Wage Differentials by Skill.

Boschma, R. (2015). Towards an Evolutionary Perspective on Regional Resilience. *Regional Studies*, 49(5):733–751.

Boschma, R. and Iammarino, S. (2009). Related Variety, Trade Linkages, and Regional Growth in Italy. *Economic Geography*, 85(3):289–311.

Brown, L. and Greenbaum, R. T. (2017). The role of industrial diversity in economic resilience: An empirical examination across 35 years. *Urban Studies*, 54(6):1347–1366.

Byun, S.-Y., Irvin, M. J., and Meece, J. L. (2015). Rural–Nonrural Differences in College Attendance Patterns. *Peabody Journal of Education*, 90(2):263–279.

Callais, J. (2022). Free to Grow? A Matching Methods Analysis of Economic Freedom in the United States. *Journal of Regional Analysis & Policy*, 52(1):88–104. Publisher: Mid-Continent Regional Science Association.

Cameron, A. C. and Windmeijer, F. A. G. (1996). R-Squared Measures for Count Data Regression Models with Applications to Health-Care Utilization. *Journal of Business & Economic Statistics*, 14(2):209.

Capra, F. and Jakobsen, O. D. (2017). A conceptual framework for ecological economics based on systemic principles of life. *International Journal of Social Economics*, 44(6):831–844.

Carr, P. J. and Kefalas, M. (2011). *Hollowing out the middle: the rural brain drain and what it means for America*. Current affairs / sociology. Beacon Press, Boston, Mass.

Chen, J., Li, X., and Zhu, Y. (2024). Shock absorber and shock diffuser: the multiple roles of industrial diversity in shaping regional economic resilience after the Great Recession. *The Annals of Regional Science*, 72(3):1015–1045.

Chicco, D., Warrens, M. J., and Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science*, 7:e623.

Content, J. and Frenken, K. (2016). Related variety and economic development: a literature review. *European Planning Studies*, 24(12):2097–2112.

Counts, A. (2021). 12 States Make up the Midwest Region of the Country. Section: Government.

Danesh Shakib, M. (2020). Using system dynamics to evaluate policies for industrial clusters development. *Computers & Industrial Engineering*, 147:106637.

Delgado, M., Porter, M. E., and Stern, S. (2010). Clusters and entrepreneurship. *Journal of Economic Geography*, 10(4):495–518.

EDA.gov (2023). StatsAmerica.

Fitzgerald, D. (1993). Farmers Deskilled: Hybrid Corn and Farmers' Work. *Technology and Culture*, 34(2):324–343. Publisher: [The Johns Hopkins University Press, Society for the History of Technology].

Forni, M. and Paba, S. (2002). Spillovers and the Growth of Local Industries. *The Journal of Industrial Economics*, 50(2):151–171. Publisher: Wiley.

Frenken, K., Van Oort, F., and Verburg, T. (2007). Related Variety, Unrelated Variety and Regional Economic Growth. *Regional Studies*, 41(5):685–697.

Grabner, S. M. and Modica, M. (2022). Industrial resilience, regional diversification and related variety during times of crisis in the US urban–rural context. *Regional Studies*, 56(10):1605–1617.

Greve, H. R. (1994). Industry Diversity Effects on Job Mobility. *Acta Sociologica*, 37(2):119–139.

Grillitsch, M. (2017). Unrelated knowledge combinations: Unexplored potential for regional industrial path development.

Hanna, T. M. (2019). Public Finance Chapter 5 - Community wealth building and resilient local economies: The role of anchor institutions.

Hinzmann, S., Cantner, U., and Graf, H. (2019). The role of geographical proximity for project performance: evidence from the German Leading-Edge Cluster Competition. *The Journal of Technology Transfer*, 44(6):1744–1783.

Isaksen, A., Jakobsen, S.-E., Njøs, R., and Normann, R. (2019). Regional industrial restructuring resulting from individual and system agency. *Innovation: The European Journal of Social Science Research*, 32(1):48–65.

Jablonski, B. B., Bauman, A., and Thilmany, D. (2021). Local Food Market Orientation and Labor Intensity. *Applied Economic Perspectives and Policy*, 43(3):916–934. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/aepp.13059.

Johnson, K. M. and Lichter, D. T. (2019). Rural Depopulation: Growth and Decline Processes over the Past Century. *Rural Sociology*, 84(1):3–27.

Korez-Vide, R. and Tominc, P. (2016). Competitiveness, Entrepreneurship and Economic Growth. In

Trapczyński, P., Puślecki, , and Jarosiński, M., editors, *Competitiveness of CEE Economies and Businesses*, pages 25–44. Springer International Publishing, Cham.

Kosfeld, R. and Mitze, T. (2023). Research and development intensive clusters and regional competitiveness. *Growth and Change*, 54(4):885–911.

Manski, C. F. (2013). *Public Policy in an Uncertain World: Analysis and Decisions*. Harvard University Press, Cambridge.

