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Spatial Determinants of Community Well-Being: A Geographically Weighted Regression Analysis of U.S. Counties*

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Abstract: As well-being gains traction as an economic development strategy, scholars and practitioners face two key challenges: the large number of factors associated with community well-being and the heterogeneity of places, which necessitates a local perspective on these relationships. Following Isserman et al. (2009), we construct a U.S. county-level well-being index using four well-being indicators. We then apply Bayesian model averaging to select from 77 candidate community variables, organized within the Community Capitals Framework, and estimate a geographically weighted regression to assess whether these associations vary across space. We find that the variables most associated with community well-being span four capital types: human, social, financial, and natural, with human capital measures dominating. We also find most community variables show significant spatial variation. Together, these findings suggest that policies aimed at improving community well-being should prioritize investments in people while remaining responsive to local assets and contextual conditions.

Keywords: Well-Being, Livability, Community Capitals Framework, Bayesian Model Averaging, Geographically Weighted Regression

JEL Codes: I31, R11, C21

1. INTRODUCTION

Gross domestic product and income have historically served as proxies for the well-being of a nation. But these traditional measures are generally linked to economic performance rather than the conditions that people experience. Sen (1999) argued that income matters because

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it is a means to more freedom to lead a life people value. Easterlin (1974; see also Easterlin and O'Connor, 2022) found that in the cross-section the relationship between income and life satisfaction, or happiness, is positive but longitudinally it is negligible creating a paradox. This gap between economic performance and well-being has motivated alternative measures that reflect peoples's lived experience such as the human development index (UNDP, 1990; Sen, 1999; Stiglitz et al., 2009), quality of life (Rosen, 1974; Liu, 1976; Roback, 1982), livability (Pacione, 1990), and life satisfaction (Campbell et al., 1976; Diener, 1984) among others.

Within community economic development it has been widely established that factors associated with quality of life contribute to economic growth (e.g., Deller et al., 2001; Rickman, 2014), but increasingly community development economists are questioning how this process plays out. Historically, thinking has centered around the idea that people follow jobs, but has that relationship changed? Is it now the case that jobs follow people (Williams and Jobes, 1990)? If the answer is "yes," then communities must rethink what drives the growth and development process. Specifically, the question becomes why people would select to move to or remain in a particular community. Notions of quality of life move to the front and center of community economic development discussions. Deller (2021, 2025) articulated this shift as the "fourth wave" of economic development. If well-being drives where people choose to live, have a family, and start a business, which in turn drives local economic growth, then understanding what shapes community well-being becomes essential for regional policy.

Well-being is conceptually multidimensional, meaning it spans several dimensions such as health, education, employment, and amenities (Stiglitz et al., 2009; Joshanloo et al., 2019). As a result, there is a plethora of factors associated with well-being. Weijers (2014) called it the "everything matters" problem, and Veréb et al. (2024) described it as chaos with a review of 9,000 related indicators. But at the same time, in a review of 26 quality-of-life tools, Mittal et al. (2020) found that not a single tool captures all theoretical dimensions. In short, scholarship on well-being faces a dilemma: including too many candidate variables risks diluting policy relevance, while excluding variables risks inaccurate policy inferences. In both cases, insights into policy options at the local level become "cloudy."

This dilemma leads to empirical model uncertainty. Because excluding variables risks omitted variable bias, researchers often consider dozens or hundreds of candidates, but no standard method can determine which ones belong. R-squared or stepwise selection compares specifications but offers no conceptual grounding why variables belong in the model (Chatfield, 1995; Brock et al., 2007; Steel, 2020). Organizing frameworks, such as the Community Capitals Framework (Flora et al., 1992; Flora and Flora, 2008) and the Shaffer Star (Shaffer et al., 2004), narrow the field of variables and provide structure but a formal selection method is still needed.

Even with the "right" variables in hand, another challenge in studying well-being is the heterogeneity of place. Places differ in economic structures and demographics, yet a global regression assumes each variable's relationship with well-being is the same everywhere (Hurter and Martinich, 1989). For example, life satisfaction studies in Europe found different leading factors across sub-regions (Aslam and Corrado, 2012; Dissart and Kuentz-Simonet, 2025), and the association between urban sprawl and well-being reversed direction from eastern to western U.S. counties (Wang et al., 2025). If the policy is meant to be crafted for

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local communities (Kilkenny and Johnson, 2007), or place-based policy (Barca et al., 2012; Rodríguez-Pose, 2018), it is vital to gain insight into what drives well-being in their local context. Yet studies that combine formal variable selection with spatially varying coefficient estimation for community well-being in the U.S. remain scarce.

In this study, we explore which community capitals (characteristics) are associated with county-level well-being and how those associations vary across the 3,100 contiguous U.S. counties, following a similar study design as Boyce (2025). We measure well-being using four indicators identified by Isserman et al. (2009): poverty, housing affordability, educational attainment, and employment. To address model uncertainty, we apply Bayesian model averaging (BMA) to a wide set of community characteristics organized within the Community Capitals Framework to identify the specific community characteristics associated with well-being. Next, we use geographically weighted regression (GWR) to estimate how these associations vary across places. The results provide county-level evidence on which capitals bind in which places and which ones communities associate with well-being.

Our results show that 20 variables are selected from four of the seven capital types when we run BMA on each capital type separately and adopt a posterior inclusion probability (PIP) of 0.85. Human and social capital each contribute seven, the most of any type, followed by financial capital with five, and natural capital with one. By contrast, there are no variables from built, cultural, and political capital that exceed the inclusion threshold under BMA. The GWR results show that global estimates can mask locally important relationships. Eleven of the 20 selected variables show significant spatial variation. We find three variables with coefficients that reverse sign across regions, seven that vary in magnitude, and one false negative that is insignificant globally but significant in some counties.

The remainder of this study is organized as follows. We review the related literature in Section 2. In Section 3, we discuss the well-being measure and candidate community characteristic variables and outline the variable selection process through BMA and define the GWR specification. The results of the analysis are presented in Section 4. We conclude the study in Section 5 with policy implications.

2. LITERATURE REVIEW

Conflating growth of places with well-being of people is broadly problematic, with rural areas as the starkest example. In rural areas, growth metrics that lag their urban counterparts usually produce a narrative of perpetual decline, and even stable communities appear stagnant despite being widely regarded as good places to live (Isserman, 2005; Isserman et al., 2009; Schmidt et al., 2026). While the inadequacy of growth as a measure of well-being is generally acknowledged, how to measure well-being remains an open question (Etuk and Acock, 2017; Dsouza et al., 2023; Veréb et al., 2024).

Among various indices of well-being, the prosperity index developed by Isserman, Feser, and Warren (2009, hereafter IFW) has been adopted as one of the few measures with a sustained track record (e.g., Schmidt et al., 2026). The IFW index captures community well-being from a stability perspective (Isserman et al., 2009), and it has successfully challenged the rural decline narrative (Honadle, 2011). The index asks whether residents face

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less economic hardship, can afford their housing, have adequate education, and find work. Although critics have called the index ad hoc (why those four indicators and not others?), Cheng et al. (2026b) showed that the four IFW variables carry the largest importance even when other dimensions such as health and environment are included.

Several studies have since applied the IFW index across different contexts and time periods. Drawing on ERS and BEA data Irwin et al. (2010) showed that from 1969 to 2007 farm-dependent counties lost ten percent of their population, compared to growth for all nonmetropolitan counties. Taken at face value, if people vote with their feet in search of the highest level of utility based on Tiebout's theory, farm-dependent counties have been "losing" or declining. Based on the IFW prosperity index, however, farm-dependent rural counties tell a different story. In 2000, 26 percent performed better than the nation on all four measures, and 62 percent did better on at least three. Khatiwada (2014) applied the same IFW index to U.S. counties and found that more prosperous counties have lower minority populations, more economic opportunities, and higher social and human capital. Longitudinally, Wilson and Rahe (2016) tracked the IFW index and found it stable even during economic downturns like the Great Recession. More recently, Schmidt et al. (2026) used the index in a sequential analysis across four time periods from 1990 through 2020 and found that more prosperous counties performed better in almost all aspects of community well-being.

While Isserman and colleagues offered a straightforward path for considering well-being distinctly from growth, many have tried to move beyond growth by adopting alternative variable lists, but the result is often chaos. Veréb et al. (2024), in their review of 159 rural studies, documented that the resulting space of well-being indices spans more than 30 broad classifications and thousands of individual indicators with little consistency across studies. The IFW index provides a measure of community well-being, but it does not identify what shapes it; in other words, it is a descriptive but not prescriptive tool.

In this setting absent a strong theoretical foundation, a conceptual structure can be useful for organizing the factors associated with well-being. One such framework is the Community Capitals Framework. Drawing on fieldwork in rural communities, Flora and colleagues (Flora et al., 1992; Emery and Flora, 2006; Flora and Flora, 2008) classified community resources into seven types of capital covering different aspects of community life: physical infrastructure (built), norms and behaviors (cultural), wealth, investment, and credit (financial), health and ability (human), climate and environment (natural), power structure and governance (political), and networks and trust (social). The Community Capitals Framework is a way to organize community assets, but not a formalized theory. Still, researchers have adopted it as it maps directly onto the assets available to local decision-makers (Emery and Flora, 2006; Pigg et al., 2020; Ringwood and Watson, 2024).

Although classified into distinct types, these capitals are not mutually exclusive and are both conceptually and empirically correlated. Taking voter turnout as an example, Rupasingha and colleagues (2006) used it as a key variable in their social capital index because it reflects civic engagement. It, however, also serves as an important variable for political capital (Flora and Flora, 2008). Across capital types, cultural and social capital are highly correlated because people with shared culture tend to interact with one another, resulting in intangible social connections within a locality. Forcing a clean separation of community cap-

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itals warrants caution. In addition, quantifying community capitals is challenging, mainly because each capital type can be measured using dozens of indicators. For instance, human capital is often proxied by education which can be measured by the high school graduation rate, the share with a bachelor's degree, the STEM workforce share, or even the creative class. An extensive discussion of how each capital type is defined and measured, and why each variable is selected for each capital, is beyond the scope of this study (see, for example, Ringwood and Watson, 2024; Boyce et al., 2026).

The literature that examines the relationship between community capitals and community well-being has mixed results. For example, social capitals, proxied by the association density, census participation, voter turnout, and non-profit organizations, are associated with higher economic growth and lower poverty at the county level (Rupasingha et al., 2000; Rupasingha and Goetz, 2007), but Chetty et al. (2022) found that civic engagement, which captures participation in civic organizations, voter turnout, nonprofits, and volunteering rates, has virtually no association with upward economic mobility (e.g., income percentiles). Another example is built capital, specifically broadband infrastructure, which is generally associated with gains in employment and income in rural counties, though effects are sometimes contested across geographic contexts or rurality (see Mack et al., 2024, for a review).

One potential explanation for these mixed findings is that the relationship between community capitals and community well-being varies depending on the geographic context in which it operates. Blank (2005) argued that five place-specific attributes, namely the natural environment, economic structure, public and community institutions, social norms, and demographic characteristics, interact in ways that produce fundamentally different community outcomes across locations, such that spatially neutral policies can generate spatially heterogeneous effects. Park and Deller (2021), reviewing decades of research on farm structure and community well-being, similarly concluded that inconsistent findings in that literature may be explained by significant heterogeneity in the underlying relationship across regions. Studies examining community-level outcomes have recognized such spatial heterogeneity (Deller, 2010; Deller and Deller, 2012; Conroy and Deller, 2020; Dissart and Kuentz-Simonet, 2025). When a global regression model imposes a single coefficient across all locations, it obscures this heterogeneity and may produce estimates that are misleading for any given region. This study aims to address this geographic heterogeneity by estimating spatially varying relationships between community capitals and community well-being across U.S. counties using a geographically weighted regression.

