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ORIGINAL RESEARCH

Move, Stay, and Commit: Place-based Quality of Life in the U.S.

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Abstract
Attracting and retaining people and jobs through a high quality of life is an increasingly common community development strategy. Identifying places with high quality of life, and the factors that drive it, remain challenging. This study uses a revealed-preference framework, based on people's observed choices and behaviors, to develop an indicator of place-based quality of life. We conceptualize quality of life as a latent variable reflected in eight behaviors capturing decisions to move, stay, and invest. Using spatial Bayesian factor analysis, we construct a revealed-preference quality-of-life index that accounts for spatial spillovers and rank 3,100 U.S. counties in 2019. High-quality-of-life counties are indicated by dynamic migration patterns, strong residential retention, shorter commutes, lower homeownership rates, and higher rates of entrepreneurship and family formation. Four indicators, retention, homeownership, in-migration, and commuting, account for 87 percent of the index weight. The index reveals strong spatial spillovers, highlighting the importance of regional context. While urban counties rank higher on average, many rural counties also exhibit high quality of life.

Keywords Economic development · Revealed preference · Quality of life · Spatial factor analysis · Bayesian

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1 Introduction

The idea that "people follow jobs" has long shaped U.S. economic growth and development policy at the local or community level. From early industrial tax incentives, such as New Jersey's attempt to attract investments by industrialists such as Alexander Hamilton, to the Mississippi Balancing Agriculture and Industry Act of 1933 to modern deals for facilities like Amazon's headquarters in Virginia or New York's Green CHIPS program to lure investments by Micron Technologies, policy has often assumed that job creation attracts people (Goetz et al., 2009). More recently, however, this relationship has shifted toward "jobs follow people." Deller (2021, 2025) describes a "fourth wave" of economic growth and development policies that emphasizes improving quality of life to attract and retain residents, which in turn stimulates business formation and job growth. As quality of life has become central to development strategies (Deller et al., 2001; Florida, 2002; Glaeser et al., 2001), identifying and measuring place-based quality of life has become increasingly important for policymakers and practitioners.

To understand how quality of life influences economic growth and development it is necessary to create meaningful empirical measures. Extensive reviews by Dissart and Deller (2000), Decancq and Lugo (2013), Veréb et al. (2024) and Cheng et al. (2026) suggest that place-based quality-of-life measurement falls into three primary measurement approaches: (1) survey evaluation, (2) composite indices, and (3) hedonic modeling. Survey-based approaches often rely on Likert-type questionnaires designed to capture individuals' subjective life satisfaction. One example is the Illinois Rural Life series of studies conducted by the Illinois Institute for Rural Affairs (e.g., Athiyaman & Walzer, 2006). These surveys, unfortunately, are challenging to compare across regions and over time due to sampling biases and substantial collection costs. In addition, what residents subjectively experience sometimes does not align with the quality of life or livability of places (Okulicz-Kozaryn, 2013). In the end, within this framework of community economic development (e.g., the 4th wave approach), local policymakers are more concerned with community-level notions of well-being and quality of life.

The composite index approach summarizes multidimensional characteristics of places by aggregating them into indices for comparison (e.g., Liu, 1976, 1977; Isserman et al., 2009; and Schmidt et al., 2026). This approach provides replicable and direct insight into what is associated with quality of life in a place. Unfortunately, in the absence of a strong unifying theory, empirical measurement by composite index relies heavily on researchers' subjective assumptions. This subjectivity has two main limitations. First, personal preferences for specific place-based characteristics lead to wide variation in how quality of life is defined, with some emphasizing environmental endowments (e.g., Liu, 1976, 1977) while others highlighting cultural amenities typical of urban centers (e.g., Blomquist et al., 1988). The various definitions have been described as "chaos" (Veréb et al., 2024) or "open challenges" (Tomaselli et al., 2021), producing inconsistent findings across studies (Mittal et al., 2020). Barrington-Leigh and Escande (2018) reviewed 82 well-being indicators and found that arbitrary selection and aggregation of variables tend to produce less meaningful measures. Second, composite indices rely on expansive "laundry lists" of variables to offset the ad hoc nature of selection. Veréb et al. (2024), for example, identified 33 dimensions encompassing more than 9,000 variables used to measure rural well-being. Tomaselli et al. (2021) faced 130 indicators across 12 dimensions in their well-being measure. Similar long

lists appear in the popular press, such as those compiled by *Money* Magazine and AARP. As these lists grow, they often fail to distinguish clearly between outcomes of quality of life and its underlying determinants. In extreme cases, this approach implies that "everything matters," diluting analytical focus and policy relevance.

