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Quality of Life Differences across Rural Counties*

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Abstract: This study examines the role of quality of life (QOL) in predicting long-run population change across rural (nonmetropolitan) U.S. counties from 1970 to 2019. Employing a derivative of the Rosen–Roback spatial equilibrium framework, we treat local variations in nominal wages and housing costs as compensating differentials that reveal household valuation of place-specific attributes. Because the individual-level microdata the traditional approach requires are unavailable for most nonmetropolitan areas, we instead combine aggregate county-level residuals from housing and labor market regressions, following a specification developed by Hicks et al. (2026), to isolate an index of localized amenity demand and extend the framework to rural counties. Decadal population growth modeling across Rural-Urban Continuum Codes (RUCC 4 through 9) confirms that higher QOL strongly predicts subsequent population growth across all rural categories, with coefficients peaking at 0.21–0.22 in the largest rural counties and falling to 0.09 in the most isolated. To address high-dimensional covariate correlation, we embed a Least Absolute Shrinkage and Selection Operator (LASSO) framework with a post-LASSO Ordinary Least Squares (OLS) estimation to isolate specific predictors of quality of life. The findings highlight spatial heterogeneity across amenity bundles: natural amenities (such as surface water) and local public goods (such as education funding) strongly predict quality of life across rural counties, while private amenities shift from specialized services (fitness, golf) concentrated near metro areas to basic restaurants and grocery stores everywhere else. These results suggest that rural economic development policy should prioritize targeted, place-based amenity development to retain population and sustain regional welfare.

Keywords: Quality of Life; Metropolitan and Rural Counties; Spatial Equilibrium; Population Growth Amenities

JEL Codes: R11, R12, R23, Q51

1. INTRODUCTION

Rural America is characterized by significant heterogeneity in population size, growth, and economic structure. Many rural counties have experienced sustained population loss and out-migration over recent decades, while others have grown (Carr and Kefalas, 2009). At

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the same time, the gap between rural and non-rural America has widened across income, employment, and population growth (Farrigan et al., 2024). These divergent trajectories have renewed interest in place-based economic development, an approach that tailors policy to a place's specific assets rather than treating all rural places alike (Austin et al., 2018, 2022).

Place-based approaches to rural development have often emphasized natural amenities: scenic landscapes, mild climates, and access to water and recreation (McGranahan, 1999). These amenities matter, but they tell only part of the story. Quality of life is broader than natural amenities alone. It also reflects public services, demographic composition, and private consumption opportunities. A full account of rural quality of life must capture this broader amenity bundle, and how its value shifts across places and across people.

Understanding these preferences is essential for effective place-based policy. Policymakers need to know which amenities matter most, for whom, and where, so that scarce public resources target investments that genuinely improve the health, livability, and long-run sustainability of rural places. Quality of life (QOL) methodologies offer a way to reveal these preferences directly from household behavior. Grounded in the Rosen–Roback spatial equilibrium framework, this approach treats local variations in nominal wages and housing costs as compensating differentials. In equilibrium, households accept lower wages or pay higher housing costs to live where they value the local amenities. Observed price differentials therefore reveal the implicit value households place on specific local attributes, and how that value differs across places and populations.

A substantial literature estimates regional QOL within this framework, but fewer studies systematically compare the composition of valued amenities across different types of rural counties. We address this gap using Rural-Urban Continuum Codes (RUCC), which classify nonmetropolitan counties along two dimensions likely to shape which amenities matter most: population scale and proximity to a metropolitan area. Larger, more urban nonmetro counties can support a wider range of market-based amenities, such as specialized retail and recreation. Smaller, more isolated counties depend more heavily on natural features and public goods. RUCC codes let us test directly how the value of specific amenities shifts along this rural continuum, rather than treating rural America as a single, undifferentiated category.

Testing this, however, raises conceptual and econometric challenges. Amenities span natural, public, demographic, and private domains, and many are highly correlated or act as proxies for similar phenomena. To address these issues, and understand the dynamics of QOL, this paper reports findings from two types of models. The first produces QOL estimates using a method developed by (Hicks et al., 2026). This QOL measure is then used to predict population change over five decades across nearly all the United States. We then repeat this separately across the six RUCC categories (RUCC 4 through 9).

Second, we examine differences in inferred county-level QOL across these RUCC categories using a regularized regression framework. Weinstein et al. (2023) employ Least Angle Regression (LAR) for a similar purpose. Building on their approach, we apply the Least Absolute Shrinkage and Selection Operator (LASSO) to select among a broad set of natural, public, demographic, and private-market amenities. Estimating these models separately across RUCC categories allows the set of selected amenities to vary by rural context. The

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results highlight two patterns: certain natural and public amenities are consistently valued across county types, while private consumption amenities show substantial heterogeneity.

2. LITERATURE REVIEW

Quality of life and amenities are central to rural economic outcomes, a theme running through a long line of rural development research using methods ranging from single-amenity regressions to composite amenity indexes to explain variation in population growth, housing prices, income, and employment across counties (Irwin et al., 2010). Natural amenities drive long-run rural population change and shape landscape-driven migration patterns more broadly (McGranahan, 1999, 2008). Comprehensive amenity indices covering climate, land, water, and recreation, built from more than 2,200 nonmetropolitan counties, show that natural and recreational assets are significant covariates of rural population, employment, and income growth. Climate and water resources stimulate population inflows, while land and winter recreation assets affect both demographic and employment gains (Deller et al., 2001). These amenity effects are not constant across space, however: a geographically weighted regression approach applied to nonmetropolitan counties finds substantial heterogeneity in the growth returns to amenities and human capital across U.S. regions, with effects that sometimes reverse sign entirely under a one-size-fits-all national model (Partridge et al., 2008).

This heterogeneity is visible at the regional level, too. In the Great Lakes region, a spatial error model applied to 242 counties tells a different story than the national pattern: natural amenities generally lack a significant relationship with population, income, or employment growth, and only lake-based attributes show a marginal positive association with retail and service employment. Amenities also show no direct effect on income inequality, suggesting that amenity-driven development operates through broader spatial processes rather than direct economic channels (Kim et al., 2005). A closer look at the region's lake amenities specifically reinforces this ambiguity: coastal counties see rising shares of college graduates, consistent with amenity-driven sorting on human capital, but little evidence that lake amenities drive broader household migration, particularly after 2000—likely because industrial legacy and environmental degradation offset the Great Lakes' natural advantages in parts of the region (Stephens and Partridge, 2015).

Rural Appalachia broadly follows national amenity-growth trends, but climate and land characteristics play a distinct role there (Deller and Lledo, 2007). A rural county's growth depends on its entrepreneurial context and its share of "creative class" workers, not natural amenities alone (McGranahan and Wojan, 2007; McGranahan et al., 2011). Population turnover and growth in small urban areas, moreover, follow different patterns than in large metros (Brown and Tousey, 2020). Together, this literature establishes that amenities matter for rural growth, but leaves open exactly which amenities matter, and where.

This rural literature sits within a broader tradition of estimating quality of life (QOL) that has evolved considerably in its methods. A place's livability, not just its production efficiency, drives its long-run success (Jacobs, 1961), and quality of life and the presence of a skilled, mobile workforce reinforce one another in shaping which cities grow (Rogerson, 1999; Florida, 2002; Shapiro, 2006). The foundational empirical approach estimates the impact of a specific set of amenities directly on local wages and housing prices, then sums households'

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implied willingness to pay for each amenity into a single QOL measure for a place (Rosen, 1979; Roback, 1982).

This direct approach has documented the capitalization of a wide range of amenities into wages and housing costs. Temperature, precipitation, coastal proximity, and environmental quality are capitalized into wages and housing costs, demonstrating that households systematically value mild climates and scenic features (Blomquist et al., 1988; Gyourko and Tracy, 1991). Local public service expenditures are capitalized as compensating differentials in metropolitan housing markets as well (Welch et al., 2007), as are crime rates, school quality, health conditions, infrastructure, and fiscal variables, with disamenities such as violent crime and poor health outcomes often exhibiting negative capitalization effects that sometimes exceed the positive valuation of natural amenities (Glaeser and Gottlieb, 2006; Albouy, 2016). Consumer city dynamics, such as restaurants, cultural institutions, and recreational opportunities, play an increasing role in residential location decisions as well, particularly for high-skill households, and are strongly associated with the sorting of high-income and high-education workers into large metropolitan areas (Glaeser et al., 2001; Diamond, 2016).

Directly regressing wages and housing prices on a specific list of amenities, however, risks omitted variable bias: no study can observe and include every relevant local amenity, and unobserved amenities are often correlated with the ones that are measured. To sidestep this problem, later work replaced the direct list of amenities with a place-based fixed effect, estimated from large samples of individual-level housing and wage microdata, that captures the combined value of all local amenities at once, observed and unobserved (see, for example, Albouy, 2008; Reynolds and Weinstein, 2021). Researchers could then test which specific amenities explain variation in estimated quality of life. This fixed-effects approach requires microdata samples that are only available for larger metropolitan areas, however, leaving rural counties out of this literature for decades.

Aggregate approaches have since filled this gap. Using the residual from a housing-price regression as a general proxy for county-level amenity value sidesteps the need for microdata entirely (Glaeser et al., 2001; Carruthers and Mulligan, 2006). Building on this approach, county-level residuals from housing and labor market regressions can estimate QOL for nearly all U.S. counties, including those without adequate microdata, and a smaller, more interpretable set of amenities selected through Least Angle Regression (LAR) explains much of the cross-county variation in inferred QOL, with substantial differences in amenity composition between metro and rural counties (Weinstein et al., 2023).

Together, this literature establishes that quality of life shapes economic outcomes, that it can now be estimated even where microdata are unavailable, and that rural amenities matter for population and economic growth. Far less is known, however, about how the value of specific amenities varies across the rural–urban continuum itself. This motivates our empirical approach: we estimate QOL using an aggregate, county-level method suited to data-scarce rural geographies, then use a regularized regression framework to identify which amenities matter most, separately for each Rural-Urban Continuum Code.