3. METHOD AND DATA

3.1. Method

Following Isserman et al. (2009), we use poverty rate below 200 percent of the federal poverty level, percentage of renters paying 35 percent or more of income on housing (high rent burden), percentage of adults aged 25 and older without a high school diploma, and unemployment rate to proxy well-being. Although this measure, which Isserman and coauthors called "prosperity," has been criticized for the limitations noted in the literature review, we believe it remains a suitable approach for considering community well-being beyond growth.

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We use county-level estimates from the American Community Survey (ACS) 2022 five-year estimates for all four variables. Since these are deprivation measures, we multiply them by negative one. To construct the index, we standardize each variable to a z-score. We analyze the 3,100 contiguous U.S. counties.

The community well-being index is the simple average of the four standardized variables; a higher value means better well-being. Even though the simple average has been criticized as agnostic or unrealistic (Decancq and Lugo, 2013), Cheng et al. (2026b) found that it is highly correlated with more complex approaches, including principal component analysis and factor analysis, or even spatial indices with spatial dependence or spatial heterogeneity. So, we argue our aggregation is sufficient. Descriptive statistics for the four variables and the aggregated well-being index are provided in Table 1.

Table 1: Descriptive Statistics of Well-Being Component Variables

Variables	Mean	SD	Min	Max	Source
Poverty Rate (%)	27.39	8.35	0.00	78.10	ACS 2022
High Rent Burden (%)	34.80	9.52	0.00	100.00	ACS 2022
No HS Diploma (%)	12.10	6.00	0.60	81.55	ACS 2022
Unemployment Rate (%)	3.57	1.20	0.60	14.90	ACS 2022
Well-being index	0.00	0.69	−6.13	1.98	Authors' calculation

Note: We include 3,100 contiguous U.S. counties. The four component variables are measured in their original scales. The well-being index is the simple average of the four z-scored, sign-flipped components and the higher means better well-being.

We map the well-being index of the 3,100 counties in Figure 1. To facilitate interpretation, we convert the index to percentile rank. Counties in the upper Midwest, Northern Plains, and much of the Northeast score highest. The lowest-scoring counties concentrate in the Deep South, Appalachia, the Texas border region, and parts of the Southwest. West Coast counties also score lower, which is likely driven by the region's high housing cost burden.

3.1.1. Bayesian Model Averaging to Select Community Capitals

We conceptualize well-being as a function of community capitals:

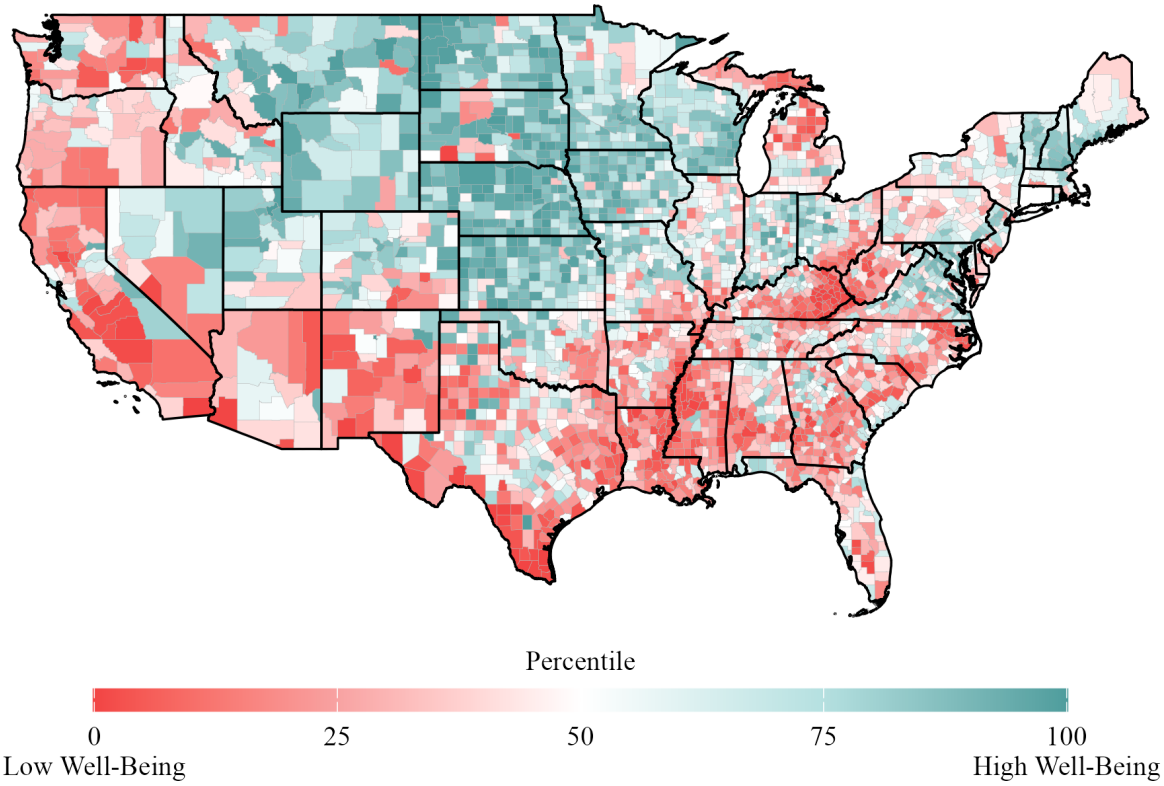
$$\text{Well-being}_i = f(\text{Community Capitals}_i) + \varepsilon_i \tag{1}$$

With 77 candidate variables spanning seven capital types, a single specification risks overfitting. BMA provides a framework to manage this modeling uncertainty, more specifically variable selection, as applied by Watson and Deller (2017), Conroy et al. (2021), and Schmidt et al. (2024), to name a few. The selected variables then set the stage for our GWR analysis.

An intuitive understanding of BMA is that rather than committing to a single most preferred model, BMA treats the model itself as uncertain and averages across all possible specifications, referred to as the model space, weighting each model by how well it fits the data (LeSage and Parent, 2007; Steel, 2020). This technique provides diagnostics such as the

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Figure 1: County-Level Well-Being Index



Note: We include 3,100 contiguous U.S. counties. To facilitate interpretation, we convert to percentile rank, where 100 is the highest well-being.

highest posterior probability model, posterior inclusion probabilities of variables (PIP), and top model frequencies, which tell us which model specification has the highest probability in the model space, and which variables have the highest probability across the model space.

Formally, BMA operates over a model space $\mathcal{M} = \{M_1, M_2, \ldots, M_K\}$, where each model represents a different combination of explanatory variables. For each model M_k, BMA computes an integrated likelihood $p(y|M_k) = \int p(y|\theta_k, M_k) \cdot p(\theta_k|M_k)\, d\theta_k$, which averages the likelihood over all possible parameter values weighted by the prior. By Bayes' theorem, the posterior model probability is $p(M_k|y) \propto p(y|M_k) \cdot p(M_k)$. The posterior density of a quantity of interest θ, that is $p(\theta|y)$, then combines information across the entire model space:

$$p(\theta|y) = \sum_{k=1}^{K} p(\theta|y, M_k) \cdot p(M_k|y) \tag{2}$$

A key criterion for variable selection we use is the PIP of each variable: the probability that a variable appears across the model space. We use a 0.85 cutoff for the variable selection, which is more conservative than the median probability model of Barbieri and Berger (2004) with a PIP of 0.50, or the 0.80 threshold used in Conroy et al. (2021). By choosing a conservative cutoff, we strike a balance between inclusiveness and parsimony.

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We implement BMA in MATLAB using the LeSage Spatial Econometrics Toolbox (LeSage, 2009). We use a uniform model prior and a g-prior ($g = 1/n^2$) with 25,000 MCMC draws.

BMA supports an expanded model space in addressing specification uncertainty. We, however, run a separate BMA for each community capital dimension, for two reasons. From a policy perspective, the Community Capitals Framework organizes community assets into seven separate dimensions, which provides a structure for communities to understand the capitals most relevant to well-being. Brock and Durlauf (2001), who used model averaging to address model uncertainty in growth empirics, argued that empirical analysis becomes policy relevant only when it is organized around the decision the policymaker faces. The Community Capitals Framework provides a direction for what communities can act on across the different aspects of community characteristics, and running the BMA by dimension preserves this policy relevance.

The second reason concerns statistical features of BMA. A unified BMA that puts all the variables in one model space imposes a default prior in which every variable has the same prior weight, meaning the more variables a capital has, the more prior weight that dimension receives. In our case, natural capital has the largest candidate set, 18 variables compared to just seven for political capital, so a unified prior would automatically treat natural capital as more likely to matter for well-being, which we do not seek to impose. Also, variables in different dimensions can be correlated because they partly measure the same underlying activity. For example, road density in built capital and particulate matter in natural capital are correlated, as both might reflect or associate with the intensity of economic activity. When such variables enter a unified model, they split the posterior mass, so the PIPs dilute and can fall below the threshold even though the data have not changed. In the spirit of the block-structured model priors of George (1999, 2010) and Durlauf et al. (2008), where each block receives the same preset probability regardless of its number of variables, we partition the BMA by dimension, giving each dimension equal prior standing and partially limiting the effect of multicollinearity on the variable selection.

3.1.2. Geographically Weighted Regression Specification

The assumption that each variable has the same association with well-being everywhere is unlikely to hold. This relates to heterogeneity uncertainty, the question of whether a single model fits all observations, which with spatial data amounts to assuming the relationship holds constant across space (Schmidt et al., 2024). In the growth literature, Durlauf et al. (2008) found that unexplained regional heterogeneity stayed robust even after all candidate theories or variables competed in the model space. To explore this heterogeneity and provide suggestive evidence, GWR relaxes this assumption by allowing coefficients to vary across space (Fotheringham et al., 2002). At each county, GWR fits a weighted least squares regression using neighboring counties as observations in its sample and where the weight applied to each neighbor attenuates with distance. The result is a separate set of coefficient estimates for every county. More formally:

$$\text{Well-being}_i = \beta_0(u_i, v_i) + \sum_{k=1}^{K} \beta_k(u_i, v_i) \cdot x_{ik} + \varepsilon_i \tag{3}$$

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where Well-being$_i$ is the well-being index for county i, x_{ik} are the k community capital variables selected by BMA, (u_i, v_i) are the geographic coordinates of county i's centroid, and $\beta_k(u_i, v_i)$ is the local coefficient for x_k at county i.

The bandwidth determines how many neighbors are included in each local regression. Because the geographic sizes of counties in the U.S. vary enormously, particularly between densely populated, yet geographically small eastern counties and expansive western ones, we use an adaptive bandwidth that draws on the same number of neighbors at each location rather than a fixed distance. The optimal number (h) is selected via golden section search minimizing AICc.

Within each local regression, not all neighbors contribute equally. Counties close to i receive higher weight; counties further away receive less. Formally, the weight assigned to county j in the regression for county i follows an adaptive bi-square kernel: $w_{ij} = [1 - (d_{ij}/b_i)^2]^2$ when $d_{ij} \leq b_i$, and $w_{ij} = 0$ otherwise, where d_{ij} is the Euclidean distance between counties i and j computed from centroid coordinates, and b_i is the distance to the hth nearest neighbor. Counties beyond the hth neighbor receive zero weight. We collect these weights into a diagonal matrix $W(i) = \text{diag}(w_{i1}, \ldots, w_{in})$.

The local coefficient estimate is $\widehat{\beta}(i) = (X'W(i)X)^{-1}X'W(i)Y$, where X is the matrix of community capital variables from BMA and Y is the vector of well-being scores. We implement GWR using GWR4 software (Nakaya et al., 2016).