People's actions or choices, commonly referred to as revealed preferences, offer an alternative way to approach quality of life by building on the seminal work of Tiebout (1956) and Rosen (1974, 1979) and later Roback (1982). This approach assumes individuals sort into locations that maximize utility and interpret compensating differentials in wages and housing prices as proxies for quality of life. Building on Rosen-Roback (1982), the hedonic framework uses spatial equilibrium to value local amenities, with place fixed effects capturing premiums for high-quality-of-life locations (e.g. Albouy, 2008; Chen & Rosenthal, 2008; Gabriel & Rosenthal, 2004). Hedonic models, however, have been criticized for strong assumptions, including perfect spatial mobility (Carlsen & Leknes, 2021; Evans, 1990; Greenwood et al., 1991) and homogeneous preferences (Diamond, 2016; Diamond & Gaubert, 2022). In addition, most applications focus on metropolitan areas, with relatively limited attention to rural places due to data constraints (Weinstein et al., 2023). Largely relying on the location choice of people, another potential limitation of Rosen–Roback arises in the context of declining mobility, which encourages scholarship to explore other signals of place-based preferences. Extending beyond location choice might provide a richer and more comprehensive view of how people interact with places and, therefore, place-based quality of life.

While these three approaches have advanced our understanding of quality of life, each has important limitations. Addressing these challenges calls for integrative frameworks (hereafter the hybrid approach) that combine the revealed-preference foundations of hedonic models with the multidimensional scope of composite indices. On one hand, this hybrid approach identifies high-quality-of-life places directly through revealed preferences rather than assuming which place attributes matter. The analytical advantage of revealed preferences overcomes the subjectivity in composite index approaches. The outcome of individual choices is also less vulnerable to questions of causal directionality. Where we might ask if low mortality, for example, is a cause or result of high quality of life, a location choice is more clearly structured as the result of an individual optimizing location choice based on a suite of place-based characteristics. On the other hand, such hybrid approaches also keep the multidimensional feature of drawing on revealed preferences expressed not only through location choices but also through residential tenure and related behaviors. By integrating behavioral indicators into composite measures, the hybrid approach provides a stronger empirical basis for understanding how individuals choose among places and sets the stage to rigorously study the place-based characteristics that matter.

This hybrid approach can be strengthened by adopting a regional perspective on quality of life. As several studies (e.g., Boyce, 2025; Cheng et al., 2026) note, place-based decisions are not confined to administrative boundaries such as counties. Residential choices often reflect access to nearby cultural and natural amenities as well as economic linkages beyond local borders. For example, job opportunities in adjacent counties shape commuting behavior, consistent with evidence of expanding commuting sheds in the U.S. (Jang et al., 2025; Kures & Deller, 2023). A recent study by Fowler (2024) found that any given commuting zone could be composed of multiple counties. These cross-community interactions create functional connections among places, linking their quality-of-life outcomes. Not accounting

for this spatial dependency from a purely statistical perspective could result in biased and inefficient estimates which could in turn lead to incorrect statistical inferences. Although most studies measure quality of life within jurisdictional units, such social phenomena are more appropriately interpreted within a broader regional context (Okulicz-Kozaryn, 2011).

The objective of this study is to develop a quality-of-life index for U.S. counties using revealed preferences across three dimensions: moving, staying, and committing. We conceptualize quality of life as a latent variable that shapes place-based decisions and is indirectly observed through revealed-preference indicators, including migration flows, residential retention, commuting out of the community (county) for work, homeownership, business formation, birth rates, and the presence of families with school-age children. We estimate this latent factor using spatial Bayesian factor analysis (SBFA), which accounts for spatial dependence across places. The resulting quality-of-life index applies analytically derived weights to each indicator and is constructed at the county level. Data are drawn from the ACS five-year estimates (2015–2019) and the Business Dynamics Statistics (BDS), covering 3,100 counties in the contiguous U.S. These indices allow us to rank counties and examine spatial variation in quality of life.