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3. DATA AND ESTIMATION

The introduction of differing approaches based on availability of local data is important for considering rural places. It is also useful for better understanding the dynamic spatial adjustment that is the hallmark of quality of life. Weinstein et al. (2023) address the data limitations of rural locations. They built upon the traditional Rosen–Roback model outlined by Albouy and others by approximating the county fixed effects in the QOL estimations with the residuals from equations 1 and 2. The residuals, or the difference between observed and predicted values, proxy for the premium that households and firms are willing to pay to locate in county j; they are the portion of the county housing values and wages above or below what the characteristics of the housing stock or workforce would suggest they should be.[1]

$$\ln(r_j) = \alpha^r + \beta^r X_j^r + \varepsilon_j^r \tag{1}$$

$$\ln(w_j) = \alpha^w + \beta^w X_j^w + \varepsilon_j^w \tag{2}$$

In this paper, we combine the Weinstein et al. (2023) approach with methods used by Glaeser et al. (2001) who regress housing prices on per capita income then use the residual as a proxy for the amenity value of large cities (without adjusting for housing characteristics or labor market characteristics). Carruthers and Mulligan (2006) similarly estimate a general amenity value for all U.S. counties using the residual from a regression of the natural logarithm of the median housing value. We first estimate housing and wage regressions (equations 1 and 2) and use the predicted values of each in a regression of predicted housing prices on predicted wages (equation 3):

$$\ln(\widehat{r_j}) = \alpha + \beta \ln(\widehat{w_j}) + e_i \tag{3}$$

Here in equation 3, the error term, e_i is interpreted as the demand for local amenities, controlling for housing and labor market characteristics. This approach by Hicks et al. (2026) better measures local quality of life than either approach separately (better able to predict population growth, for example). Hereafter, we refer to the residual from equation 3 as county-level quality of life (QOL).

We use equation 3 to estimate QOL measures over the 1970–2019 period using county-level data. Because we are interested in examining QOL across different types of rural areas along the rural–urban continuum, we employ the Rural-Urban Continuum Codes from 2013, which is the closest definition to our set of amenities (2010), and focus on the six codes for nonmetropolitan counties that are defined by size and proximity to metropolitan areas (RUCC 4–9). These six codes reflect two dimensions: urban population size (20,000 or

[1]In the housing regression, they control for housing characteristics such as the share of the housing stock that has 2–3 bedrooms, the share of the housing stock that was built after the year 2000, children as a share of the population, etc. In the wage regression, they control for aggregate county-level characteristics of the population such as the share of the population with a bachelor's degree, the share of employment in manufacturing, etc. See Appendix.

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more, 5,000 to 20,000, or fewer than 5,000 residents) and whether the county is adjacent to a metropolitan area. RUCC 4, 6, and 8 are the adjacent counties at each size tier; RUCC 5, 7, and 9 are not adjacent, with RUCC 9 representing the smallest, most isolated counties in the sample. Using the 2013 RUCC definition to classify counties over the entire period largely focuses on the more recent definitions of places, though there has been some change over time, which we acknowledge and leave to further work.

Table 1: Summary Statistics (2019)

	Population					**Quality of Life**				
	Mean	**Median**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
RUCC 4	64,331	58,972	24,553	31,086	185,242	0.00	−0.05	0.27	−0.55	0.89
RUCC 5	55,337	48,630	26,265	22,234	199,750	−0.02	−0.08	0.32	−0.60	0.87
RUCC 6	24,593	22,151	12,654	3,429	71,453	−0.08	−0.10	0.27	−0.99	1.00
RUCC 7	18,672	16,377	10,993	3,086	67,232	−0.09	−0.12	0.30	−0.86	1.04
RUCC 8	9,609	8,395	6,453	590	37,126	0.00	−0.04	0.31	−1.06	1.15
RUCC 9	5,969	4,506	5,105	251	29,788	−0.12	−0.16	0.36	−1.76	1.26

Table 1 reports summary statistics for population and the QOL index for each of the nonmetropolitan Rural-Urban Continuum Code counties in 2019.

The QOL index is approximately centered around zero in the full sample, consistent with a standardized measure. However, systematic differences emerge across county types. Larger metropolitan-adjacent rural counties tend to exhibit higher average quality of life values than smaller and more remote rural counties. Despite these differences in levels, the dispersion of QOL is broadly similar across the various rural county groups, suggesting comparable within-group variation. To further illustrate the variation and persistence of QOL, Figure 1 depicts quality of life in 2019, and Figure 2 depicts the correlation of QOL over time. Figure 1 shows large regional patterns with the rural mountain west, which has experienced steady population growth, with high estimated quality of life across the region. Figure 2 shows that while quality of life can evolve across places, it appears to be largely consistent over time.

To better understand the role of QOL over time and the spatial adjustment effect, we estimate a basic model that examines the effect of QOL on population change in each decade from 1970 to 2019 (our end date). The basic model is shown in Equation 4.

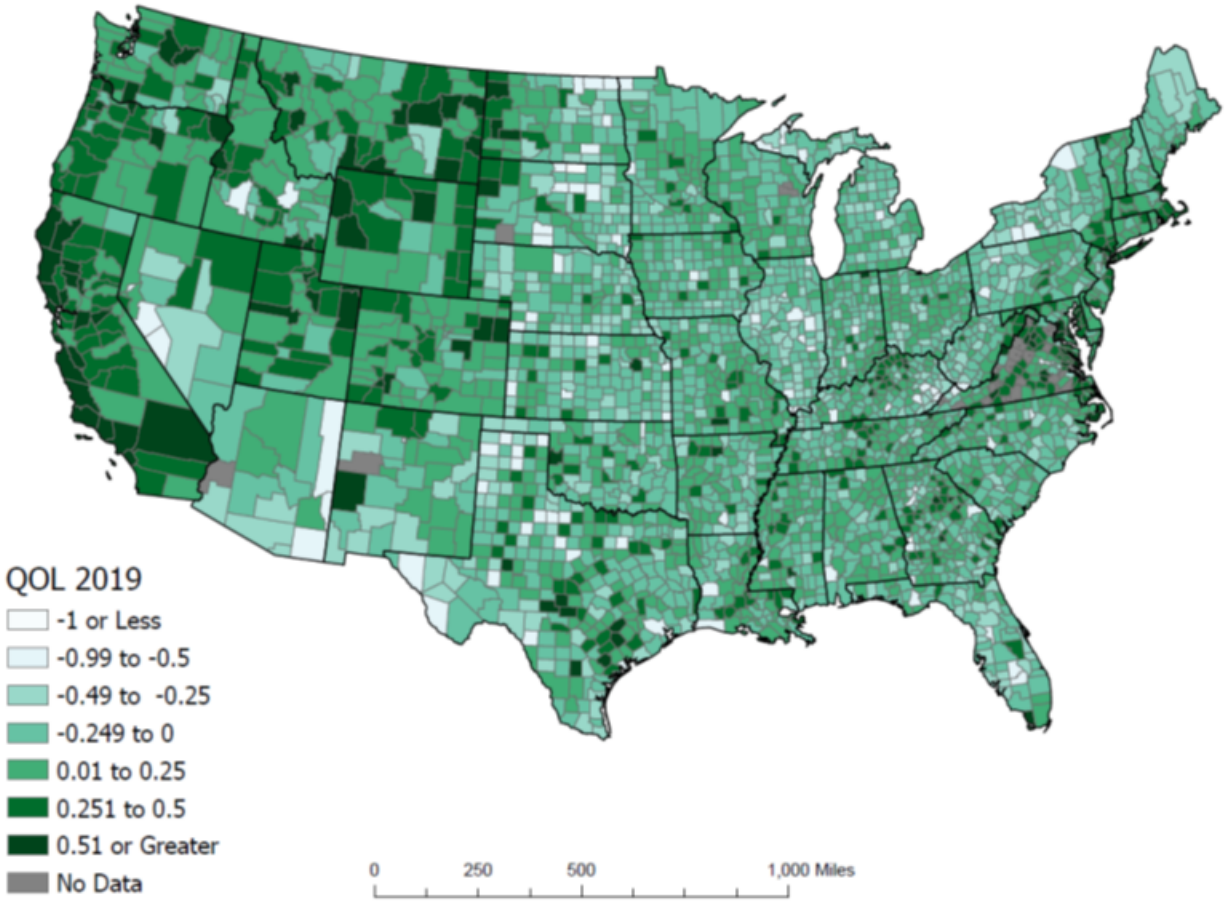
$$\ln(\text{Pop})_t - \ln(\text{Pop})_{t-1} = \alpha + \delta\left(\text{QOL}_{i,t}\right) + e_{i,t} \tag{4}$$

It is important to address the potential for joint determination of our Quality of Life measure and population growth. This work tests theory on data in the Rosen–Roback framework, and as such has none of the hallmarks of a randomized control trial. We attempt to address endogeneity by using quality of life in period t to examine population change over the following decade. Additionally, we contend, in the model above, (1992) approach to causation that should further limit endogeneity concerns.

We estimate our model for subsets of the RUCC 4–9 counties separately. We estimate with year fixed effects to get a basic estimate with controls for economywide changes in population growth rates.