3.2. Community Capitals Data

We organize the explanatory variables using the community capitals framework by Flora and colleagues (Flora et al., 1992; Emery and Flora, 2006; Flora and Flora, 2008). We build on the community capitals dataset by the Rural Livability Project at the University of Wisconsin–Madison, which quantified community capitals using empirical evidence linking them to well-being, quality of life, and livability (Boyce et al., 2026; Cheng et al., 2026a).

Building on and extending the community capitals dataset mentioned above, we compile 82 variables across the seven capital types, 77 of which are unique. Specifically, by capital type, we have 11 variables in built, 12 in cultural, 9 in financial, 12 in human, 18 in natural, 8 in political, and 12 in social. Among them, five variables appear in two different capitals but are not double counted in the subsequent analysis. The 77 unique variables used in this study are detailed in Appendix A. Our data are from publicly available datasets such as the American Community Survey, County Health Rankings, Bureau of Labor Statistics, and EPA air quality data, aimed to reflect the year 2020 where the most overlap in data availability occurred.

4. RESULTS

Our results are presented in two parts. Section 4.1 shows the BMA variable selection results. And the OLS and GWR estimates are presented in Section 4.2. We discuss each in turn.

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4.1. Selected Community Capitals

As shown in Table 2, 20 variables pass the 0.85 posterior inclusion probability (PIP) threshold. A less conservative choice is the median probability model (Barbieri and Berger, 2004), which would select 37 variables spanning all seven capital types. Our higher PIP cutoff discards 17 variables and three entire capital types. The highest posterior probability model in column (4) of Table 2 supports this selection because 18 of our 20 variables appear in it, with farm credit count and off-election-year voter turnout as the only exceptions. All community capitals with their PIPs are provided in Appendix A.

Table 2: Bayesian Model Averaging Selected Variables

Capital type	Capitals	Posterior inclusion probabilities	If in highest posterior probability model
Financial	Banks	0.875	Yes
Financial	Farm credit lenders	0.875	No
Financial	CDFI dollars	0.875	Yes
Financial	Deposits	0.875	Yes
Financial	Dollars lent	0.875	Yes
Human	Obesity rate	0.889	Yes
Human	STEM employment	0.889	Yes
Human	Creative class	0.889	Yes
Human	Arts employment	0.889	Yes
Human	Physicians	0.889	Yes
Human	Reading scores	0.889	Yes
Human	Math scores	0.889	Yes
Natural	January temperature	0.862	Yes
Social	Voter turnout	0.889	No
Social	Native-to-state share	0.889	Yes
Social	Census self-response	0.889	Yes
Social	Economic connectedness	0.889	Yes
Social	Religious concentration (Herfindahl)	0.889	Yes
Social	Ethnic homogeneity (Herfindahl)	0.889	Yes
Social	Nonprofits	0.870	Yes

Note: We present variables with posterior inclusion probability (PIP) above 0.85 from OLS BMA. Full variable list in Appendix A. Religious concentration (Herfindahl), ethnic homogeneity (Herfindahl), voter turnout, and arts employment are dual coded across capital types; each enters the model once under the capital type with the higher PIP than 0.85.

Across capital types, human and social capital together account for 14 of the 20 selected variables; financial capital contributes five and natural capital one; built, cultural, and political capital produce none. This selection of variables might be related to the choice of measurements in each dimension, the unconditional probabilities of variables in those models, or the criteria for variable selection. Still, the pattern of selected variables in human and social capital can be loosely interpreted as people centered. That is, what is likely to correlate with community well-being is not limited to physical infrastructure or natural amenities but

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includes the skills, health, and social connections of people. This aligns with the non-growth conception of well-being of the IFW narratives and the fourth wave's emphasis on investing in place and people rather than jobs alone.

Within individual capitals, social capital has the highest selection rate: seven of its 12 candidates pass the threshold, including voter turnout, census participation, economic connectedness, nonprofit, native-to-state share, and two Herfindahl concentration measures (religion and ethnicity). That civic engagement and social cohesion emerge so consistently is unsurprising. Rupasingha et al. (2000) found that social capital contributed to county-level economic growth, and both Emery and Flora (2006) and Halstead et al. (2022) argued that social capital serves as a catalyst that activates investment in other community capitals. Human capital accounts for seven variables spanning health (obesity, physician access), education (reading and math scores), and workforce composition (STEM, creative class, arts employment). Prior work showed that human capital, whether measured through education, creative-class workers, or skilled labor, contributed to community well-being or quality of life beyond its effect on growth alone (Glaeser et al., 2001; Florida, 2002; Shapiro, 2006; McGranahan and Wojan, 2007; Boschma and Fritsch, 2009; Hoyman and Faricy, 2009; Winters, 2011).

In addition to social and human capitals, financial capital enters through access to credit and local banking institutions (bank count, farm credit lenders, CDFI investment, and local lending) rather than solely through wealth such as deposits. Access to financial institutions, rather than accumulated wealth, appears to matter for community well-being. Kilkenny and Nalbarte (2002) found the banks are one of the keystone sectors uniquely shaping community stability. Petach et al. (2021) found that community banks provided relationship lending that supports local economic resilience, and Mencken et al. (2023) showed that locally headquartered banks contributed to rural community prosperity. By contrast, natural capital contributes a single variable, January mean temperature. Although the built, cultural, and political capitals do not enter the final selected set, we caution against concluding that they are unrelated to community well-being. Rather, under our prior and model choices, their variables have low inclusion probabilities under the BMA criteria and are therefore not included in the next stage of the analysis.

4.2. Geographically Weighted Regression Results

Before turning to the results of our estimation, we use both OLS and GWR to compare global and local specifications (Table 3).[1] A central interest of this study is the spatial variation in the coefficients provided by the GWR method. Table 3 column (6) reports the diff-Criterion test (Nakaya et al., 2005). A value below -2 indicates significant spatial variation, and above $+2$ a global coefficient. Among the 20 community capital variables included in the GWR, 11 show spatial variation and 9 are globally stable based on diff-Criterion statistics.

[1]In comparing model performance, the GWR improves substantially over OLS as adjusted R^2 rises from 0.54 to 0.73 and AICc drops from 4,167 to 2,912. The global VIFs for all 20 variables are below 2.32. At the local level, only reading and math scores exceed a local VIF of 10 in roughly 16 percent of counties. Neither raises major concerns about multicollinearity. GWR residuals have a significant but modest spatial autocorrelation with Moran's I being 0.07 with $p < 0.001$.

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As a robustness check, multiscale GWR (Fotheringham et al., 2017) confirms sub-national variation for nine of the 11 spatially varying variables (Appendix B). Overall, our results show there is substantial heterogeneity in the community capital associations across most variables[2].

Table 3: OLS and GWR Coefficient Estimates

		OLS		**GWR**			
Capital	**Variable**	**Estimates** (1)	***t*-statistics** (2)	**Q1** (3)	**Median** (4)	**Q3** (5)	**diff-Criterion** (6)
Financial	Banks	0.59***	17.53	−0.02	0.17	0.31	−15.5
Financial	Farm credit lenders	−0.05	−0.36	−0.42	0.12	0.61	27.7
Financial	CDFI dollars	−0.09***	−4.48	−0.29	−0.04	0.08	26.1
Financial	Deposits	0.06	0.92	0.03	0.40	1.88	26.1
Financial	Dollars lent	0.01	0.05	−0.25	0.04	0.36	41.8
Human	Obesity rate	−2.07***	−8.07	−3.80	−2.25	−0.95	−65.6
Human	STEM employment	−2.67***	−7.98	−2.14	−1.10	−0.20	32.1
Human	Creative class	1.21**	2.08	−3.51	−1.65	0.42	−11.9
Human	Arts employment	44.32***	7.56	14.76	62.06	137.51	−31.8
Human	Physicians	0.09***	4.51	−0.08	0.00	0.07	28.3
Human	Reading scores	0.02	1.55	−0.05	0.03	0.11	15.6
Human	Math scores	−0.02	−1.57	−0.11	−0.04	0.06	7.6
Natural	January temperature	−0.01***	−12.10	−0.02	−0.01	0.00	−282.9
Social	Voter turnout	0.49***	6.02	0.30	0.95	1.71	−74.9
Social	Native-to-state share	−0.46***	−6.40	−0.87	−0.50	−0.17	−38.6
Social	Census self-response	1.58***	17.83	0.92	1.55	2.10	−57.7
Social	Economic connectedness	0.45***	9.20	0.25	0.44	0.80	−38.0
Social	Religious concentration (Herfindahl)	−0.32**	−2.39	−0.43	0.11	0.76	−31.1
Social	Ethnic homogeneity (Herfindahl)	0.06	0.87	−0.14	0.19	0.52	11.7
Social	Nonprofits	0.00	1.36	−0.02	−0.00	0.01	−6.2
	Intercept	−0.20	−1.23	−1.53	−0.36	0.71	−958.8
	Adj. R^2	0.54		0.73			
	AICc	4,167		2,912			

Note: Our sample size is 3,100. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. GWR uses an adaptive bi-square kernel with a bandwidth of 282 nearest neighbors, optimized via AICc (GWR4).

In terms of globally stable coefficients, we find nine variables by the diff-Criterion. Of these, three are significant in the OLS model: physician ratio, STEM employment, and CDFI fund. The physician coefficient is 0.09, implying that an increase of 10 physicians per 1,000 residents is associated with a 0.9 unit increase in the county well-being index. The positive association between physician access and well-being is consistent with previous studies that linked higher physician supply to better health outcomes at the county level (see Macinko

[2]The search selects a bandwidth of 282 nearest neighbors by Euclidean distance. This window has a median great-circle radius of 420 km, with regional medians ranging from 356 km in the dense Southeast to 1,263 km in the sparse Far West. The substantial heterogeneity in the coefficients still holds when we drop each of the four well-being components in turn, when we use a 0.80 PIP threshold, and when we adopt a fixed-distance bandwidth selected by the same golden-section AICc search. Sensitivity analyses are available upon request.

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et al., 2007, for a review). The negative coefficient for STEM, which is −2.67, reflects that high-STEM counties tend to be growth-centered or more urban places that do not necessarily score higher on non-growth dimensions of well-being. STEM growth raises housing rents and other non-tradable prices that may absorb up to half of the wage gain, and less educated workers gain little in real wages (Peri et al., 2015; Lee and Clarke, 2019). This skill-biased wage growth, combined with the rising cost of living, might explain the lower measured community well-being in high-STEM counties. This negative association brings up the challenges in what we choose to measure: community well-being as people experience it or the economic growth of places. The negative coefficient for CDFI investment (−0.09) likely reflects targeting by design, as these programs restrict subsidized investment to low-income or underserved communities. The remaining six variables—farm credit count, deposits, dollars lent, reading scores, math scores, and ethnic homogeneity—are not statistically significant. BMA selected these variables because they contribute consistently across model combinations, yet in a single 20-variable regression, correlated predictors from different capitals share explanatory power so they turn insignificant.