This study contributes to the existing literature in three ways. First, we offer a new quality-of-life index that goes beyond location choices alone. Based on our factor analysis, a high-quality-of-life place is signaled by high residential retention, relatively dynamic population, and residents who often work and live within the same county; while owning a home is less common in these places, likely due in part to high demand, people show their commitment to the place by starting businesses, as well as having and raising children there. This broadened revealed-preference framework provides an alternative to hedonic modeling that depends on the revealed preferences of location choices alone. Second, we adopt a regional perspective on quality of life, recognizing that it is shaped not only by local conditions but also by interactions with neighboring areas (Cheng et al., 2026; Montorsi & Giglirano, 2024). Our spatial specification reveals significant spillover effects, and mapping quality of life across the U.S. shows clear spatial clustering of both high- and low-quality-of-life regions. These patterns show that regional analysis and coordinated policy efforts are important to improve quality of life across places. Finally, consistent with Reynolds and Rohlin (2014) and Weinstein et al. (2023), our approach extends quality-of-life measurement to rural areas, where granular individual-level data are often limited. By leveraging aggregated revealed-preference data across the urban–rural spectrum, we provide broader coverage of regions typically underrepresented in empirical research. While rural counties score lower on average, we find that several highly rural areas still rank among the highest in quality of life.

Beyond these introductory comments, our study comprises three parts. In the next section, we provide insight into how these observed behaviors reflect the place-based quality of life. We also present the data and the SBFA model. Then, in Sect. 3 we discuss the empirical results of the quality-of-life index. We conclude the study with a discussion of our findings and the policy implications.

2 Data and Model

2.1 Revealed Preferences and the Connection to Quality of Life

Like many related studies, we first consider migration to be a signal of place-based preferences. Glaeser et al., (2001: 35) argued that "consumer sovereignty is pushing population toward areas with attributes that consumers value." Since then, a growing body of research has demonstrated that people move to areas with high perceived quality of life such as places with pleasant weather and coastlines (Albouy et al., 2016; Rappaport & Sachs, 2003) as well as consumption amenities like art, culture, and entertainment (Albouy, 2008; Chen & Rosenthal, 2008; Glaeser et al., 2001).

Disaggregated migration flows indicate that quality of life also influences out-migration, particularly among low-income and low-skill individuals. Many local amenities, such as professional sports venues or performing arts centers, could be considered luxury goods (Lee, 2010) and disproportionately consumed by higher-income households (Bils & Klenow, 2001). Such amenity-rich areas, therefore, are likely to attract high-income and high-skilled migrants (Albouy et al., 2021; Diamond & Gaubert, 2022; Rappaport, 2008, 2009), increasing housing demand and driving up housing costs. This process leads to sorting: higher-skill workers remain and pay the amenity premium, while lower-skill workers either accept lower real wages or exit as living costs rise (Gyourko et al., 2013). Thus, in the sorting literature, in-migration and out-migration can signal high quality of life through different mechanisms: amenities attract households while pricing out lower-skill residents. Paired with in-migration, out-migration completes the picture of population dynamics, serving as a revealed-preference signal of high quality of life.

In the migration literature, however, out-migration is typically treated as a signal of low quality of life, which, alongside sorting theory, makes its relation to quality of life theoretically ambiguous. Empirically, individual-level analysis can identify whether out-migration signals high quality of life (sorting) or low quality of life (location choice), conditional on personal characteristics. At the aggregate level, without those controls, the prevailing motivation for out-migration is unidentifiable. Still, aggregate preference variables, in our case out-migration, are useful for first identifying the correlated signals of quality of life. These signals can then be further disaggregated and deciphered in future research.