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Figure 1: Quality of Life in 2019

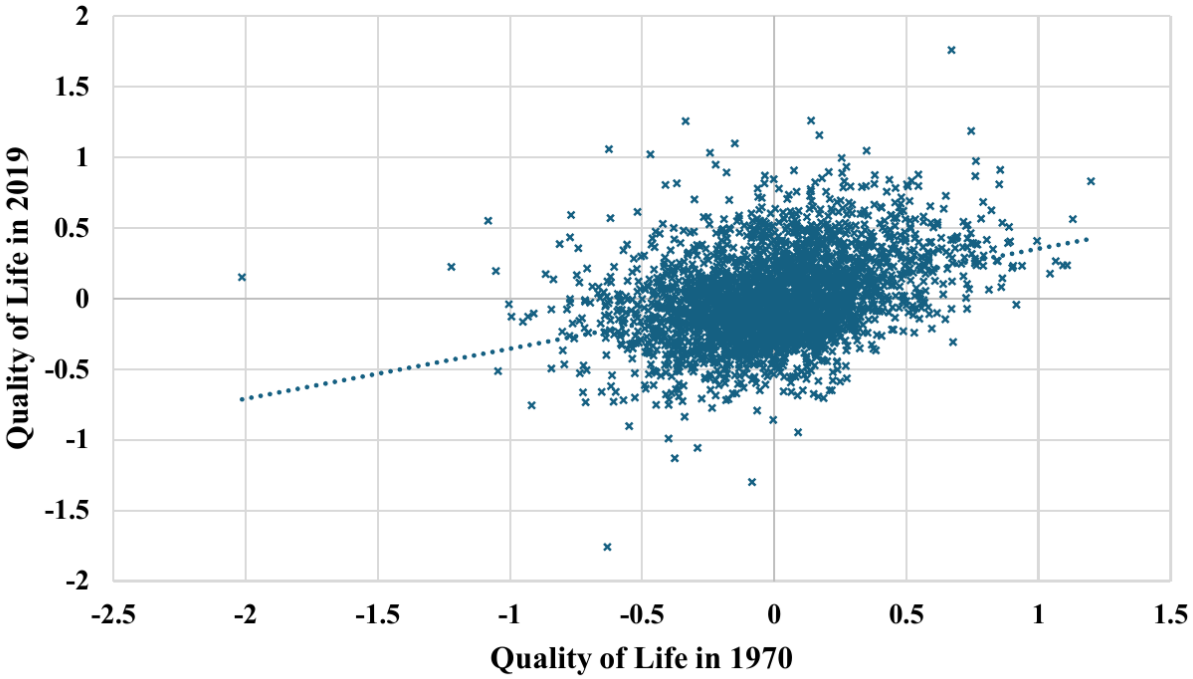


As shown in Table 2, across all specifications, QOL is positive and statistically significant at the one percent level, indicating a strong association between QOL and subsequent population growth. However, the magnitude of this effect depends heavily on a county's baseline urban population and metropolitan adjacency. The returns on quality of life are most pronounced in larger rural counties containing 20,000 or more urban residents, where the QOL coefficients reach their peak at 0.21 for adjacent (RUCC 4) and 0.22 for non-adjacent (RUCC 5) areas. This suggests that natural or social amenities yield the highest demographic dividends when paired with a foundational level of proximity to urban agglomeration.

As county populations and urbanization levels decrease, the effect of quality of life diminishes but remains critical. In mid-sized counties with 5,000 to 20,000 urban residents (RUCC 6 and 7), the QOL coefficient stabilizes at 0.12 regardless of metropolitan adjacency. In the smallest county cohorts (fewer than 5,000 urban residents), adjacency acts as a critical buffer; adjacent counties (RUCC 8) exhibit a QOL coefficient of 0.13, which is not statistically different from either of the mid-sized RUCC's with 5,000 to 20,000 residents (employing a Wald test). However, smaller non-adjacent counties (RUCC 9) register the lowest QOL coefficient in the sample at 0.09.

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Figure 2: Correlation of Quality of Life over Time (1970–2019)



The baseline growth dynamics, captured by the models' intercepts, further highlight the vulnerability of isolated rural areas. While more urbanized rural counties maintain positive baseline growth intercepts, completely rural and non-adjacent counties (RUCC 9) display a significantly negative intercept of −0.02. This indicates that smaller counties farther from urban areas face systemic population decline in the absence of strong quality of life amenities, making amenity development a defensive necessity against out-migration. Data visualization makes this even clearer. In Figure 3, we depict the coefficients for the different RUCCs. A standard Wald test yields three different sets. The two counties with more than 20,000 urban residents (RUCC 4 and 5) are not statistically different from one another. The next three RUCC codes, counties with 5,000 to 20,000, and the metro adjacent counties with fewer than 5,000 all share coefficients that are statistically identical. The RUCC results for counties with fewer than 5,000 urban residents that are not metro adjacent is statistically different from both other sets of coefficients.

Taken together, these results support a Rosen–Roback interpretation in which quality of life functions as a compensating differential influencing long-run population sorting. However, the strength of this mechanism differs across space.

We are also interested in the evolution of the effect of quality of life on population growth over time, and we look at this by examining decadal differences for each of our six RUCC samples as shown in Table 3.

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Table 2: Quality of Life Effects on Population Growth, across Rural Counties (1970–2019)

	20,000 or more urban residents, adjacent to Metro **RUCC 4**	20,000 or more urban residents, not adjacent to Metro **RUCC 5**	5,000 to 20,000 urban residents, adjacent to Metro **RUCC 6**	5,000 to 20,000 urban residents, not adjacent to Metro **RUCC 7**	< 5,000 urban residents, adjacent to Metro **RUCC 8**	< 5,000 urban residents, not adjacent to Metro **RUCC 9**
Intercept	0.08***	0.07***	0.05***	0.03***	0.02***	−0.02***
	(23.44)	(13.70)	(27.95)	(13.63)	(6.65)	(−8.12)
Quality of Life	0.21***	0.22***	0.12***	0.12***	0.13***	0.09***
	(14.27)	(10.96)	(14.56)	(12.03)	(9.62)	(8.72)
N	1,015	442	4,616	2,035	1,042	1,991
(i, t)	(205, 5)	(89, 5)	(580, 5)	(410, 5)	(209, 5)	(400, 5)
Adj. R^2	0.29	0.32	0.31	0.26	0.24	0.13
F-Stat	82.53***	41.72***	246.64***	141.71***	65.05***	58.54***

Note: *** denotes statistical significance to the 0.01 level; ** to the 0.05 level; and * at the 0.10 level.

Table 3: Time Varying Summary Statistics

	Population					**Quality of Life**				
	Mean	**Median**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
					RUCC 4					
1970	47,249	42,105	25,036	5,461	159,666	0.05	0.07	0.25	−1.08	0.65
1980	53,083	47,998	24,987	9,485	160,431	−0.05	−0.08	0.16	−0.40	0.50
1990	55,361	49,913	24,145	15,792	174,462	−0.02	−0.06	0.20	−0.38	0.70
2000	60,488	55,932	24,356	27,519	182,597	−0.02	−0.08	0.24	−0.47	0.93
2010	63,659	58,992	24,839	31,323	189,892	0.04	−0.01	0.28	−0.68	0.99
2019	64,331	58,972	24,553	31,086	185,242	0.00	−0.05	0.27	−0.55	0.89
					RUCC 5					
1970	39,516	37,522	16,672	2,793	99,708	0.00	0.02	0.29	−0.87	0.76
1980	45,066	42,082	17,240	8,960	108,931	−0.02	−0.05	0.21	−0.45	0.88
1990	46,775	42,324	18,224	13,124	121,572	0.01	−0.04	0.19	−0.35	0.63
2000	50,755	45,006	20,055	22,616	149,244	−0.03	−0.08	0.27	−0.55	0.96
2010	54,099	48,927	23,703	22,994	185,296	0.00	−0.09	0.34	−0.58	1.28
2019	55,337	48,630	26,265	22,234	199,750	−0.02	−0.08	0.32	−0.60	0.87
					RUCC 6					
1970	19,698	17,703	9,669	2,436	58,203	−0.08	−0.07	0.23	−1.05	0.55
1980	22,044	19,775	10,574	4,038	62,988	−0.07	−0.07	0.14	−0.55	1.03
1990	22,183	20,007	10,886	4,479	63,048	−0.06	−0.08	0.16	−0.47	0.83
2000	24,178	22,180	12,032	3,290	69,507	−0.08	−0.09	0.21	−0.59	0.81
2010	25,005	22,987	12,632	3,341	71,681	−0.09	−0.11	0.28	−1.09	1.33
2019	24,593	22,151	12,654	3,429	71,453	−0.08	−0.10	0.27	−0.99	1.00
					RUCC 7					
1970	16,476	14,249	10,157	1,983	94,201	−0.08	−0.05	0.28	−1.05	1.20
1980	18,192	15,632	10,869	2,305	91,153	−0.03	−0.05	0.17	−0.51	1.05
1990	17,857	15,267	10,651	3,130	87,024	−0.02	−0.04	0.20	−0.52	1.45
2000	18,924	16,611	10,969	3,335	73,872	−0.08	−0.11	0.25	−0.60	0.99

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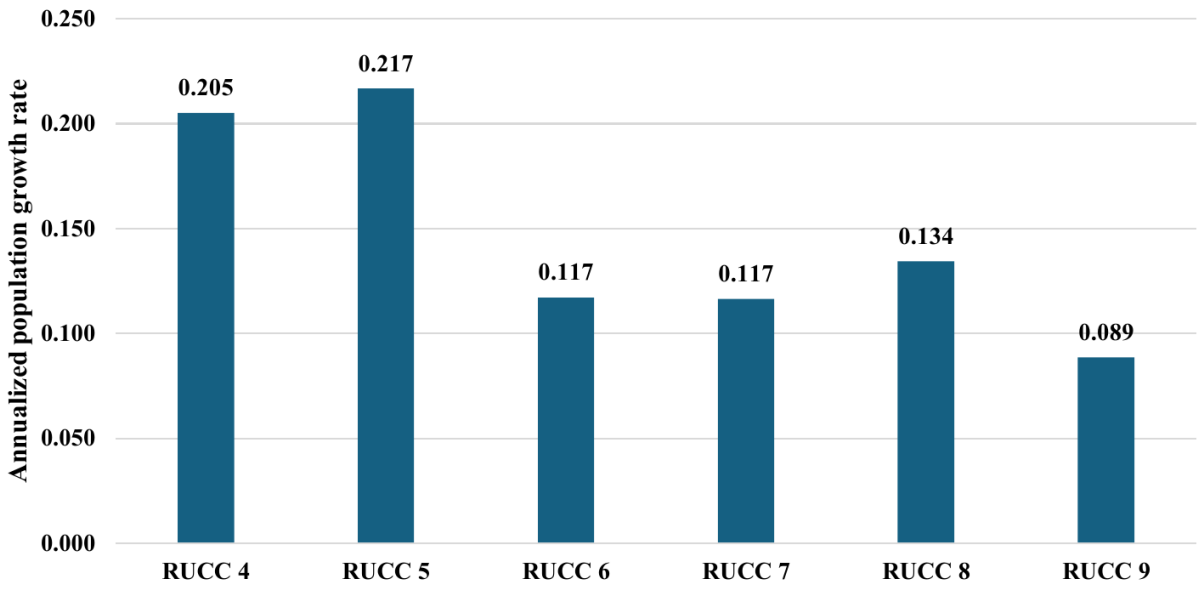
	Population					Quality of Life				
	Mean	**Median**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
2010	18,947	16,476	11,035	3,578	71,702	−0.11	−0.15	0.34	−0.90	1.31
2019	18,672	16,377	10,993	3,086	67,232	−0.09	−0.12	0.30	−0.86	1.04
					RUCC 8					
1970	8,235	7,623	4,528	508	28,863	−0.13	−0.13	0.25	−0.84	0.49
1980	9,105	8,671	5,099	856	31,288	−0.01	−0.02	0.16	−0.50	0.61
1990	8,953	7,984	5,264	794	31,803	−0.01	−0.03	0.19	−0.85	0.74
2000	9,734	8,495	6,082	715	38,215	−0.03	−0.04	0.24	−0.73	1.15
2010	9,870	8,982	6,370	644	34,395	−0.03	−0.07	0.33	−0.79	1.17
2019	9,609	8,395	6,453	590	37,126	0.00	−0.04	0.31	−1.06	1.15
					RUCC 9					
1970	6,104	5,419	4,108	151	32,251	−0.19	−0.18	0.25	−1.22	0.51
1980	6,439	5,413	4,733	90	37,960	0.05	0.06	0.18	−0.59	0.47
1990	6,068	4,909	4,637	105	31,224	−0.02	−0.03	0.21	−0.91	0.88
2000	6,291	4,939	5,069	358	28,381	−0.01	−0.05	0.24	−0.63	1.27
2010	6,183	4,822	5,195	81	28,956	−0.13	−0.20	0.36	−0.87	1.40
2019	5,969	4,506	5,105	251	29,788	−0.12	−0.16	0.36	−1.76	1.26