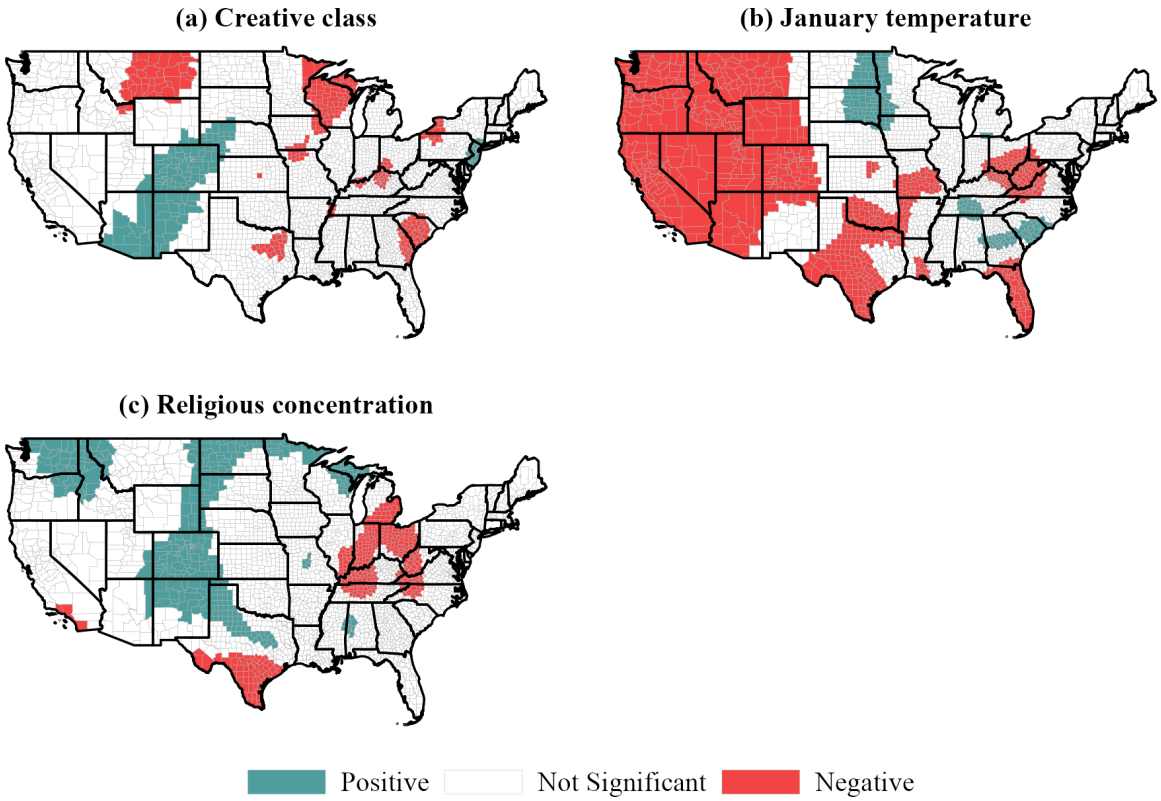
Now we turn to the remaining 11 variables with significant spatial variation. We group these into three patterns: mixed associations, magnitude variation, and false negative. Figure 2 shows the first pattern: the same variable can be associated with well-being in opposite directions across places. For example, the creative class coefficient is positive and significant at 1.21 in the global OLS model, meaning that, controlling for other factors, a ten percent point higher creative class associates with on average 0.12 higher well-being index. The positive association aligns with the growth findings of Florida (2002) and McGranahan and Wojan (2007). Other studies, however, found insignificant or even negative associations between the creative class and community outcomes (Glaeser, 2005; Donegan et al., 2008; Donegan and Lowe, 2008; Hoyman and Faricy, 2009; Mellander et al., 2012). One explanation for these mixed conclusions is that the association itself depends on place characteristics, such as natural amenities and entrepreneurial context, urban proximity, natural resource endowments, or labor costs, among others (Boschma and Fritsch, 2009; McGranahan et al., 2011).

This GWR finding provides a potential explanation for the mixed results of creative class in the literature, as spatial context matters for its role in community well-being. As shown in Figure 2(a), the local coefficient of the creative class varies in both direction and magnitude across places. There are some pockets of negative association, while the northern coastal regions and the part of Southwest are positive. The interquartile range of local coefficients is (−3.51, 0.42), which means a 10-percentage-point increase in creative class employment share can be associated with the well-being index from a 0.35-unit decrease to a 0.04-unit increase, even excluding the most extreme counties. These are associations rather than causal effects, but they suggest a blanket creative-class strategy would miss places where the association is ineffective or even harmful.

Similarly, January temperature is negative in the global model but changes to positive in some northern counties, signaling climate amenity trade-offs across space and differences in preferences among households. The negative OLS association aligns with Partridge and Rickman (2006), who found the persistent-poverty belts sitting in the warm South, so January temperature partly proxies economic deprivation rather than amenity value. Other studies

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Figure 2: Community Capitals with Mixed Associations across Space



Note: We classify county coefficients into three types: significantly associated with higher well-being, not significant, and significantly associated with lower well-being, using $|t| > 1.96$ as the threshold for significance. We include 3,100 contiguous counties.

found warm winters attracting people (McGranahan, 1999; Rappaport, 2009) or mixed valuations of warmth across places and households (Albouy et al., 2016; Sinha et al., 2018). Our local coefficients provide place-specific estimates of the association between winter climate amenity and local well-being, partially differentiating the amenity association in the North from the deprivation association in the Deep South.

Religious concentration, or religious denomination Herfindahl, shows the third mixed association, where in the Upper Midwest and Mountain West, religious concentration changes from its negative global association to positive. This opposite association between religious diversity and well-being aligns with views that in communities where one denomination dominates (Traunmüller, 2011), higher religious fragmentation may disrupt the social cohesion that a dominant denomination provides, while in more pluralistic regions, religious diversity may proxy for social tolerance or bridging (Putnam and Campbell, 2010). The pattern of mixed associations among the creative class, winter climate, and religious concentration suggests how a successful policy intervention might work in one place but fail in another. The same factor can play a completely different role in community well-being across spatial contexts.

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A second pattern is that some variables mostly have the same sign of coefficients across the interquartile range but geographically vary in magnitude. Bank count is significant in the global model, with a coefficient of 0.59, yet its GWR median of 0.17 is less than a third of its OLS estimate, meaning that the global coefficient overstates the relationship in most counties. Figure 3(a) shows the strongest positive association in the agricultural interior, where local banking or credit access may matter most for community well-being, consistent with evidence that bank access matters most where alternatives are absent (Nguyen, 2019) and that community-bank effects concentrate in nonmetropolitan areas (Petach et al., 2021; Mencken et al., 2023). In the far West and parts of the East, bank count shows no significant association at all.

Arts employment, census participation, nonpresidential voter turnout, and economic connectedness are all significantly positive in the OLS model, and their local coefficients mostly are significantly positive but vary by a factor of two to nine in size (Figures 3(b)-(e)). Local conditions might explain the varying association between those community capitals and community well-being. For example, artists are footloose and gather where institutions and fellow artists sustain them, leaving arts specialization thriving in only some counties and weaker associations elsewhere (Markusen and Schrock, 2006; Wojan et al., 2007; Wojan and Nichols, 2018). Likewise, census participation and nonpresidential voter turnout reflect the civic engagement of a place, and its association with community outcomes shows a rural-urban divide, strongest in nonmetropolitan counties (Rupasingha and Goetz, 2007; Weber et al., 2017). Because economic connectedness may act on community outcomes by opening access to information, mentorship, and jobs (Chetty et al., 2022), a connection is worth more where local opportunities are richer, and its association with well-being are likely not to be uniform across space.

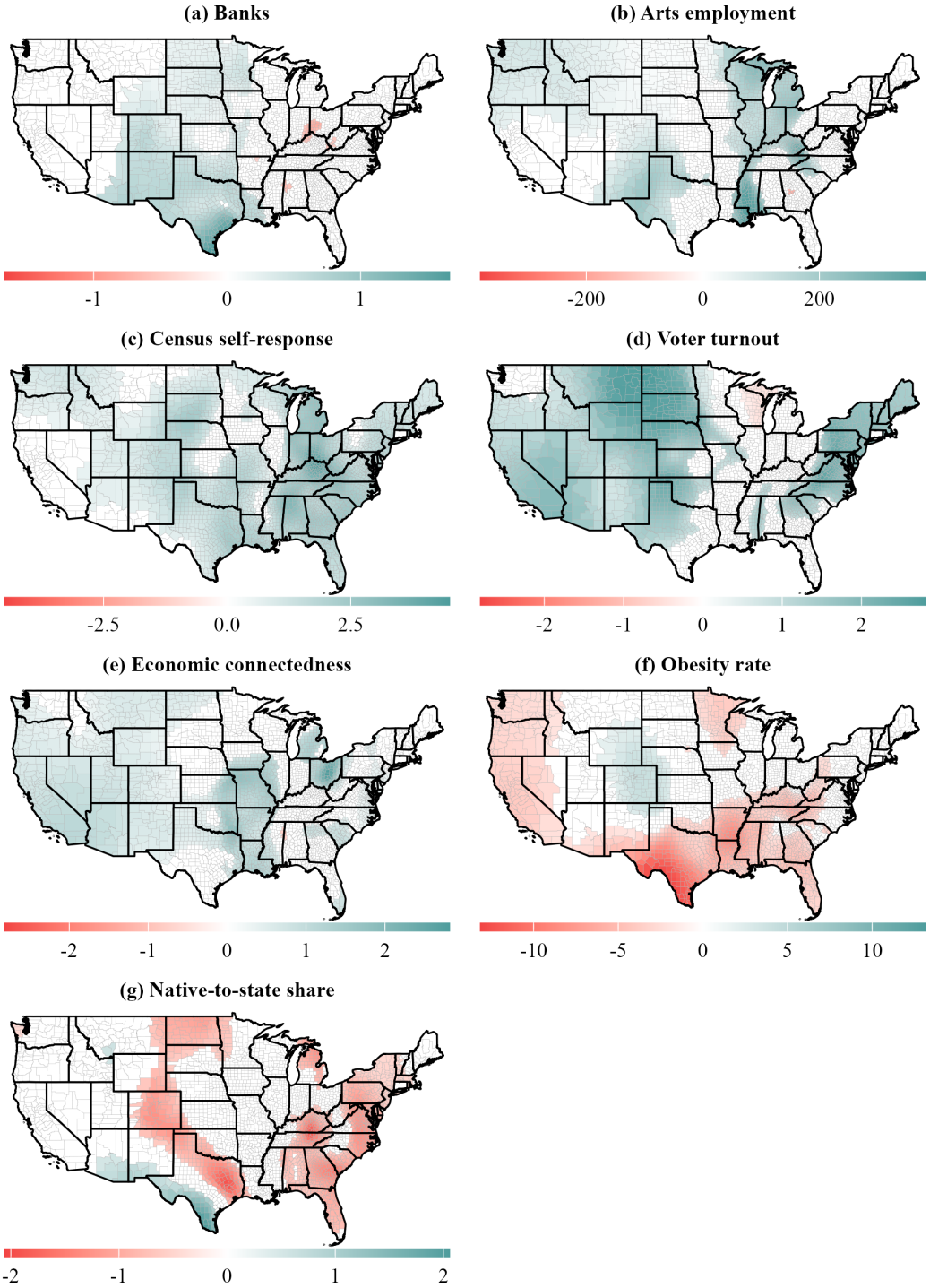
Adult obesity and native-to-state share also show magnitude variation in GWR results, with predominantly the same direction of OLS association but some regions showing opposite associations as in Figures 3(f) and 3(g). For obesity, the OLS coefficient in Table 3 is -2.07 and significant, with local coefficients running from -3.80 to -0.95 across the interquartile range. Myers et al. (2015) found a similar pattern in their spatial regime analysis, where obesity's association with unemployment appeared only in the Midwest and West. For native-to-state share, the local coefficients run from -0.87 to -0.17 across the interquartile range against an OLS estimate of -0.46, from roughly a third to nearly double the global association. Counties along the Mexican border in south Texas, southern New Mexico, and southern Arizona show the opposite association, with native-to-state share positively associated with well-being, as in Figure 3(g). Attachment is valuable for individuals when it reflects social ties (Theodori, 2001), but a high native-to-state share also marks low mobility in economically depressed places (Zabek, 2024). The negative association and the varying local coefficients may therefore reflect a mix of constraints and choice.

The third pattern is that there is a false negative. Nonprofit count is the only variable that is globally insignificant but locally significant. As shown in Figure 4, a mix of mostly insignificant and some opposing associations explains why the global average washes out this local variation entirely. Different nonprofit types could explain the different signs, but our data do not distinguish.