Martin, R. and Sunley, P. (2006). Path dependence and regional economic evolution. *Journal of Economic Geography*, 6(4):395–437.

Martin, R., Sunley, P., Gardiner, B., and Tyler, P. (2016). How Regions React to Recessions: Resilience and the Role of Economic Structure. *Regional Studies*, 50(4):561–585.

McAreavey, R. (2022). Finding rural community resilience: Understanding the role of anchor institutions. *Journal of Rural Studies*, 96:227–236.

Morgan, S. L. and Winship, C. (2010). *Counterfactuals and causal inference: methods and principles for social research*. Analytical methods for social research. Cambridge Univ. Press, Cambridge, 7. print edition.

Neffke, F., Henning, M., and Boschma, R. (2011). How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions. *Economic Geography*, 87(3):237–265. Publisher: Clark University.

Neumann, T. (2021). The impact of entrepreneurship on economic, social and environmental welfare and its determinants: a systematic review. *Management Review Quarterly*, 71(3):553–584.

Nutley, S., Walter, I., and Davies, H. T. O. (2014). *Using evidence: how research can inform public services*. Policy Press, Bristol.

Oman, X. and Alisherovich, T. S. (2022). THE ROLE AND IMPORTANCE OF CLUSTERS IN THE AGRICULTURAL SECTOR. *Gospodarka i Innowacje.*, 29:202–206.

Pacheco, A. J., Braekkan, K., and Albaum, S. (2021). Applying Geographic Models to Examine the Impact of Gross Domestic Product as a Proxy for Economic Well-Being. *Journal of Applied Economics and Business*, 9(4):65–88.

Pilinkienė, V. and Mačiulis, P. (2014). Comparison of Different Ecosystem Analogies: The Main Economic Determinants and Levels of Impact. *Procedia - Social and Behavioral Sciences*, 156:365–370.

Plummer, L. A., Parker, S. C., and Reyes, S. C. (2022). Regional Path Breaking: The Role of Industry Switching, Industry Diversity, and New Knowledge in New Venture Exit. *Entrepreneurship Theory and Practice*, 46(5):1231–1255.

Porter, M. E. (2011). U.S. Cluster Mapping Project.

Potts, D. (2022). Reshaping the Urban-Rural Divide in the 21st Century: Shifts in the Geographies of Urban-Based Livelihoods. *Journal of International Affairs*, 74(1):60–78.

Previtali, F. S. and Fagiani, C. C. (2015). Deskilling and degradation of labour in contemporary capitalism: the continuing relevance of Braverman. *Work Organisation, Labour and Globalisation*, 9(1).

Price, M. H. (2023). *Mastering ArcGIS Pro*. McGraw Hill LLC, New York, NY, second edition edition. OCLC: 1251737365.

Ragin, C. C. and Fiss, P. C. (2016). *Intersectional Inequality: Race, Class, Test Scores, and Poverty*. University of Chicago Press.

Reddy, S. (2006). Processing plants' dangers don't scare off migrants: One in 10 workers injured each year at meatpacking factories. *Dallas Morning News, The (TX)*.

Rodríguez-Pose, A. (2013). Do Institutions Matter for Regional Development? *Regional Studies*, 47(7):1034–1047.

Ross, M. and Bateman, N. (2017). Meet the low-wage workforce.

Samuel, M. and Okey, L. E. (2015). THE RELEVANCE AND SIGNIFICANCE OF CORRELATION IN SOCIAL SCIENCE RESEARCH.

Sisk, B. and Donato, K. M. (2018). Weathering the Storm? The Great Recession and the Employment Status Transitions of Low-Skill Male Immigrant Workers in the United States [1]. *International Migration Review*, 52(1):90–124.

StatsAmerica (2023). Innovation Intelligence: StatsAmerica.

Storsletten, V. M. L. and Jakobsen, O. D. (2015). Development of Leadership Theory in the Perspective of Kierkegaard's Philosophy. *Journal of Business Ethics*, 128(2):337–349.

Thurlow, J., Dorosh, P., and Davis, B. (2019). Demographic change, agriculture, and rural poverty. In

Sustainable Food and Agriculture, pages 31–53. 1st edition edition.

Toma, S.-G., Grigore, A.-M., and Marinescu, P. (2014). Economic Development and Entrepreneurship. *Procedia Economics and Finance*, 8:436–443.

Vazzana, C. M. and Rudi-Polloshka, J. (2019). Appalachia Has Got Talent, But Why Does It Flow Away? A Study on the Determinants of Brain Drain From Rural USA. *Economic Development Quarterly*, 33(3):220–233. Publisher: SAGE Publications Inc.

Watkins, J. P. and Seidelman, J. E. (2019). The Last Gasp of Neoliberalism. *Journal of Economic Issues*, 53(2):363–369.

Woerter, M. (2009). Industry diversity and its impact on the innovation performance of firms: An empirical analysis based on panel data (firm-level). *Journal of Evolutionary Economics*, 19(5):675–700.