An analysis of the time-varying summary statistics presented in Table 3 reveals a widening demographic and amenity divergence between larger, metro-adjacent counties and those with smaller urban populations from 1970 to 2019. In terms of population, larger rural counties (RUCC 4 and 5) experienced robust, continuous growth across the 50-year period, with mean populations increasing by approximately 36% and 40%, respectively. Conversely, the most remote rural non-adjacent counties (RUCC 9) exhibited a distinct pattern of long-term depopulation; their mean population peaked in 1980 at 6,439 and steadily contracted to 5,969 by 2019, while the median population dropped even more sharply from 5,419 to 4,506. Mid-sized counties (RUCC 6 and 7) occupy a middle ground, experiencing modest growth through the late twentieth century before plateauing or entering slight decline after 2010.

Parallel to these shifting demographic trajectories is a persistent quality of life effect that seems to favor urban scale and metropolitan adjacency. While the standardized quality of life index for larger nonmetropolitan counties consistently hovers near the national average, mean QOL values progressively decline as counties become more rural. Several forces likely contribute to this pattern: larger, metro-adjacent counties may benefit from proximity to metropolitan job markets and amenities even when their own population is modest, from the scale needed to support a wider range of private-market amenities, and from a larger tax base to fund public goods such as schools and infrastructure (Weinstein et al., 2026). Isolated counties may also face a reinforcing cycle, in which weaker amenities and access to economic opportunity encourage out-migration of younger, more mobile residents, further eroding the local market and tax base needed to sustain amenities going forward. This rural penalty is most pronounced in RUCC 9 counties, which routinely record the lowest average QOL scores in the sample, frequently dropping below −0.12 (despite the abundant access to natural amenities in many remote rural areas). However, a uniform decline does not characterize all rural spaces; rather, the data demonstrate growth of intra-group inequality from 1980 onward. In nearly every RUCC tier, the standard deviation for QOL expanded

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Figure 3: Effect of a One Unit Change in Quality of Life on Population Change across Rural-Urban Continuum Codes in the USA, 1970–2019



dramatically over time, doubling from 0.18 to 0.36 in RUCC 9 by 2019, driven by a widening gulf between outliers (with minimums plunging to −1.76 and maximums climbing to 1.26), consistent with some isolated counties falling into this reinforcing cycle while others do not.

To further explore this, Table 4 presents a specification that allows the effect of quality of life (QOL) on population growth to vary by decade from 1970 to 2019. The empirical results demonstrate that the demographic returns to quality of life are not historically uniform but rather peaked in the late twentieth century. In the 1980s, the demographic effects on quality of life diverged sharply along lines of urban scale, reaching coefficients of 0.44 in larger metro-adjacent counties (RUCC 4) and 0.32 in larger, non-adjacent counties (RUCC 5). Conversely, smaller, non-adjacent rural counties (RUCC 9) exhibited a significantly negative QOL coefficient of −0.07 during this decade. This negative relationship may reflect the shocks of the 1980s farm crisis, during which severe economic dislocation triggered widespread out-migration from remote rural areas (Goetz and Debertin, 1996).

Following this divergence, the 1990s marked the historical high point for QOL effects on population across all nonmetropolitan regions. During the 1990–2000 period, the estimated QOL coefficients became uniformly positive, large, and statistically significant across all six nonmetropolitan tiers, ranging from a low of 0.26 in small, metro-adjacent counties (RUCC 8) to a peak of 0.42 in large, non-adjacent counties (RUCC 5). The post-2000 results reveal a moderation of the QOL effect on population change. While these contemporary estimates remain highly statistically significant, their diminished magnitude implies that the capacity of amenities to generate population growth has softened over time for rural areas. This may be due to broader macroeconomic headwinds such as aging rural demographics, declining

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Table 4: Time Varying Effects of Quality of Life on Population Growth in Rural Counties (1970–2019)

	20,000 or more urban residents, adjacent to Metro **RUCC 4**	20,000 or more urban residents, not adjacent to Metro **RUCC 5**	5,000 to 20,000 urban residents, adjacent to Metro **RUCC 6**	5,000 to 20,000 urban residents, not adjacent to Metro **RUCC 7**	< 5,000 urban residents, adjacent to Metro **RUCC 8**	< 5,000 urban residents, not adjacent to Metro **RUCC 9**
Intercept	0.08***	0.07***	0.05***	0.03***	0.02***	−0.02***
	(25.34)	(14.10)	(29.30)	(13.50)	(6.45)	(−7.55)
1970–1980	0.07**	0.25***	−0.01	0.10***	0.10***	0.07***
	(2.46)	(6.17)	(−0.65)	(5.34)	(3.32)	(3.08)
1980–1990	0.44***	0.32***	0.22***	0.12***	0.02	−0.07**
	(9.90)	(5.94)	(8.48)	(4.00)	(0.43)	(−2.23)
1990–2000	0.36***	0.42***	0.28***	0.30***	0.26***	0.27***
	(9.73)	(7.08)	(12.07)	(11.87)	(6.70)	(9.78)
2000–2010	0.24***	0.21***	0.17***	0.12***	0.22***	0.15***
	(8.10)	(4.95)	(9.44)	(6.05)	(7.05)	(6.36)
2010–2019	0.13***	0.10***	0.10***	0.06***	0.09***	0.05***
	(5.11)	(2.86)	(7.32)	(4.35)	(4.18)	(3.16)
N	1,015	442	4,616	2,035	1,042	1,991
(i, t)	(205, 5)	(89, 5)	(580, 5)	(410, 5)	(209, 5)	(400, 5)
Adj. R^2	0.333897	0.353095	0.337042	0.278992	0.253055	0.159182
F-Stat	57.47636	27.74533	158.997	88.45027	40.18639	42.86038

Note: *** denotes statistical significance to the 0.01 level; ** to the 0.05 level; and * at the 0.10 level.

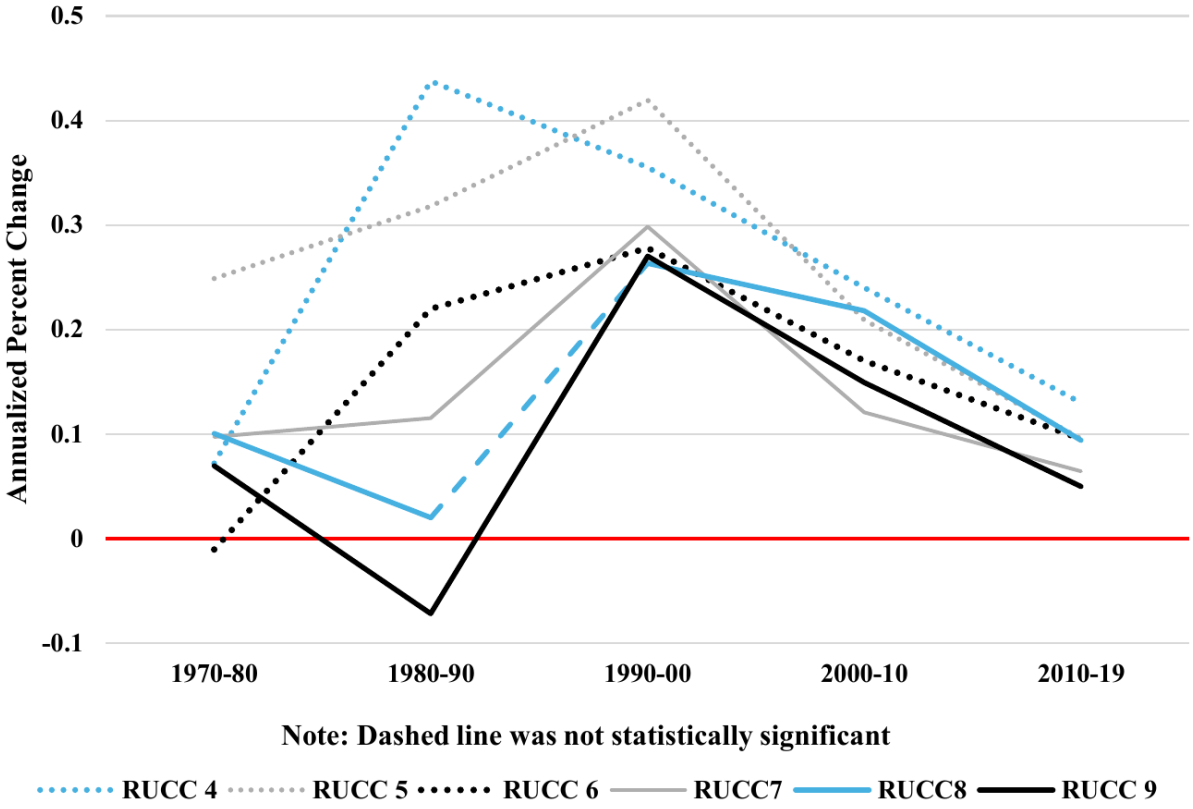
geographic mobility, or housing supply constraints in high-amenity zones. It may also reflect a structural shift in where economic growth concentrates: as the economy has shifted from manufacturing toward tradable services, growth increasingly benefits large incumbent higher-resourced cities rather than spreading to new or smaller places, in contrast to the more geographically dispersed industrialization of the early twentieth century (Eckert et al., 2023). If population growth is increasingly tied to a county's position in this incumbent-city-centered service economy, high quality of life alone may no longer be enough to draw population the way it once did outside those hubs, many of which are high quality of life metropolitan areas.