Taken together, some community capitals, such as physician access, show global associ-

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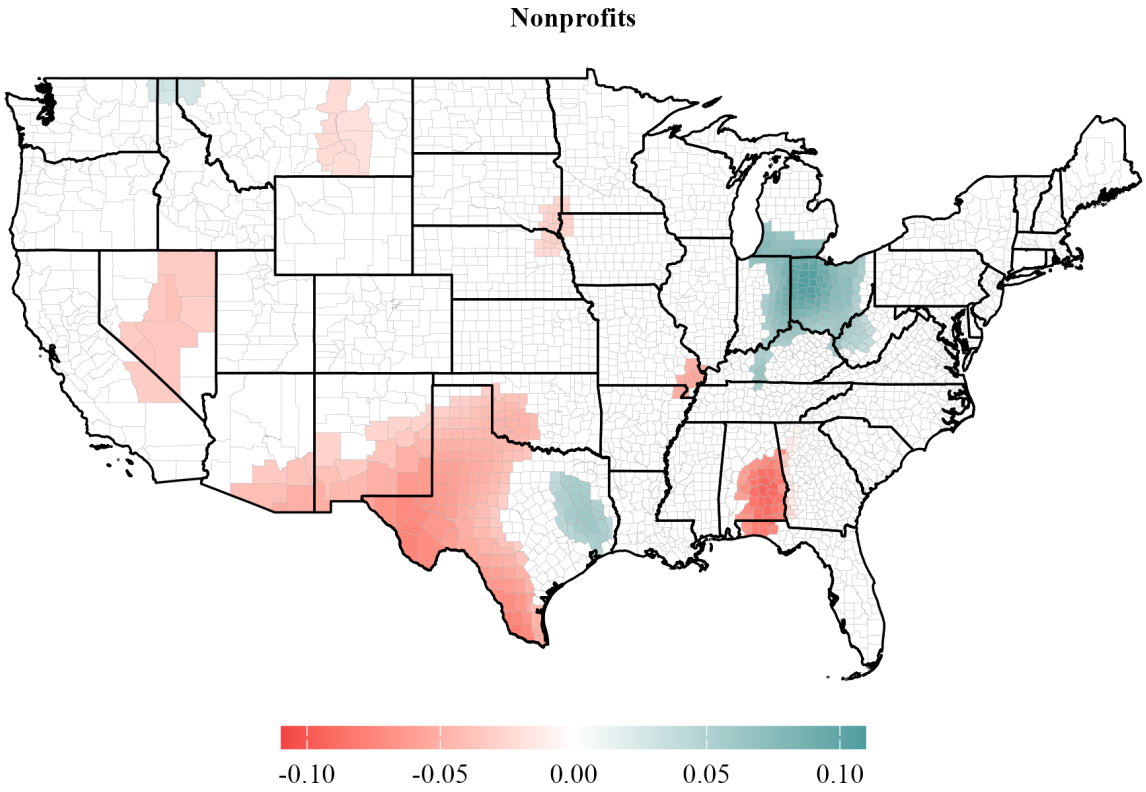
Figure 3: Community Capitals with Varying Coefficients in Magnitude across Space



Note: We classify county coefficients into three types: significantly associated with higher well-being, not significant, and significantly associated with lower well-being, using $|t| > 1.96$ as the threshold for significance. We include 3,100 contiguous counties.

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Figure 4: False Negative of the Nonprofit Count Coefficient



Note: In the OLS, the nonprofit count is insignificant at the ten percent level. We classify county coefficients of GWR into three types: significantly associated with higher well-being, not significant, and significantly associated with lower well-being, using $|t| > 1.96$ as the threshold for significance. County counts by coefficient sign: positive 221, not significant 2,602, negative 277. We include 3,100 contiguous counties.

ations with community well-being; others show the spatial heterogeneity in the association. Although we estimate associations rather than causal effects, the detected heterogeneity, whether a mixed association, magnitude variation, or a false negative, suggests that the role of community capitals differs by place and calls for locally tailored strategies, because even the same actions can help in one place and hurt in another. Identifying which lever to pull and where, instead of a one-size-fits-all approach, requires local experience and evidence.

5. CONCLUDING REMARKS AND DISCUSSION

This study examines the association between community capitals and well-being across 3,100 counties in the U.S. using the Isserman et al. (2009) measure of prosperity. While this index is helpful in thinking about community economic development in ways beyond simple notions of growth, it is a descriptive measure and not prescriptive. In other words, the index tells us how communities are doing but not why. As such, its insights into policy recommendations are limited. The aim of this study is to provide for such insights using the Community Capitals Framework outlined by Flora and colleagues. We accomplish this using Bayesian model averaging to select the strongest community capitals for well-being in separate dimen-

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sions. Accounting for this heterogeneity in the relationship between community capitals and community well-being, we estimate spatially varying coefficients using GWR.

We find that the 20 selected variables come overwhelmingly from human capital, social capital, and financial capital, while built, cultural, and political capital produce no variables above the inclusion threshold in BMA. Perhaps more importantly, our GWR results outperform the OLS model and show that at least half of the variables have significant local variation. We find three mixed associations (creative class, January temperature, and religious concentration) where the direction of association changes across places; seven magnitude-variation variables (bank count, obesity, arts employment, voter turnout, native-to-state share, census participation, and economic connectedness) where nationally significant relationships differ in strength across counties; and one false negative (nonprofit count) where the global model misses a locally significant relationship. Admittedly, three variables are globally significant in OLS. Physician access associates positively with well-being everywhere. STEM employment and CDFI lending are negatively associated with well-being across all counties, flagging the distinction between economic growth and non-growth well-being.

The policy implications of how the community invests in well-being are threefold. First, investing in people, not just in places or jobs, is a reliable path to community well-being. The dominance of human-centered capital among well-being predictors echoes previous literature (Rupasingha et al., 2000; Deller et al., 2001; Shaffer et al., 2004; Khatiwada, 2014; Schmidt et al., 2026). Sen (1999) argued that for well-being, what people can do matters more than what resources exist. If the fourth wave of economic development centers on well-being, quality of life, and livability, then the policy toolkit should extend beyond growth to include health, education, civic engagement, and social cohesion. Only implementing growth-oriented strategies such as infrastructure investment and business incentives may not translate into resident well-being.

Second, locally tailored interventions are essential for improving community well-being. Communities should adopt place-based rather than place-blind strategies: what may be an effective strategy in one place may not be effective in another (Barca et al., 2012; Rodríguez-Pose, 2018). Religious concentration, for example, associates negatively with well-being in the deep South but positively in the Upper Midwest; treating it as uniformly positive or negative misleads policy in both regions. Bank count associates strongly with well-being in interior agricultural communities but shows no significant relationship on the coasts. The mixed associations and magnitude variation in our results suggest that interventions or policies that build on existing community assets should consider local context, so that they are more likely to succeed than a one-size-fits-all approach (Moser et al., 2018).

Finally, social capital might be the strongest candidate if communities must choose where to begin for community well-being. Human capital accumulates slowly, while social capital can be built in the shorter term and is relatively more actionable. Emery and Flora (2006) argued that social capital can catalyze growth in other capitals, a process they called "spiraling up". Social capital facilitates information sharing, trust building, and relationship building in ways that mobilize resources within the community and therefore acts like an intermediate output that in turn connects to community well-being. But which form of social capital matters most, or acts most effectively, for community well-being differs by place: in some counties it is census participation; in others, voter turnout. Rather than a generic call

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to build social capital, local leaders can identify which specific forms matter in their county and invest there, giving the spiraling-up process a starting point for community well-being.

This study is not without limitations. First, we cannot claim causal identification since associations may run in both directions. For example, counties with higher well-being may attract more physicians rather than physicians causing higher well-being. Still, the association and spatial heterogeneity we find remain informative for policy regardless of causal direction. Taking physician access as an example, if it is associated with community well-being, then attracting and training the rural health workforce, such as nurse practitioners, might be the way to improve well-being in the most rural places. But the heterogeneity in our results implies a relation like this might not apply everywhere, and in some places the rural health workforce may not relate to well-being. Future work with causal designs could explore this relationship and, more importantly, the heterogeneity. The same extension applies to other capitals such as civic engagement, social connection, and third places, or other placemaking investments. Second, our BMA uses OLS rather than spatial specifications such as spatial BMA (LeSage and Parent, 2007), though Schmidt et al. (2024) found substantial overlap between spatial and nonspatial BMA results in a similar county-level application. We expect similar results for variable selection. In addition, the BMA is a global estimate, which implies that in some regions variable selection could omit variables that are associated with geography, as the most likely variables in the West might differ from those in the Northeast. With the same set of selected community capitals, we could omit variables that might explain the heterogeneity in association, but the GWR modeling remains a suggestive and practical way to explore the association between well-being and community capitals across space. Finally, GWR captures spatial heterogeneity in associations but does not model spatial dependence in the error term. But residual autocorrelation is modest. Spatial error or spatial lag extensions could improve inference. We leave these and other extensions, including nonlinear specifications, to future work.

CRediT Authorship Contribution Statement

Yang Cheng: Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. Mckenzie Boyce: Conceptualization, Data curation, Methodology, Writing – review & editing.

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Declaration of Interests

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

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REFERENCES

Albouy, David, Walter Graf, Ryan Kellogg, and Hendrik Wolff. (2016) "Climate Amenities, Climate Change, and American Quality of Life," *Journal of the Association of Environmental and Resource Economists*, 3(1), 205–246. http://doi.org/10.1086/684573.

Aslam, A. and L. Corrado. (2012) "The Geography of Well-Being," *Journal of Economic Geography*, 12(3), 627–649. http://doi.org/10.1093/jeg/lbr041.

Barbieri, Maria Maddalena and James O. Berger. (2004) "Optimal Predictive Model Selection," *The Annals of Statistics*, 32(3), 870–897. http://doi.org/10.1214/009053604000000238.

Barca, Fabrizio, Philip McCann, and Andrés Rodríguez-Pose. (2012) "The Case for Regional Development Intervention: Place-Based versus Place-Neutral Approaches," *Journal of Regional Science*, 52(1), 134–152. http://doi.org/10.1111/j.1467-9787.2011.00756.x.

Blank, Rebecca M.. (2005) "Poverty, Policy, and Place: How Poverty and Policies to Alleviate Poverty Are Shaped by Local Characteristics," *International Regional Science Review*, 28(4), 441–464. http://doi.org/10.1177/0160017605278999.

Boschma, Ron A. and Michael Fritsch. (2009) "Creative Class and Regional Growth: Empirical Evidence from Seven European Countries," *Economic Geography*, 85(4), 391–423. http://doi.org/10.1111/j.1944-8287.2009.01048.x.

Boyce, Mckenzie, Danielle Schmidt-Larios, Erin Gaede, and Yang Cheng. (2026) "The Community Capitals Dataset: Quantifying the Community Capitals Framework in the United States," Oklahoma State University: Stillwater, OK. Working paper.

Boyce, Mckenzie L.. (2025). *Quality of Life as an Economic Development Strategy: Revealed and Stated Preference Approaches to Assessing Quality of Life and Valuing Broadband*. PhD thesis, University of Wisconsin–Madison. ProQuest Dissertations & Theses Global.

Brock, William A. and Steven N. Durlauf. (2001) "What Have We Learned from a Decade of Empirical Research on Growth? Growth Empirics and Reality," *The World Bank Economic Review*, 15(2), 229–272. http://doi.org/10.1093/wber/15.2.229.

Brock, William A., Steven N. Durlauf, and Kenneth D. West. (2007) "Model Uncertainty and Policy Evaluation: Some Theory and Empirics," *Journal of Econometrics*, 136(2), 629–664. http://doi.org/10.1016/j.jeconom.2005.11.009.