These estimates end in 2019, however, and therefore predate the sharp rise in remote work following the COVID-19 pandemic. Subsequent research finds that the association between quality of life and population growth more than doubled after the onset of the pandemic, with the largest gains concentrated in rural and micropolitan areas, as remote work allowed households to decouple their residence from their employer's location (Weinstein and Blatchly, 2025). This suggests that the incumbent-city advantage documented by Eckert et al. (2023) may not extend uniformly into the post-pandemic period, and that the amenity-driven population dynamics identified here could reassert themselves, or even strengthen, once remote work loosens the link between where people live and where the tradable service economy is concentrated.

Finally, the model's intercepts and explanatory power reaffirm the persistent structural vulnerabilities inherent to isolated rural geography. Even when accounting for decade-specific

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Figure 4: Time Varying Coefficients of Quality of Life Effects on Population Change across Rural RUCC's, 1970–2019



amenity shocks, the baseline growth intercepts exhibit a strict linear decline from the largest, metro-adjacent counties to the smaller remote nonmetropolitan counties. This negative baseline intercept confirms that less urbanized and more rural and remote counties face systemic, long-term depopulation pressures. Moreover, the model fit suggests that while the decade-specific model explains roughly one-third of the growth variation in larger nonmetropolitan counties, its explanatory power drops to 0.16 in the smallest remote counties, reinforcing that population dynamics in those locations may be increasingly governed by highly idiosyncratic or unobserved localized shocks.

We next turn our attention to identifying the ability of individual amenities to predict quality of life across rural and urban areas.

4. INDIVIDUAL AMENITIES AND QOL

To identify the county-level amenities that best predict spatial variation in quality of life (QOL), we estimate a penalized regression model within the canonical spatial equilibrium framework developed by Rosen (1979) and Roback (1982). In this framework, households sort across locations until utility is equalized, implying that local amenities are capitalized

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into wages and housing costs. Following the amenity capitalization literature, we treat our estimated QOL index as a sufficient statistic for the bundle of local non-market amenities valued by households.

Because counties differ along a high-dimensional set of natural, consumption, demographic, and public-service amenities, conventional OLS may suffer from overfitting and multicollinearity. To address this, we employ the Least Absolute Shrinkage and Selection Operator (LASSO) introduced by Tibshirani (1996). LASSO performs simultaneous estimation and variable selection by minimizing the residual sum of squares subject to an ℓ_1 penalty on coefficients. This penalty shrinks many coefficients toward zero and sets others exactly to zero, thereby selecting a sparse subset of predictors. In high-dimensional settings, LASSO has well-established consistency properties under regularity conditions (e.g., Hastie et al., 2015; van de Geer, 2016).

Formally, we estimate:

$$\hat{\beta} = \arg\min_{\beta} \left\{ \frac{1}{N} \sum_{i=1}^{N} \left(\mathrm{QOL}_i - X_i' \beta \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{5}$$

where QOL_i is the county-level quality-of-life measure, X_i is a vector of standardized amenity measures, and λ is a tuning parameter selected via cross-validation to minimize out-of-sample mean squared error. All amenity variables are standardized prior to estimation to ensure comparability of coefficient β magnitudes.

We also perform a post-LASSO ordinary least squares estimate to remove the coefficient shrinkage bias created by the LASSO tuning and to establish the classical statistical properties of the OLS. We report the LASSO estimates in the appendix but rely upon the OLS estimates for magnitude and statistical significance (Belloni and Chernozhukov, 2013). This approach preserves the model-selection advantages of LASSO while allowing unbiased coefficient estimation conditional on the selected covariates.

Our amenity set is selected, with one modification, from Weinstein et al. (2023). These include natural amenities (climate, topography, water access), private or endogenous consumption amenities (industry mix, arts and recreation establishments, restaurants), and public and demographic characteristics (school expenditures, crime rates, population density, and educational attainment). Our use of the religion data changed from a count variable of religious establishments used in Weinstein et al. (2023) to the share of residents who belonged to a congregation (American Religious Data Archives). This was done because the count variable may be an artifact related to the year the county was most heavily populated (pre- or post-automobile). This classification aligns with the Rosen–Roback distinction between exogenous site characteristics and equilibrium outcomes that reflect local production and public policy.

By embedding LASSO within the Rosen–Roback framework, our empirical strategy isolates the subset of county-level amenities that are most strongly associated with spatial variation in quality of life, while mitigating overfitting and improving out-of-sample predictive performance. This approach is particularly well-suited to the modern amenity literature, where large administrative datasets generate many plausible and highly correlated predictors of local utility.

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For ease of analysis, we separate the LASSO results into three amenity-based groupings. They appear in the following tables.

Table 5 reports LASSO-selected estimates for natural amenities and climate variables across the five nonmetropolitan RUCC codes and provides a coefficient of variation across these estimates. This provides evidence of the dispersion of effects across these regions. As mentioned, these are OLS estimates of the variables selected by the LASSO, and column one of this table, and the following tables list the full set of variables employed in this analysis. Those reported here are only those variables that were a) selected by the LASSO and b) statistically significant at the 0.10 level in the second stage OLS.

Table 5: Natural Amenities and Climate (OLS Estimates from LASSO Variable Selection on Quality of Life)

Variable Name	20,000 or more urban residents, adjacent to Metro **RUCC 4**	20,000 or more urban residents, not adjacent to Metro **RUCC 5**	5,000 to 20,000 urban residents, adjacent to Metro **RUCC 6**	5,000 to 20,000 urban residents, not adjacent to Metro **RUCC 7**	< 5,000 urban residents, adjacent to Metro **RUCC 8**	< 5,000 urban residents, not adjacent to Metro **RUCC 9**	**Coefficient of Variation**
Distance to Coast	...	...	...	−0.0013	...	...	...
Hilliness	0.0001	0.0001	0.0001	0.0000	0.0001	0.0000	5.2064
Mean July relative humidity	...	...	...	−0.0037	...	...	...
Mean January temperature	0.0081	...	...	...	0.0109	0.0149	4.0561
Mean July temperature	−0.0153	−0.0131	...	−0.0075	−0.0361	−0.0403	−1.7098
Water square miles	0.9023	...	0.7204	0.4891	1.6970	1.2081	2.3946

Note: ... denotes that these variables were not selected in the LASSO estimates.

These empirical results reveal that while certain environmental factors yield stable, ubiquitous premiums across nonmetropolitan counties, climate related amenities are not uniform across nonmetropolitan geographies and the climate related variables are negative or not statistically significant across most of our samples. Mean July temperature exerts a consistently negative and statistically significant effect across almost all nonmetropolitan RUCC areas, yet the magnitude of this penalty escalates dramatically as population density and metropolitan adjacency decline.

In urban-adjacent areas (RUCC 4) and micro-adjacent counties (RUCC 5), the negative coefficients are between −0.0153 and −0.0131, respectively, before rising to −0.0361 in RUCC 8 and peaking at −0.0403 in completely isolated rural counties (RUCC 9). This pattern suggests that urban climate-mitigation infrastructure or occupational composition may buffer closer-in regions, whereas rural economies are highly sensitive to extreme summer heat. In contrast, warmer winter conditions, captured by Mean January temperature, act as a positive amenity premium primarily in urban-adjacent hubs (0.0081) and in the smallest RUCC's (0.0109 and 0.0149), reflecting a persistent baseline preference for temperate winters.

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Geographic features and landscape characteristics display the highest degree of structural stability across the continuum, though their marginal effects are modest. Hilliness (the difference between the highest and lowest point in a county) is retained by the LASSO and remains statistically significant across all rural tiers (RUCC 4 through 9) in the subsequent OLS. Despite its universal statistical strength, the near-zero absolute magnitude of the coefficients suggests that scenic topographic variation is a marginal predictor of QOL. In contrast, surface water coverage (Water square miles) commands a substantial and highly resilient QOL premium across nearly all cohorts. The localized valuation of water coverage spans from 0.9023 in RUCC 4 to a substantial peak of 1.6970 in RUCC 8, suggesting that this variable is a robust predictor of QOL.

The mean July relative humidity and distance to the coast achieve statistical significance exclusively within moderately rural, non-adjacent counties (RUCC 7), where closer coastal proximity predicts higher QOL (-0.0013) while higher summer humidity imposes a localized penalty (-0.0037). Conversely, universally significant variables like water coverage and winter temperatures exhibit low coefficients of variation (2.3946 and 4.0561, respectively).

These estimates report some familiar findings: hilliness, mild winters, cooler summers and more water area tend to predict local QOL across all or most of the nonmetropolitan counties in the United States.

Notably, several of these natural amenity effects are not just present but most pronounced in the smallest, most isolated counties: the summer heat penalty nearly triples between RUCC 4 and RUCC 9, and the water coverage premium peaks in RUCC 8. Yet these same isolated counties recorded the weakest overall relationship between QOL and population growth. Strong natural amenity endowments, in other words, do not appear sufficient to reverse population decline in the most remote places. This suggests that quality of life in these counties depends on more than natural amenities alone, and that limited access to economic opportunity, a constraint documented to be most severe in exactly these small, remote geographies, may outweigh even a strong natural amenity base in shaping population outcomes.

We next turn our attention to public amenities, those which we define as being provided by government and demographic conditions which might be, but are not necessarily, affected by policy. These results are shown in Table 6.

Table 6 reports the OLS estimates for the public amenities that meet the 0.20 level of statistical significance, finding that socioeconomic inequality and public health vulnerabilities present a persistent negative predictor of QOL. The Gini coefficient yields a strictly negative and statistically significant effect across the middle to smallest nonmetropolitan counties. Poor public health outcomes as measured by physically unhealthy days are negatively correlated with QOL in both urban-adjacent hubs (RUCC 4) and less urbanized, nonmetropolitan non-adjacent counties (RUCC 9 coefficient of -0.04). This bimodal pattern likely reflects two distinct mechanisms: in urban-adjacent RUCC 4 counties, health may function as an environmental or lifestyle amenity tied to pollution and general urban health conditions, whereas in the most isolated RUCC 9 counties, it more plausibly reflects deficits in healthcare access, such as distance to care and rural hospital closures. The mortality measure (years of potential life lost) has very modest effects. However, since these measures, like violent crime rates, are small values, any statistical significance indicates they remain

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Table 6: Public Amenities and Demographics (OLS Estimates from LASSO Variable Selection on Quality of Life)

Variable Name	20,000 or more urban residents, adjacent to Metro **RUCC 4**	20,000 or more urban residents, not adjacent to Metro **RUCC 5**	5,000 to 20,000 urban residents, adjacent to Metro **RUCC 6**	5,000 to 20,000 urban residents, not adjacent to Metro **RUCC 7**	< 5,000 urban residents, adjacent to Metro **RUCC 8**	< 5,000 urban residents, not adjacent to Metro **RUCC 9**	**Coefficient of Variation**
Absolute mobility	...	...	...	...	...	...	...
Forest coverage	...	...	0.17	0.22	0.19	0.19	9.48
Gini	...	...	−0.87	...	−1.44	−0.89	−4.05
Ln(Population)	...	...	0.08	0.15	...	0.12	3.68
Mentally unhealthy days	...	...	...	...	...	...	...
Physically unhealthy days	−0.07	...	...	...	...	−0.04	−3.06
Population density	0.00	...	0.00	...	0.01	...	1.38
Park square miles	...	...	...	...	...	...	...
Relative mobility	...	...	...	...	0.00	...	...
Road miles	0.00	...	...	...	...	...	...
School spending share	...	...	...	...	0.93	0.90	48.24
Share worked at home	1561.79	...	...	...	...	...	...
Violent crime rate	...	...	0.00	...	...	...	...
Mortality YPLL Rate	...	0.00	0.00	0.00	0.00	0.00	−1.66

Note: The year of our data (2010) differs from the RUCC definition (2013), so there are discrepancies across a handful of counties in metropolitan status. This affected distance to metro, metro adjacency and metro status. Of these, only one variable (metro adjacency) was statistically significant in only one RUCC, but was not meaningful in an economic interpretation. None of these are policy relevant, so were omitted from this table.

... denotes that these variables were not selected in the LASSO estimates.

important in predicting QOL.

In terms of public infrastructure and investments, education spending emerges as a powerful predictor of QOL in isolated economies. School spending share exhibits a large positive correlation within the smallest areas of the RUCC with coefficient of 0.93 in RUCC 8 and 0.90 in RUCC 9. Unlike natural amenities, which are fixed by geography, or private consumption amenities, which require population scale to sustain, education spending is a policy lever that local governments can adjust regardless of market size. Its outsized importance in RUCC 8 and 9 suggests that public investment can substitute for amenities that private markets are otherwise unable to support in the smallest, most isolated counties.

Demographic context and geographic connectivity variables further illustrate these sorting dynamics. The natural log of population yields a consistently positive relationship QOL across RUCC 6 (0.08), RUCC 7 (0.15), and RUCC 9 (0.12), while population density carries a small positive coefficient in RUCC 4, 6, and 8. That these two measures of scale matter in

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different, only partially overlapping sets of RUCC tiers suggests that population scale effects operate continuously even within a given RUCC classification, rather than being fully captured by the RUCC categories themselves: counties on the larger or denser end of their tier still command an additional QOL premium. Finally, the share of the population working at home displays a very large association with QOL within urban-adjacent RUCC 4 counties. This concentration in RUCC 4 is consistent with the county type most likely to combine adequate broadband infrastructure with a workforce holding remote-capable jobs. It may also reflect the rise of hybrid work arrangements, which let households live farther from a metro area than a daily commute would allow, while still permitting occasional in-person attendance, making metro-adjacent but lower-density counties an attractive middle ground between urban proximity and rural space. The same connectivity and workforce-skill gaps documented in rural broadband research (Weinstein et al., 2024), by contrast, may prevent more isolated, non-adjacent counties from converting remote-work availability and quality of life into a similar locational advantage.

Table 7 displays results from private, market-driven endogenous amenities that predict QOL. Unlike exogenous natural endowments, these amenities reflect consumer markets, retail infrastructure, and local services that adjust endogenously to population thresholds and local demand. When modeled under a Rosen–Roback structure, the capitalized values of these commercial amenities reveal distinct differences along the rural–urban continuum. The empirical results demonstrate that while structured consumer options and specialized health services command immense premiums in metro-adjacent hubs, less dense rural spaces rely on commercial "third places" and generalized recreational options to improve household utility.

Eating and drinking places per capita drop out entirely in larger metro-adjacent (RUCC 4) and micro-adjacent (RUCC 5) counties, but emerge as a strong positive predictor of QOL across the RUCC 6 through 9 samples. This suggests that in the absence of dense urban infrastructure, local commercial dining and social establishments serve as indispensable pillars for community socialization and regional sorting. Food stores per capita exhibit a similar mid-continuum bridging effect, generating positive coefficients across RUCC 5, 6 and 7, indicating that localized retail access to essential goods is a strong predictor of QOL in moderately populated nonmetropolitan counties.

Specialized commercial recreational facilities, such as fitness places per capita and golf courses per capita, are strong predictors of QOL in metro-adjacent RUCC 4 and 6 areas (1224.85 and 895.60, respectively). While fitness places maintain a strong positive capitalization through RUCC 7, they lose all statistical significance in the most remote areas (RUCC 8 and 9). In these smaller, more remote counties (RUCC 9), more general recreation places take over as the primary positive market amenity. Home furnishing places per capita reverse sign across the smallest counties, positive in RUCC 6 and 7 but negative in RUCC 8, suggesting that large-format retail infrastructure becomes increasingly difficult to sustain for smaller counties.

Urgent care facilities positively correlate with QOL only within metro-adjacent RUCC 4 counties, while general health service is positively correlated in RUCC 5 and 7. This split plausibly reflects a healthcare-access gradient: urgent care is a more specialized, higher-cost service that requires the customer base only metro-adjacent counties can offer, while more basic health service establishments remain viable in mid-sized, non-adjacent counties

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that still have enough population to support them, echoing the healthcare access constraints discussed above. In contrast, personal care places per capita are a negative predictor of QOL in urban-adjacent RUCC 4 and nonmetropolitan metro-adjacent RUCC 5 (−200.28) counties. The share of religious adherents (a proxy for those active in organized religion) is negatively correlated with QOL across RUCC 4, RUCC 6, and RUCC 8, the metro-adjacent RUCCs. One plausible contributor to this pattern is fiscal rather than social: religious congregations typically hold tax-exempt property, so counties with a larger share of religious adherents may also have more land removed from the local tax base, constraining the public investment discussed above. We note this cautiously, since we cannot distinguish this fiscal channel from other explanations with the data at hand.

Table 7: Private and Consumption (Endogenous) Amenities (OLS Estimates from LASSO Variable Selection on Quality of Life)

Variable Name	20,000 or more urban residents, adjacent to Metro **RUCC 4**	20,000 or more urban residents, not adjacent to Metro **RUCC 5**	5,000 to 20,000 urban residents, adjacent to Metro **RUCC 6**	5,000 to 20,000 urban residents, not adjacent to Metro **RUCC 7**	< 5,000 urban residents, adjacent to Metro **RUCC 8**	< 5,000 urban residents, not adjacent to Metro **RUCC 9**	**Coefficient of Variation**
Arts & Culture Places	...	...	...	...	...	...	...
Bowling places per capita	...	...	...	−574.84	...	...	...
Eating & drinking places per cap	...	...	94.56	88.72	60.72	31.07	2.72
Fitness places per capita	1224.85	...	608.32	595.13	...	...	2.76
Food stores per capita	...	485.02	91.50	107.79	...	...	1.25
Golf courses per capita	895.60	...	...	...	...	...	...
Health service places per cap	...	101.25	...	53.13	...	...	3.21
Home furnishing places per cap	...	...	1175.64	933.62	−1499.85	...	0.17
Movie theaters per capita	...	...	...	...	...	...	...
Personal care places per cap	−238.76	−200.28	...	...	...	...	−11.41
Recreation places	...	825.49	...	322.33	...	60.28	1.27
Share of Religious Adherents (replaces houses of worship)	−0.30	...	−0.18	...	−0.32	...	−4.30
Urgent care facilities	3670.06	...	...	...	...	...	...

Note: ... denotes that these variables were not selected in the LASSO estimates.

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Evaluating the coefficients of variation (CV) reveals that home furnishing places (0.17), food stores (1.25), and eating and drinking establishments (2.72) are strongly correlated predictors of QOL are the most stable, consistent predictors of QOL across the rural–urban continuum. Conversely, specialized private services and social institutions carry much higher variation, illustrating that their capitalized effects are uneven across space.

With Tables 5 and 6, this pattern completes a consistent story across all three amenity types: private market amenities do not just weaken in the most isolated counties, several lose statistical significance entirely, meaning the market likely genuinely cannot sustain them there. This is precisely why natural amenities and public investment carry more of the burden in the smallest, most remote places; private markets may not be a viable substitute at that scale (or at least not without government subsidies). A comparative analysis of the empirical results across the three tables reporting natural, public and demographic, and price or endogenous amenities reveals how different types of regional attributes predict QOL across the rural–urban continuum as measured within the Rosen–Roback spatial equilibrium framework. The common element all three amenity bundles is the presence of spatial heterogeneity and non-linear threshold effects. Rather than acting as static, nationally uniform predictors of QOL, environmental endowments, public investments, and market-driven commercial services are highly sensitive to a county's specific degree of urbanization and metro adjacency.