Campbell, Angus, Philip E. Converse, and Willard L. Rodgers. (1976) *The Quality of American Life: Perceptions, Evaluations, and Satisfactions*. Russell Sage Foundation, New York.

Chatfield, Chris. (1995) "Model Uncertainty, Data Mining and Statistical Inference," *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 158(3), 419–444. http://doi.org/10.2307/2983440.

Cheng, Yang, Tessa Conroy, and Mckenzie Boyce. (2026a) "Rethinking (Rural) Livability: Why Existing Methods Fall Short and A New Approach to Measurement Using Community Assets," University of Wisconsin–Madison: Madison, WI. Working paper.

Cheng, Yang, Tessa Conroy, and Steven C. Deller. (2026b) "Multidimensional Measures of Quality of Life: A Comparison of Methods Using U.S. County-Level Data," *Papers in Regional Science*, 105(1), 100129. http://doi.org/10.1016/j.pirs.2025.100129.

Chetty, Raj, Matthew O. Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B. Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Ja-

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cob, Drew Johnston, Martin Koenen, Eduardo Laguna-Muggenburg, Florian Mudekereza, Tom Rutter, Nicolaj Thor, Wilbur Townsend, Ruby Zhang, Mike Bailey, Pablo Barberá, Monica Bhole, and Nils Wernerfelt. (2022) "Social capital I: Measurement and Associations with Economic Mobility," *Nature*, 608(7921), 108–121. http://doi.org/10.1038/s41586-022-04996-4.

Conroy, Tessa and Steven C. Deller. (2020) "Regional Level Social Capital and Business Survival Rates," *The Review of Regional Studies*, 50(2), 230–259. http://doi.org/10.52324/001c.13161.

Conroy, Tessa, Steven C. Deller, and Philip Watson. (2021) "Regional Income Inequality: A Link to Women-Owned Businesses," *Small Business Economics*, 56(1), 189–207. http://doi.org/10.1007/s11187-019-00224-y.

Decancq, Koen and María Ana Lugo. (2013) "Weights in Multidimensional Indices of Wellbeing: An Overview," *Econometric Reviews*, 32(1), 7–34. http://doi.org/10.1080/07474938.2012.690641.

Deller, Steven C.. (2010) "Rural Poverty, Tourism and Spatial Heterogeneity," *Annals of Tourism Research*, 37(1), 180–205. http://doi.org/10.1016/j.annals.2009.09.001.

Deller, Steven C.. (2021) "Are We in the 4th Wave of Economic Development?" *The Review of Regional Studies*, 51(3), 233–245. http://doi.org/10.52324/001c.30813.

Deller, Steven C.. (2025) "Are We at an Inflection Point in Community Economic Development? The 4th Wave," *Economic Development Quarterly*, 39(4), 215–231. http://doi.org/10.1177/08912424251339139.

Deller, Steven C. and Melissa A. Deller. (2012) "Spatial Heterogeneity, Social Capital, and Rural Larceny and Burglary," *Rural Sociology*, 77(2), 225–253. http://doi.org/10.1111/j.1549-0831.2012.00076.x.

Deller, Steven C., Tsung-Hsiu (Sue) Tsai, David W. Marcouiller, and Donald B.K. English. (2001) "The Role of Amenities and Quality of Life In Rural Economic Growth," *American Journal of Agricultural Economics*, 83(2), 352–365. http://doi.org/10.1111/0002-9092.00161.

Diener, Ed. (1984) "Subjective Well-Being," *Psychological Bulletin*, 95(3), 542–575. http://doi.org/10.1037/0033-2909.95.3.542.

Dissart, Jean-Christophe and Vanessa Kuentz-Simonet. (2025) "Spatial Determinants of Life Satisfaction on the Aquitaine Coast: A Geographically-Weighted Regression Approach," *Journal of Happiness Studies*, 26(2), 21. http://doi.org/10.1007/s10902-024-00842-8.

Donegan, Mary, Joshua Drucker, Harvey Goldstein, Nichola Lowe, and Emil Malizia. (2008) "Which Indicators Explain Metropolitan Economic Performance Best? Traditional or Creative Class," *Journal of the American Planning Association*, 74(2), 180–195. http://doi.org/10.1080/01944360801944948.

Donegan, Mary and Nichola Lowe. (2008) "Inequality in the Creative City: Is There Still a Place for "Old-Fashioned" Institutions?" *Economic Development Quarterly*, 22(1), 46–62. http://doi.org/10.1177/0891242407310722.

Dsouza, Nishita, Amy Carroll-Scott, Usama Bilal, Irene E. Headen, Rodrigo Reis, and Ana P. Martinez-Donate. (2023) "Investigating the Measurement Properties of Livability: A Scoping Review," *Cities & Health*, 7(5), 839–853. http://doi.org/10.1080/23748834.2023.2202894.

Durlauf, Steven N., Andros Kourtellos, and Chih Ming Tan. (2008) "Are Any Growth

©Southern Regional Science Association 2026.

Theories Robust?" *The Economic Journal*, 118(527), 329–346. http://doi.org/10.1111/j.1468-0297.2007.02123.x.

Easterlin, Richard A.. (1974) "Does Economic Growth Improve the Human Lot? Some Empirical Evidence," In David, P. A. and M. W. Reder, eds., *Nations and Households in Economic Growth: Essays in Honor of Moses Abramovitz*. Academic Press: New York, pp. 89–125.

Easterlin, Richard A. and Kelsey J. O'Connor. (2022) "The Easterlin Paradox," In Zimmermann, K. F., ed., *Handbook of Labor, Human Resources and Population Economics*. Springer International Publishing: Cham, pp. 1–25.

Emery, Mary and Cornelia Butler Flora. (2006) "Spiraling-Up: Mapping Community Transformation with Community Capitals Framework," *Community Development*, 37(1), 19–35. http://doi.org/10.1080/15575330609490152.

Etuk, Lena E. and Alan Acock. (2017) "Toward a Rural Community Vitality Measurement Practice," *Community Development*, 48(1), 141–153. http://doi.org/10.1080/15575330.2016.1251480.

Flora, Cornelia Butler and Jan L. Flora. (2008) *Rural Communities: Legacy and Change*. Westview Press, Boulder, CO, 3rd edition.

Flora, Cornelia Butler, Jan L. Flora, J. D. Spears, and L. E. Swanson. (1992) *Rural Communities: Legacy and Change*. Westview Press, Boulder, CO.

Florida, Richard. (2002) *The Rise of the Creative Class: And How It's Transforming Work, Leisure, Community and Everyday Life*. Basic Books, New York.

Fotheringham, A. Stewart, C. Brunsdon, and M. Charlton. (2002) *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Wiley, Chichester, England.

Fotheringham, A. Stewart, Wenbai Yang, and Wei Kang. (2017) "Multiscale Geographically Weighted Regression (MGWR)," *Annals of the American Association of Geographers*, 107(6), 1247–1265. http://doi.org/10.1080/24694452.2017.1352480.

George, Edward I.. (1999) "Sampling Considerations for Model Averaging and Model Search," In Bernardo, J. M., J. O. Berger, A. P. Dawid, and A. F. M. Smith, eds., *Bayesian Statistics 6*. Oxford University Press: Oxford. Invited discussion of "Bayesian Model Averaging and Model Search Strategies" by M. A. Clyde.

George, Edward I.. (2010) "Dilution Priors: Compensating for Model Space Redundancy," In Berger, James O., T. Tony Cai, and Iain M. Johnstone, eds., *Borrowing Strength: Theory Powering Applications – A Festschrift for Lawrence D. Brown*. Institute of Mathematical Statistics: Beachwood, OH, pp. 158–165.

Glaeser, Edward L.. (2005) "Review of Richard Florida's The Rise of the Creative Class," *Regional Science and Urban Economics*, 35(5), 593–596. http://doi.org/10.1016/j.regsciurbeco.2005.01.005.

Glaeser, Edward L., Jed Kolko, and Albert Saiz. (2001) "Consumer City," *Journal of Economic Geography*, 1(1), 27–50. http://doi.org/10.1093/jeg/1.1.27.

Halstead, John M., Steven C. Deller, and Kevin M. Leyden. (2022) "Social Capital and Community Development: Where Do We Go From Here?" *Community Development*, 53(1), 92–108. http://doi.org/10.1080/15575330.2021.1943696.

Honadle, Beth Walter. (2011) "Rural Development Policy in the United States: A Critical Analysis and Lessons from the "Still Birth" of the Rural Collaborative Investment Program," *Community Development*, 42(1), 56–69. http://doi.org/10.1080/15575330.2010.

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500393.

Hoyman, Michele and Christopher Faricy. (2009) "It Takes a Village: A Test of the Creative Class, Social Capital, and Human Capital Theories," *Urban Affairs Review*, 44(3), 311–333. http://doi.org/10.1177/1078087408321496.

Hurter, Arthur P. and Joseph S. Martinich. (1989) *Facility Location and the Theory of Production*. Kluwer Press, Boston, MA. http://doi.org/10.1007/978-94-009-2518-2.

Irwin, Elena G., Andrew M. Isserman, Maureen Kilkenny, and Mark D. Partridge. (2010) "A Century of Research on Rural Development and Regional Issues," *American Journal of Agricultural Economics*, 92(2), 522–553. http://doi.org/10.1093/ajae/aaq008.

Isserman, Andrew M.. (2005) "In the National Interest: Defining Rural and Urban Correctly in Research and Public Policy," *International Regional Science Review*, 28(4), 465–499. http://doi.org/10.1177/0160017605279000.

Isserman, Andrew M., Edward Feser, and Drake E. Warren. (2009) "Why Some Rural Places Prosper and Others Do Not," *International Regional Science Review*, 32(3), 300–342. http://doi.org/10.1177/0160017609336090.

Joshanloo, Mohsen, Veljko Jovanović, and Tim Taylor. (2019) "A Multidimensional Understanding of Prosperity and Well-Being at Country Level: Data-Driven Explorations," *PLOS ONE*, 14(10), e0223221. http://doi.org/10.1371/journal.pone.0223221.

Khatiwada, Lila Kumar. (2014) "Modeling and Explaining County-Level Prosperity in the US," *Journal of Regional Analysis & Policy*, 44(2), 143–156.

Kilkenny, Maureen and S. Johnson. (2007) "Rural Development Policy," In Gardner, Bruce and Daniel Sumner, eds., *Agricultural Policy for the 2007 Farm Bill and Beyond*. American Enterprise Institute: Washington, DC.

Kilkenny, Maureen and Laura Nalbarte. (2002) "Keystone Sector Identification," In Hewings, G. J. D., M. Sonis, and D. Boyce, eds., *Trade, Networks and Hierarchies*, Advances in Spatial Science. Springer Berlin Heidelberg: Berlin, pp. 289–314.

Lee, Neil and Stephen Clarke. (2019) "Do Low-Skilled Workers Gain from High-Tech Employment Growth? High-Technology Multipliers, Employment and Wages in Britain," *Research Policy*, 48(9), 103803. http://doi.org/10.1016/j.respol.2019.05.012.

LeSage, James P.. (2009) Econometrics Toolbox for MATLAB. https://www.spatial-econometrics.com/.

LeSage, James P. and Olivier Parent. (2007) "Bayesian Model Averaging for Spatial Econometric Models," *Geographical Analysis*, 39(3), 241–267. http://doi.org/10.1111/j.1538-4632.2007.00703.x.

Liu, Ben-Chieh. (1976) *Quality of Life Indicators in U.S. Metropolitan Areas: A Statistical Analysis*. Praeger, New York.

Macinko, James, Barbara Starfield, and Leiyu Shi. (2007) "Quantifying the Health Benefits of Primary Care Physician Supply in the United States," *International Journal of Health Services*, 37(1), 111–126. http://doi.org/10.2190/3431-g6t7-37m8-p224.