At the same time, the absence of private amenities in rural and remote counties may not solely reflect insufficient local demand; rural entrepreneurs also face persistent barriers to the private capital needed to start and scale such businesses in the first place (Weinstein and Dewbury, 2025). The scarcity of private amenities in the most isolated counties therefore likely reflects both supply-side financing constraints and demand-side limits on market scale.

Taken together, these results suggest that while the composition and magnitude of valued amenities vary across space, the dominant drivers of spatial welfare differences remain natural capital and public goods provision. The following section situates these findings within the broader literature and discusses their methodological and policy implications.

5. CONCLUSION

This study examines the role of quality of life (QOL) in predicting long-run population change across rural U.S. counties from 1970 to 2019. Grounded in the Rosen–Roback spatial equilibrium framework, it treats nominal wage and housing cost variations as compensating differentials that reveal household valuation of place-specific attributes. Methodologically, the paper combines aggregate county-level residuals from housing and labor market regressions following a specification by Hicks et al. (2026) to measure QOL.

Decadal population growth modeling across the nonmetropolitan Rural-Urban Continuum Codes (RUCC 4 through 9) confirms that higher QOL is strongly associated with subsequent population growth across all rural categories. However, this association is not constant across time or space. The effect of QOL peaks in large nonmetropolitan counties (RUCC 4 and 5), where coefficients reach 0.21 and 0.22. In contrast, small, non-adjacent counties (RUCC 9) register a diminished QOL coefficient of 0.09 and a significantly negative

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baseline intercept of −0.02, signaling longer-term population decline.

This relationship has also shifted markedly over time. The return to QOL was weakest, and even negative in the most isolated counties, during the 1980s farm crisis, peaked across nearly all county types in the 1990s at coefficients as high as 0.42, and has since moderated substantially. This decline may partly reflect a broader structural shift in the economy: as growth has moved from manufacturing toward tradable services, that growth appears to concentrate in large incumbent cities with high quality of life rather than spreading to new or smaller places (Eckert et al., 2023). Because our quality of life data end in 2019, these estimates predate the sharp rise in remote work following the COVID-19 pandemic. Subsequent research finds that the association between QOL and population growth more than doubled after the pandemic's onset, particularly in rural and micropolitan areas, as remote work let households decouple their residence from their employer's location (Weinstein and Blatchly, 2025). The amenity-driven population dynamics identified here may therefore be reasserting themselves, or strengthening further, as remote and hybrid work loosen the link between where people live and where the service economy is concentrated.

Using a LASSO framework with a post-LASSO OLS estimation to isolate specific predictors of QOL, we find spatial heterogeneity across amenity bundles among nonmetropolitan counties. Surface water coverage is a strong positive predictor of QOL, while high July temperatures are a negative predictor, and both effects grow stronger as counties become more remote. Socioeconomic inequality and poor public health outcomes serve as strong negative predictors, whereas local education investments emerge as powerful positive predictors, especially in the smallest, most isolated counties. Specialized market amenities such as fitness centers and golf courses command large premiums in metro-adjacent areas but lose significance entirely in the most remote counties; there, commercial third places, such as eating and drinking establishments and food stores, become the dominant positive market-driven predictors of regional QOL, and rural entrepreneurs' limited access to private capital may compound this gap.

These findings highlight critical implications for rural economic development policy, signaling a necessary departure from traditional, business attraction strategies (Hicks et al., 2025). Historically, many economic development initiatives have focused heavily on industrial recruitment, tax incentives, and low-cost physical infrastructure. Our results instead point to QOL as a long-term correlate of population change, one whose importance to rural communities may be growing rather than fading in the remote-work era, reversing some pre-COVID trends shown here.

This suggests that policy frameworks should consider shifting toward place-based amenity development tailored to a county's specific characteristics. In smaller, more isolated rural areas, amenity development is a defensive public necessity to buffer against low or negative population growth. Because these isolated economies face baseline population contraction, local governments cannot rely on the endogenous emergence of private commercial markets alone. Public policy must therefore prioritize investments in core public goods, specifically local education funding, which is a strong positive predictor of both QOL and population growth. A focus on rural livability should also address public health vulnerabilities, preserve natural capital such as surface water access, and expand rural entrepreneurs' access to the private capital needed to sustain the commercial amenities that markets alone are otherwise

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unable to support in these places. Ultimately, improving regional welfare and halting rural decline requires public-sector strategies that enhance local public services, expand access to capital, and foster vibrant, place-specific consumption environments.

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APPENDIX

Table A1: Housing Market Estimates for Quality of Life in 2010 (Dependent Variable Is ln(Median Home Value))

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12.9192	0.516	25.02	0.00
PKIDPOPSHARE	−0.0097	0.002	−4.81	0.00
PSINGLEHEADEDHOUSEFEMALE	0.0089	0.003	2.64	0.01
PBACHELORDEGREEORHIGHER	0.0254	0.001	32.66	0.00
PVETPOP	0.0210	0.002	10.27	0.00
PWHITE	0.0017	0.001	2.29	0.02
PBLACK	−0.0016	0.001	−2.04	0.04
PIMMIGRANT	0.0185	0.001	13.74	0.00
P2OR3ROOMS	−0.0286	0.006	−4.95	0.00
P4ROOMSORMORE	−0.0280	0.005	−5.76	0.00
PHOUSEBUILT1939OREARLIER	−0.0030	0.001	−2.33	0.02
PHOUSEBUILT1940_49	−0.0165	0.003	−5.79	0.00
PHOUSEBUILT1950_59	−0.0065	0.002	−3.05	0.00
PHOUSEBUILT1960_69	−0.0148	0.002	−6.82	0.00
PHOUSEBUILT1970_79	0.0027	0.002	1.56	0.12
PHOUSEBUILT1980_89	−0.0061	0.002	−3.28	0.00
PHOUSEBUILT1990_99	0.0080	0.002	3.80	0.00
POPDENSITY	0.0000	0.000	4.02	0.00
LOG(NTOTPOP)	0.0953	0.005	19.85	0.00
Adjusted R-squared	0.68			
F-statistic	364.5737			

Table A2: Labor Market Estimates for Quality of Life in 2010 (Dependent Variable Is ln(Median Wages))

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.9798	0.156	57.61	0.00
MEDAGE	0.0281	0.008	3.60	0.00
$MEDAGE^2$	−0.0004	0.000	−3.86	0.00
PBACHELORDEGREEORHIGHER	0.0032	0.001	4.51	0.00
PVETPOP	0.0015	0.002	0.95	0.34
PWHITE	−0.0002	0.000	−0.39	0.70
PBLACK	0.0007	0.000	1.37	0.17
PIMMIGRANT	0.0066	0.001	7.41	0.00
PCONSTRUCTION	−0.0181	0.001	−12.16	0.00
PMANUFACTURING	0.0008	0.001	0.76	0.44
PTRANSWAREUTIL	0.0057	0.002	3.27	0.00
PFORESTMINING	0.0065	0.001	5.59	0.00
PGOVERNMENT	0.0094	0.002	6.03	0.00
EMPPOPRATIO	0.0048	0.001	7.76	0.00
LOG(NTOTPOP)	0.0670	0.004	15.16	0.00
HHI	0.0000	0.000	0.46	0.65
Adjusted R-squared	0.39			
F-statistic	130.16			

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These LASSO estimates were all performed through a 100-model comparison, with no required regressors. Results are shown below.

Table A3: LASSO Results for RUCC 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ADJACENT_TO_METRO	0.0431	0.02	2.11	0.04
DIST_TO_METRO	0.0016	0.00	1.53	0.13
EATDRNKPLCS2010/TOTPOP2010	9.0704	45.84	0.20	0.84
FITPLCS2010/TOTPOP2010	1392.2220	459.89	3.03	0.00
FOODSTRS2010/TOTPOP2010	199.9459	138.38	1.44	0.15
FRSTCVRG2001	0.0636	0.09	0.68	0.50
GINI2010	0.9153	0.63	1.46	0.15
GOLFCRS2010/TOTPOP2010	892.9652	464.96	1.92	0.06
HIGHELEVATION-LOWELEVATION	0.0001	0.00	5.38	0.00
HLTHSRVCPLCS2010/TOTPOP2010	48.1094	42.90	1.12	0.26
HOMEFURNPLCS2010/TOTPOP2010	923.3405	575.41	1.60	0.11
MEANRELHMDTYJULY1941_70	0.0002	0.00	0.10	0.92
MEANTEMPJAN1941_70	0.0050	0.00	1.96	0.05
MEANTEMPJULY1941_70	−0.0057	0.00	−1.47	0.14
MENTALLYUNHEALTHY	0.0044	0.03	0.16	0.87
PHYSICALLYUNHEALTHY	−0.0712	0.03	−2.30	0.02
POPDENSITY	0.0016	0.00	3.47	0.00
PRKSQMI2019	0.0000	0.00	−0.71	0.48
PRSNLCARESRVC2010/TOTPOP2010	−244.2076	106.87	−2.29	0.02
REC2010/TOTPOP2010	116.0338	328.39	0.35	0.72
REL_SHARE_ARDA	−0.2977	0.14	−2.18	0.03
RELMBLTY	−0.0063	0.00	−1.38	0.17
ROAD_MI	−0.0003	0.00	−1.40	0.16
SCHOOL_SPENDING_SHARE_OF_GDP__US	−0.3712	0.73	−0.51	0.61
TOTWORKEDATHOME/TOTPOP2010	1769.4480	615.54	2.87	0.00
URGCAREFAC2009/TOTPOP2010	3750.8380	1222.49	3.07	0.00
VIOLENTCRIMERATE	−0.0001	0.00	−0.94	0.35
WTRCVRG2019	0.8793	0.24	3.65	0.00
YPLLRATE	0.0000	0.00	−1.60	0.11

Note: *** denotes statistical significance to the 0.01 level; ** to the 0.05 level; and * at the 0.10 level.