Mack, Elizabeth A., Scott Loveridge, Thomas Keene, and John Mann. (2024) "A Review of the Literature About Broadband Internet Connections and Rural Development (1995-2022)," *International Regional Science Review*, 47(3), 231–292. http://doi.org/10.1177/01600176231202457.

Markusen, Ann and Greg Schrock. (2006) "The Artistic Dividend: Urban Artistic Specialisation and Economic Development Implications," *Urban Studies*, 43(10), 1661–1686.

©Southern Regional Science Association 2026.

http://doi.org/10.1080/00420980600888478.

McGranahan, David A.. (1999) "Natural Amenities Drive Rural Population Change," U.S. Department of Agriculture, Economic Research Service: Washington, DC. Agricultural Economic Report No. 781, https://www.ers.usda.gov/media/7903/aer-781.pdf.

McGranahan, David A. and Timothy R. Wojan. (2007) "Recasting the Creative Class to Examine Growth Processes in Rural and Urban Counties," *Regional Studies*, 41(2), 197–216. http://doi.org/10.1080/00343400600928285.

McGranahan, David A., Timothy R. Wojan, and Dayton M. Lambert. (2011) "The Rural Growth Trifecta: Outdoor Amenities, Creative Class and Entrepreneurial Context," *Journal of Economic Geography*, 11(3), 529–557. http://doi.org/10.1093/jeg/lbq007.

Mellander, C., Richard Florida, and J. Rentfrow. (2012) "The Creative Class, Post-Industrialism and the Happiness of Nations," *Cambridge Journal of Regions, Economy and Society*, 5(1), 31–43. http://doi.org/10.1093/cjres/rsr006.

Mencken, F. Carson, Craig Wesley Carpenter, Michael Lotspeich-Yadao, and Charles M. Tolbert. (2023) "Bank on it: Do Local Banks Contribute to Rural Community Prosperity?" *Rural Sociology*, 88(3), 657–681. http://doi.org/10.1111/ruso.12488.

Mittal, Shilpi, Jayprakash Chadchan, and Sudipta K. Mishra. (2020) "Review of Concepts, Tools and Indices for the Assessment of Urban Quality of Life," *Social Indicators Research*, 149(1), 187–214. http://doi.org/10.1007/s11205-019-02232-7.

Moser, Andrea, Heike Peter, Birgit Fengler, and Renate Strohm-Lömpcke. (2018) "Improving the Quality of Life with Rural Development Programmes in Germany (2007–2013): Evidence from the Evaluation," *European Countryside*, 10(2), 321–339. http://doi.org/10.2478/euco-2018-0019.

Myers, Candice A., Tim Slack, Corby K. Martin, Stephanie T. Broyles, and Steven B. Heymsfield. (2015) "Regional Disparities in Obesity Prevalence in the United States: A Spatial Regime Analysis," *Obesity*, 23(2), 481–487. http://doi.org/10.1002/oby.20963.

Nakaya, T., M. Charlton, C. Brunsdon, P. Lewis, J. Yao, and A. Stewart Fotheringham. (2016). *GWR4 User Manual: Windows Application for Geographically Weighted Regression Modelling*. National Centre for Geocomputation, Maynooth University. Version 4.09.

Nakaya, Tomoki, A. Stewart Fotheringham, Chris Brunsdon, and Martin Charlton. (2005) "Geographically Weighted Poisson Regression for Disease Association Mapping," *Statistics in Medicine*, 24(17), 2695–2717. http://doi.org/10.1002/sim.2129.

Nguyen, Hoai-Luu Q.. (2019) "Are Credit Markets Still Local? Evidence from Bank Branch Closings," *American Economic Journal: Applied Economics*, 11(1), 1–32. http://doi.org/10.1257/app.20170543.

Pacione, Michael. (1990) "Urban Liveability: A Review," *Urban Geography*, 11(1), 1–30. http://doi.org/10.2747/0272-3638.11.1.1.

Park, SooJin and Steven C. Deller. (2021) "Effect of Farm Structure on Rural Community Well-Being," *Journal of Rural Studies*, 87, 300–313. http://doi.org/10.1016/j.jrurstud.2021.09.014.

Partridge, Mark D. and Dan S. Rickman. (2006) *The Geography of American Poverty: Is There a Need for Place-Based Policies?* W.E. Upjohn Institute, Kalamazoo, MI. http://doi.org/10.17848/9781429454872.

Peri, Giovanni, Kevin Shih, and Chad Sparber. (2015) "STEM Workers, H-1B Visas, and Productivity in US Cities," *Journal of Labor Economics*, 33(S1), S225–S255. http://doi.

©Southern Regional Science Association 2026.

org/10.1086/679061.

Petach, Luke, Stephan Weiler, and Tessa Conroy. (2021) "It's a Wonderful Loan: Local Financial Composition, Community Banks, and Economic Resilience," *Journal of Banking & Finance*, 126, 106077. http://doi.org/10.1016/j.jbankfin.2021.106077.

Pigg, Kenneth, Stephen P. Gasteyer, Kenneth E. Martin, Kari Keating, and Godwin P. Apaliyah. (2020) "The Community Capitals Framework: An Empirical Examination of Internal Relationships," In Phillips, R. and E. Trevan, eds., *50 Years of Community Development, Vol. I.* Routledge: Abingdon, pp. 117–127.

Putnam, R. D. and D. E. Campbell. (2010) *American Grace: How Religion Divides and Unites Us.* Simon & Schuster, New York.

Rappaport, Jordan. (2009) "Moving to Nice Weather," In Cherry, Todd L and Dan S Rickman, eds., *Environmental Amenities and Regional Economic Development.* Routledge: London, pp. 25–53.

Rickman, Dan S.. (2014) "Assessing Regional Quality of Life: A Call for Action in Regional Science," *The Review of Regional Studies*, 44(1), 1–12. http://doi.org/10.52324/001c.8080.

Ringwood, Lauren and Philip Watson. (2024) "Jointly Modeling the Community Capitals and Their Influence on Economic Resilience," *The Review of Regional Studies*, 53(3), 259–295. http://doi.org/10.52324/001c.91739.

Roback, Jennifer. (1982) "Wages, Rents, and the Quality of Life," *Journal of Political Economy*, 90(6), 1257–1278. http://doi.org/10.1086/261120.

Rodríguez-Pose, Andrés. (2018) "The Revenge of the Places That Don't Matter (and what to Do about It)," *Cambridge Journal of Regions, Economy and Society*, 11(1), 189–209. http://doi.org/10.1093/cjres/rsx024.

Rosen, Sherwin. (1974) "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, 82(1), 34–55. http://doi.org/10.1086/260169.

Rupasingha, Anil and Stephan J. Goetz. (2007) "Social and Political Forces as Determinants of Poverty: A Spatial Analysis," *Journal of Socio-Economics*, 36(4), 650–671. http://doi.org/10.1016/j.socec.2006.12.021.

Rupasingha, Anil, Stephan J. Goetz, and David Freshwater. (2000) "Social Capital and Economic Growth: A County-Level Analysis," *Journal of Agricultural and Applied Economics*, 32(3), 565–572. http://doi.org/10.1017/s1074070800020654.

Rupasingha, Anil, Stephan J. Goetz, and David Freshwater. (2006) "The Production of Social Capital in US Counties," *Journal of Socio-Economics*, 35(1), 83–101. http://doi.org/10.1016/j.socec.2005.11.001.

Schmidt, Claudia, Steven C. Deller, and Stephan J. Goetz. (2024) "Women Farmers and Community Well-Being Under Modeling Uncertainty," *Applied Economic Perspectives and Policy*, 46(1), 275–299. http://doi.org/10.1002/aepp.13406.

Schmidt, Danielle, Tessa Conroy, and Steven C. Deller. (2026) "Prosperity Across the United States: Revisiting the Isserman, Feser, and Warren Prosperity Index Using Sequence Analysis," *International Regional Science Review*, 49(2), 147–178. http://doi.org/10.1177/01600176251377424.

Sen, Amartya. (1999) *Development as Freedom.* Knopf, New York.

Shaffer, R., Steven C. Deller, and David W. Marcouiller. (2004) *Community Economics: Linking Theory and Practice.* Blackwell Publishing, Ames, IA, 2nd edition.

©Southern Regional Science Association 2026.

Shapiro, Jesse M. (2006) "Smart Cities: Quality of Life, Productivity, and the Growth Effects of Human Capital," *The Review of Economics and Statistics*, 88(2), 324–335. http://doi.org/10.1162/rest.88.2.324.

Sinha, Paramita, Martha L. Caulkins, and Maureen L. Cropper. (2018) "Household Location Decisions and the Value of Climate Amenities," *Journal of Environmental Economics and Management*, 92, 608–637. http://doi.org/10.1016/j.jeem.2017.08.005.

Steel, Mark F. J.. (2020) "Model Averaging and Its Use in Economics," *Journal of Economic Literature*, 58(3), 644–719. http://doi.org/10.1257/jel.20191385.

Stiglitz, J. E., A. Sen, and J.-P. Fitoussi. (2009) "Report by the Commission on the Measurement of Economic Performance and Social Progress," Commission on the Measurement of Economic Performance and Social Progress: Paris. https://www.insee.fr/en/statistiques/fichier/2662494/stiglitz-rapport-anglais.pdf.

Theodori, Gene L.. (2001) "Examining the Effects of Community Satisfaction and Attachment on Individual Well-Being," *Rural Sociology*, 66(4), 618–628. http://doi.org/10.1111/j.1549-0831.2001.tb00087.x.

Traunmüller, R.. (2011) "Moral Communities? Religion as a Source of Social Trust in a Multilevel Analysis of 97 German Regions," *European Sociological Review*, 27(3), 346–363. http://doi.org/10.1093/esr/jcq011.

UNDP. (1990) *Human Development Report 1990*. Oxford University Press, New York.

Veréb, Vanda, Carla Marques, Livia Madureira, Carlos Marques, Tigran Keryan, and Rui Silva. (2024) "What Is Rural Well-Being and How Is It Measured? An Attempt to Order Chaos," *Rural Sociology*, 89(2), 239–280. http://doi.org/10.1111/ruso.12536.

Wang, Yu, Yehua Dennis Wei, Ning Xiong, and Simon Brewer. (2025) "Urban Sprawl and Subjective Well-Being: U.S. County-Level Evidence," *Annals of the American Association of Geographers*, 115(5), 1104–1124. http://doi.org/10.1080/24694452.2025.2472998.

Watson, Philip and Steven C. Deller. (2017) "Economic Diversity, Unemployment and the Great Recession," *The Quarterly Review of Economics and Finance*, 64, 1–11. http://doi.org/10.1016/j.qref.2016.12.003.

Weber, Bruce A., J. Matthew Fannin, Sam M. Cordes, and Thomas G. Johnson. (2017) "Upward Mobility of Low-Income Youth in Metropolitan, Micropolitan, and Rural America," *The ANNALS of the American Academy of Political and Social Science*, 672(1), 103–122. http://doi.org/10.1177/0002716217713477.

Weijers, Dan. (2014) "An Interview with Alex C. Michalos," *International Journal of Well-being*, 4(1), 106–110. http://doi.org/10.5502/ijw.v4i1.7.

Williams, Anne S. and Patrick C. Jobes. (1990) "Economic and Quality-Of-Life Considerations in Urban-Rural Migration," *Journal of Rural Studies*, 6(2), 187–194. http://doi.org/10.1016/0743-0167(90)90005-s.

Wilson, Bev and Mallory L. Rahe. (2016) "Rural Prosperity and Federal Expenditures, 2000–2010," *Regional Science Policy & Practice*, 8(1-2), 3–27. http://doi.org/10.1111/rsp3.12070.

Winters, John V.. (2011) "Why Are Smart Cities Growing? Who Moves and Who Stays," *Journal of Regional Science*, 51(2), 253–270. http://doi.org/10.1111/j.1467-9787.2010.00693.x.

Wojan, Timothy R., Dayton M. Lambert, and David A. McGranahan. (2007) "The Emergence of Rural Artistic Havens: A First Look," *Agricultural and Resource Economics Re-*

©Southern Regional Science Association 2026.

view, 36(1), 53–70. http://doi.org/10.1017/s1068280500009448.

Wojan, Timothy R. and Bonnie Nichols. (2018) "Design, Innovation, and Rural Creative Places: Are the Arts the Cherry on Top, or the Secret Sauce?" *PLOS ONE*, 13(2), e0192962. http://doi.org/10.1371/journal.pone.0192962.

Zabek, Mike. (2024) "Local Ties in Spatial Equilibrium," *American Economic Journal: Macroeconomics*, 16(2), 287–317. http://doi.org/10.1257/mac.20210326.

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APPENDIX A: FULL VARIABLE INVENTORY WITH BAYESIAN MODEL AVERAGING RESULTS

Table A1: Bayesian Model Averaging Variables by Capital Type

Capital	Description	Source	Year	PIP	In Top-1	In GWR
Built	Road miles per square mile	U.S. Census Bureau	2020	0.833	Yes	No
Built	Emergency medical services stations per 1,000 residents	Geospatial Management Office	2020	0.833	Yes	No
Built	Average cell coverage share	Urban Institute	2018	0.833	Yes	No
Built	Ports per 1,000 residents	Esri and ScienceBase	2014	0.812	No	No
Built	Airports per 1,000 residents	Esri; FAA; NOAA	2024	0.125	No	No
Built	Amtrak stations per 1,000 residents	Geospatial Management Office	2020	0.125	No	No
Built	Share of population with broadband	American Community Survey	2016–2020	0.125	Yes	No
Built	Housing units per 1,000 residents	American Community Survey	2020	0.125	No	No
Built	Share of occupied housing units with kitchen and plumbing facilities	Urban Institute	2017–2018	0.125	No	No
Built	Schools per 1,000 residents	Tapestry	2020	0.125	No	No
Built	Hospitals per 1,000 residents	Urban Institute	2018	0.125	No	No
Cultural	Non-White population share	American Community Survey	2016–2020	0.833	Yes	No
Cultural	Volunteering and activism rate	Opportunity Insights, Social Capital Atlas	2018	0.833	No	No
Cultural	Self-employment ratio	American Community Survey	2016–2020	0.833	Yes	No
Cultural	Historic properties per 1,000 residents	Urban Institute	2017–2018	0.815	Yes	No
Cultural	Share of family households†	American Community Survey	2016–2020	0.111	No	No
Cultural	Colleges per 1,000 residents	Esri; IPEDS	2021–2022	0.111	Yes	No
Cultural	Herfindahl index of religious denominations†	Association of Religion Data Archives (ARDA)	2020	0.111	No	No
Cultural	Non-English spoken at home rate	American Community Survey	2016–2020	0.111	No	No
Cultural	Herfindahl index of ethnic composition†	American Community Survey	2016–2020	0.111	No	No
Cultural	Charitable tax returns per 1,000 residents	Internal Revenue Service (IRS)	2020	0.111	No	No
Cultural	Cultural institutions per 1,000 residents	Tapestry	2020	0.111	No	No
Cultural	Share of employment in arts occupations†	IMPLAN	2020	0.111	No	No
Financial	Banks per 1,000 residents	Federal Deposit Insurance Corporation	2020	0.875	Yes	Yes
Financial	Farm credit lenders per 1,000 residents	Web scraping from https://farmcredit.com/find-a-lender/	2020	0.875	No	Yes

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Table A1 continued

Capital	Description	Source	Year	PIP	In Top-1	In GWR
Financial	CDFI dollars in millions per 1,000 residents	Urban Institute	2017	0.875	Yes	Yes
Financial	Deposits in millions per 1,000 residents	Federal Deposit Insurance Corporation	2020	0.875	Yes	Yes
Financial	Dollars lent (local lending) in millions per 1,000 residents	Federal Financial Institutions Examination Council	2020	0.875	Yes	Yes
Financial	Credit union branches per 1,000 residents	National Credit Union Administration	2020	0.844	Yes	No
Financial	Dividends, interest, and rent per 1,000 residents	Bureau of Economic Analysis	2020	0.250	Yes	No
Financial	Federal investments dollars per 1,000 residents	Urban Institute	2018–2019	0.250	No	No
Financial	PPP loans per 1,000 residents	U.S. Small Business Administration	2020	0.250	No	No
Human	Adult obesity rate (age 18 and older)	County Health Rankings; BRFSS	2024	0.889	Yes	Yes
Human	Share of workers in science, technology, engineering and mathematics occupations	IMPLAN	2020	0.889	Yes	Yes
Human	Share of employment in creative-class occupations	IMPLAN	2020	0.889	Yes	Yes
Human	Share of employment in arts occupations †	IMPLAN	2020	0.889	Yes	Yes
Human	Primary care physicians per 1,000 residents	County Health Rankings; AMA	2021	0.889	Yes	Yes
Human	3rd-grade reading index	County Health Rankings	2024	0.889	Yes	Yes
Human	3rd-grade math index	County Health Rankings	2024	0.889	Yes	Yes
Human	Uninsured rate for population under age 65	County Health Rankings; SAHIE	2021	0.185	No	No
Human	Skewness of the county age distribution	American Community Survey	2016–2020	0.167	Yes	No
Human	Adult diabetes rate (age 18 and older)	County Health Rankings; BRFSS	2024	0.167	No	No
Human	Disabled insurance beneficiaries share	Social Security Administration	2020	0.167	No	No
Human	Healthy food environment index	County Health Rankings; USDA	2019 & 2021	0.167	No	No
Natural	Mean January temperature	USDA–ERS	1999	0.862	Yes	Yes
Natural	Diesel PM concentration	EPA	2017–2019 avg	0.828	Yes	No
Natural	Mean January hours of sunlight	USDA–ERS	1999	0.825	No	No
Natural	Share of county land area under tree cover	Multi-Resolution Land Characteristics Consortium	2021	0.814	Yes	No
Natural	Mean July relative humidity	USDA–ERS	1999	0.712	Yes	No
Natural	Days over ozone standard	EPA	2016–2020	0.484	Yes	No
Natural	Natural resource establishments per 1,000 residents	Tapestry	2020	0.392	Yes	No

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Table A1 continued

Capital	Description	Source	Year	PIP	In Top-1	In GWR
Natural	Recreation establishments per 1,000 residents	Tapestry	2020	0.391	Yes	No
Natural	Topography scale	USDA–ERS	1999	0.330	Yes	No
Natural	Percentage of days over PM2.5 standard	EPA	2016–2020	0.165	No	No
Natural	Mean area ruggedness across the county	USDA–ERS	2023	0.114	No	No
Natural	Acres in agricultural production as a share of total land in county	USDA	2022	0.109	No	No
Natural	Trail miles per square mile	U.S. Geological Survey	2024	0.101	No	No
Natural	Winter-summer temperature gap	USDA–ERS	1999	0.098	No	No
Natural	Share of county land area under protected status	PAD-US	2024	0.094	No	No
Natural	Composite natural risk score	FEMA	2023	0.091	No	No
Natural	Share of county area that is water	USDA–ERS	1999	0.087	No	No
Natural	River and stream miles per square mile	Esri	2024	0.084	No	No
Political	Individual dollar contributions per 1,000 residents	Stanford DIME	2014	0.833	Yes	No
Political	Peaceful protests per 1,000 residents	Armed Conflict Location & Event Data Project (ACLED)	2020	0.833	Yes	No
Political	Share of workers employed in public administration	Tapestry	2020	0.833	Yes	No
Political	Organizational dollar contributions per 1,000 residents	Stanford DIME	2014	0.800	Yes	No
Political	Average voter turnout in the 2018 and 2022 non-presidential elections†	ICPSR	2018–2022 avg	0.200	No	No
Political	Local government meetings streamed on YouTube per 1,000 residents	LocalView	2020	0.200	Yes	No
Political	Federal award dollar per 1,000 residents	USAspending.gov	2021	0.200	No	No
Political	Nonprofit 501(c)(4) revenue per 1,000 residents	Urban Institute	2018	0.200	No	No
Social	Average voter turnout in the 2018 and 2022 non-presidential elections†	ICPSR	2018–2022 avg	0.889	No	Yes
Social	Share of residents living in the state where they were born	American Community Survey	2020	0.889	Yes	Yes
Social	2020 census self-response rate	County Health Rankings	2020	0.889	Yes	Yes
Social	Economic connectedness index	Opportunity Insights, Social Capital Atlas	2022	0.889	Yes	Yes
Social	Herfindahl index of religious denominations†	ARDA	2020	0.889	Yes	Yes

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Table A1 continued

Capital	Description	Source	Year	PIP	In Top-1	In GWR
Social	Herfindahl index of ethnic composition†	American Community Survey	2016–2020	0.889	Yes	Yes
Social	Nonprofits per 1,000 residents	IRS–NCCS	2020	0.870	Yes	Yes
Social	Index of income inequality (GINI)	American Community Survey	2016–2020	0.185	No	No
Social	Associations per 1,000 residents	Tapestry	2020	0.167	Yes	No
Social	Herfindahl index of ancestry composition	American Community Survey	2016–2020	0.167	No	No
Social	Rate of female labor force participation for age 16 and above	American Community Survey	2016–2020	0.167	No	No
Social	Share of family households†	American Community Survey	2016–2020	0.167	No	No

Note: Farm credit lenders per 1,000 residents are not publicly available and are collected by web scraping. † Dual-coded variable appearing under two capital types. BMA was run separately within each capital, so the same variable may receive different PIPs depending on the pool of competing indicators. Among five dual-coded variables, family household share is not selected in either capital. Religious concentration and ethnic homogeneity are selected under social capital (PIP = 0.889) but not cultural capital (PIP = 0.111). Voter turnout is selected under social capital but not political capital (PIP = 0.200); no political capital variable met the threshold. Arts employment is selected under human capital (PIP = 0.889) but not cultural capital (PIP = 0.111).

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APPENDIX B: MULTISCALE GEOGRAPHICALLY WEIGHTED REGRESSION ROBUSTNESS CHECK

Table B1: MGWR Bandwidths and Median Coefficients

Capital	Variables	MGWR BW	MGWR Median
Financial	Banks	140	0.217
Financial	Farm credit lenders	2,994	0.064
Financial	CDFI dollars	3,096	−0.017
Financial	Deposits	3,098	0.057
Financial	Dollars lent	3,098	0.037
Human	Obesity rate	271	−2.346
Human	STEM employment	2,642	−0.813
Human	Creative class	59	−1.685
Human	Arts employment	464	58.093
Human	Physicians	3,098	0.015
Human	Reading scores	2,409	0.052
Human	Math scores	3,098	−0.035
Natural	January temperature	3,098	−0.012
Social	Voter turnout	269	1.116
Social	Native-to-state share	1,705	−0.388
Social	Census self-response	222	1.475
Social	Economic connectedness	454	0.395
Social	Religious concentration (Herfindahl)	126	0.312
Social	Ethnic homogeneity (Herfindahl)	3,098	0.238
Social	Nonprofits	3,098	−0.005
	Adj. R^2		0.761
	AICc		2,589

Note: MGWR estimated in R GWmodel with an adaptive bi-square kernel and CVR back-fitting criterion (Fotheringham et al., 2017). MGWR BW is the variable-specific optimal bandwidth with n being 3,100. Bandwidths near n means a spatially constant relationship.

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