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Table A4: LASSO Results for RUCC 5

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ABSMBLTY	−0.0009	0.007	−0.127	0.900
ADJACENT_TO_METRO	−0.0325	0.031	−1.052	0.297
EATDRNKPLCS2010/TOTPOP2010	−47.3410	53.330	−0.888	0.378
FOODSTRS2010/TOTPOP2010	505.2722	145.780	3.466	0.001
FRSTCVRG2001	0.0149	0.105	0.142	0.888
GINI2010	1.1820	0.727	1.625	0.109
HIGHELEVATION-LOWELEVATION	0.0001	0.000	3.660	0.001
HLTHSRVCPLCS2010/TOTPOP2010	94.0168	42.401	2.217	0.030
HOMEFURNPLCS2010/TOTPOP2010	712.7591	743.016	0.959	0.341
LOG(TOTPOP2010)	0.0382	0.048	0.798	0.428
MEANTEMPJULY1941_70	−0.0115	0.005	−2.558	0.013
MVIETHTRS2010/TOTPOP2010	1996.0200	1454.773	1.372	0.175
PHYSICALLYUNHEALTHY	−0.0061	0.037	−0.168	0.867
POPDENSITY	0.0005	0.001	0.687	0.495
PRKSQMI2019	0.0000	0.000	0.655	0.515
PRSNLCARESRVC2010/TOTPOP2010	−194.9946	99.871	−1.952	0.055
REC2010/TOTPOP2010	794.4968	271.036	2.931	0.005
REL_SHARE_ARDA	−0.1246	0.192	−0.650	0.518
ROAD_MI	0.0004	0.000	1.464	0.148
VIOLENTCRIMERATE	−0.0001	0.000	−0.585	0.561
WTRCVRG2019	−0.4166	0.381	−1.095	0.278
YPLLRATE	−0.0001	0.000	−3.562	0.001

Note: *** denotes statistical significance to the 0.01 level; ** to the 0.05 level; and * at the 0.10 level.

Table A5: LASSO Results for RUCC 6

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ABSMBLTY	−0.001	0.002	−0.551	0.582
ADJACENT_TO_METRO	0.006	0.008	0.784	0.434
EATDRNKPLCS2010/TOTPOP2010	89.347	24.213	3.690	0.000
FITPLCS2010/TOTPOP2010	599.220	191.680	3.126	0.002
FOODSTRS2010/TOTPOP2010	88.387	53.528	1.651	0.099
FRSTCVRG2001	0.163	0.050	3.270	0.001
GINI2010	−0.936	0.356	−2.627	0.009
GOLFCRS2010/TOTPOP2010	−331.379	176.158	−1.881	0.061
HIGHELEVATION-LOWELEVATION	0.000	0.000	10.191	0.000
HLTHSRVCPLCS2010/TOTPOP2010	41.878	28.115	1.490	0.137
HOMEFURNPLCS2010/TOTPOP2010	1201.868	461.444	2.605	0.009
LOG(TOTPOP2010)	0.060	0.019	3.109	0.002
MEANTEMPJULY1941_70	−0.005	0.003	−2.034	0.042
MENTALLYUNHEALTHY	0.010	0.009	1.126	0.261
MVIETHTRS2010/TOTPOP2010	−605.751	381.760	−1.587	0.113
POPDENSITY	0.002	0.001	3.315	0.001
REL_SHARE_ARDA	−0.177	0.076	−2.342	0.020
SCHOOL_SPENDING_SHARE_OF_GDP__US	0.605	0.405	1.493	0.136
URGCAREFAC2009/TOTPOP2010	1022.284	613.690	1.666	0.096
VIOLENTCRIMERATE	0.000	0.000	−2.670	0.008
WTRCVRG2019	0.713	0.166	4.294	0.000
YPLLRATE	0.000	0.000	−5.542	0.000

Note: *** denotes statistical significance to the 0.01 level; ** to the 0.05 level; and * at the 0.10 level.

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Table A6: LASSO Results for RUCC 7

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ABSMBLTY	0.000	0.001	−0.301	0.764
BWLNGPLCS2010/TOTPOP2010	−607.275	277.378	−2.189	0.029
DISTANCE_TO_COAST	−0.001	0.000	−3.237	0.001
EATDRNKPLCS2010/TOTPOP2010	84.860	20.822	4.075	0.000
FITPLCS2010/TOTPOP2010	580.959	149.190	3.894	0.000
FOODSTRS2010/TOTPOP2010	98.513	58.150	1.694	0.091
FRSTCVRG2001	0.214	0.066	3.232	0.001
GINI2010	−0.602	0.407	−1.479	0.140
HIGHELEVATION-LOWELEVATION	0.000	0.000	4.478	0.000
HLTHSRVCPLCS2010/TOTPOP2010	60.501	24.654	2.454	0.015
HOMEFURNPLCS2010/TOTPOP2010	1009.140	444.655	2.269	0.024
LOG(TOTPOP2010)	0.101	0.024	4.230	0.000
MEANRELHMDTYJULY1941_70	−0.004	0.002	−2.758	0.006
MEANTEMPJULY1941_70	−0.011	0.003	−4.078	0.000
MVIETHTRS2010/TOTPOP2010	−418.738	301.089	−1.391	0.165
POPDENSITY	0.000	0.001	0.536	0.592
REC2010/TOTPOP2010	318.620	75.595	4.215	0.000
REL_SHARE_ARDA	−0.081	0.077	−1.055	0.292
TOTWORKEDATHOME/TOTPOP2010	7.241	44.364	0.163	0.870
URGCAREFAC2009/TOTPOP2010	258.898	500.543	0.517	0.605
WTRCVRG2019	0.470	0.253	1.860	0.064
YPLLRATE	-2.38×10^{-5}	0.000	−3.764	0.000

Note: *** denotes statistical significance to the 0.01 level; ** to the 0.05 level; and * at the 0.10 level.

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Table A7: LASSO Results for RUCC 8

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ABSMBLTY	0.0009	0.002	0.476	0.635
ADJACENT_TO_METRO	−0.0203	0.023	−0.876	0.382
ARTSCIINST/TOTPOP2010	−458.1961	672.109	−0.682	0.496
EATDRNKPLCS2010/TOTPOP2010	69.5302	29.815	2.332	0.021
FOODSTRS2010/TOTPOP2010	−89.8777	64.633	−1.391	0.166
FRSTCVRG2001	0.2346	0.115	2.040	0.043
GINI2010	−0.9662	0.524	−1.842	0.067
GOLFCRS2010/TOTPOP2010	127.7959	188.829	0.677	0.499
HIGHELEVATION-LOWELEVATION	0.0001	0.000	4.809	0.000
HLTHSRVCPLCS2010/TOTPOP2010	43.6643	49.263	0.886	0.377
HOMEFURNPLCS2010/TOTPOP2010	−1466.6370	643.078	−2.281	0.024
LOG(TOTPOP2010)	0.1635	0.050	3.293	0.001
MEANRELHMDTYJULY1941_70	−0.0024	0.002	−1.062	0.290
MEANTEMPJAN1941_70	0.0044	0.003	1.337	0.183
MEANTEMPJULY1941_70	−0.0170	0.006	−2.715	0.007
MENTALLYUNHEALTHY	0.0239	0.019	1.255	0.211
PHYSICALLYUNHEALTHY	−0.0328	0.018	−1.869	0.063
POPDENSITY	0.0054	0.002	3.207	0.002
PRKSQMI2019	0.0000	0.000	0.060	0.952
PRSNLCARESRVC2010/TOTPOP2010	48.0435	49.719	0.966	0.335
REC2010/TOTPOP2010	−114.5395	83.931	−1.365	0.174
REL_SHARE_ARDA	−0.3139	0.123	−2.542	0.012
RELMBLTY	−0.0039	0.002	−1.583	0.115
SCHOOL_SPENDING_SHARE_OF_GDP__US	1.0688	0.456	2.345	0.020
WTRCVRG2019	1.6353	0.364	4.487	0.000
YPLLRATE	0.0000	0.000	−3.024	0.003

Note: *** denotes statistical significance to the 0.01 level; ** to the 0.05 level; and * at the 0.10 level.

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Table A8: LASSO Results for RUCC 9

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ABSMBLTY	−0.0001	0.002	−0.044	0.965
ADJACENT_TO_METRO	−0.0651	0.033	−1.959	0.051
ARTSCIINST/TOTPOP2010	−837.0055	918.473	−0.911	0.363
DIST_TO_METRO	−0.0004	0.000	−0.947	0.345
EATDRNKPLCS2010/TOTPOP2010	41.4756	8.744	4.743	0.000
FITPLCS2010/TOTPOP2010	186.8219	164.630	1.135	0.257
FRSTCVRG2001	0.2270	0.112	2.032	0.043
GINI2010	−0.6118	0.412	−1.484	0.139
HIGHELEVATION-LOWELEVATION	0.0001	0.000	5.092	0.000
HLTHSRVCPLCS2010/TOTPOP2010	−3.0389	30.237	−0.101	0.920
HOMEFURNPLCS2010/TOTPOP2010	346.6775	308.854	1.122	0.262
LOG(TOTPOP2010)	0.1738	0.036	4.864	0.000
MEANRELHMDTYJULY1941_70	−0.0015	0.002	−0.743	0.458
MEANTEMPJAN1941_70	0.0091	0.003	3.170	0.002
MEANTEMPJULY1941_70	−0.0228	0.005	−4.767	0.000
PHYSICALLYUNHEALTHY	−0.0371	0.011	−3.355	0.001
POPDENSITY	−0.0001	0.002	−0.035	0.972
PRKSQMI2019	0.0000	0.000	0.282	0.778
REC2010/TOTPOP2010	76.9087	30.312	2.537	0.012
REL_SHARE_ARDA	−0.1227	0.081	−1.520	0.129
RELMBLTY	0.0006	0.002	0.267	0.790
SCHOOL_SPENDING_SHARE_OF_GDP__US	1.0134	0.301	3.363	0.001
URGCAREFAC2009/TOTPOP2010	−291.1054	302.870	−0.961	0.337
WTRCVRG2019	1.2316	0.274	4.497	0.000
YPLLRATE	0.0000	0.000	−2.812	0.005

Note: *** denotes statistical significance to the 0.01 level; ** to the 0.05 level; and * at the 0.10 level.

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