Beyond the initial decision to move, the choice to remain and commit to a place represents another important dimension of revealed preferences used in this study. This notion aligns with the literature on "place attachment" (Low & Altman, 1992) and "sense of place" (Relph, 1976; Tuan, 1979), which describes positive emotional and functional bonds between people and their environments. Such attachment is often associated with community amenities, including social cohesion, infrastructure, and natural settings, and tends to produce greater residential stability and lower turnover (Lewicka, 2011; Williams & Vaske, 2003). Behavioral indicators, such as length of residence, homeownership, and mobility, serve as revealed preferences for place attachment and, by extension, quality of life.

Length of residence is widely regarded as the most reliable indicator of place attachment and a strong proxy for perceived quality of life. Reviews by Lewicka (2011), along with empirical evidence from Brown et al. (2003) and Lewicka (2010), consistently documented this relationship. Because of its robustness, some studies rely on length of residence as the sole measure of place attachment (Kleit & Manzo, 2006; Taylor et al., 1985). Attachment

typically increases most rapidly during the first four years and then levels off (Lalli, 1992), suggesting early tenure is particularly informative about perceived quality of life. Residence tenure therefore serves as a key revealed-preference indicator of quality of life.

A common indicator of commitment to places is the decision to purchase a home (Riger & Lavrakas, 1981; Sampson et al., 1997). Homeownership is associated with higher levels of civic engagement (e.g., McCabe, 2013), volunteerism (e.g., Rotolo et al., 2010), and social capital (e.g., Grinstein-Weiss et al., 2013), reflecting stronger ties to the local community. Because homeownership entails substantial financial and social costs, it is more likely in places where residents perceive a high quality of life. Choosing to buy a home thus signals confidence not only in one's personal circumstances but also in the community's long-term amenities and opportunities. Accordingly, patterns of homeownership can be interpreted as revealed preferences for communities offering sustained quality of life.

At the same time, high-quality-of-life places often command price premiums that limit access to homeownership, potentially lowering ownership rates despite strong demand (Ratcliffe, 2015). In the context of the current housing shortage and rising home prices, home ownership in high-quality-of-life places may be especially difficult. For this reason, some scholars argue that the length of residence may better capture attachment to place than ownership status alone (Jorgensen & Stedman, 2006). Taken together, these perspectives suggest that while homeownership may actually be inversely related to quality of life, additional insights can be gained from other measures of commitment to place.

Commuting patterns provide an additional behavioral window into revealed preferences. Choosing to live in an attractive residential environment while accepting longer commutes can signal attachment to place, whether through traditional suburban commuting to urban job centers or reverse commuting from amenity-rich cities to peripheral workplaces (Glaeser et al., 2001; Van der Klis & Karsten, 2009). Under this "pull" framing, long commutes reflect the high quality of life.

Some empirical work, by contrast, suggests that long commutes are more likely to reflect constraints rather than preferences when high housing costs "push" workers farther from employment (Blumenberg & King, 2024; Sultana, 2002). Here workers prefer to live close to their place of employment and have a short commute, but lack of reasonable housing options "pushes" them into longer commutes from less desirable communities. Extended commutes are more likely associated with lower quality of life as well as reduced well-being (Clark et al., 2020; Stutzer & Frey, 2008). Under the "pull" and "push" forces, aggregate analysis cannot reach a definitive conclusion. Consistent with this, in a review of the commuting and well-being literature, Chatterjee et al. (2020) stated that commuters were generally successful in trading off the costs of long commutes against the benefits they brought, and that there are no consistent empirical links between commuting and overall life satisfaction.

Starting a business can signal a long-term commitment to and investment in a place. High-quality of-life places, such as those rich with natural amenities, tend to attract entrepreneurs even though they may have to accept lower financial returns to live there (Conroy & Watson, 2023; Kulchina, 2016). In a study of small rural manufacturers, Halstead and Deller (1997: 165) quote a respondent who advised, "Find an area that you want to live, then start your business," underscoring the consistent importance of overall quality of life in location decisions. While labor and living costs may weigh more heavily for larger firms, quality of life remains especially important for attracting and retaining high-skill profes-

sionals, particularly in small, footloose firms relocating from other regions (Love & Crompton, 1999). Even in the case of "entrepreneurship of necessity" where individuals cannot find adequate wage-salary employment and are driven into self-employment (see Ouaddi & Ait Oumazirh, 2024 for a review of the literature), the individual is making a conscience decision to remain in the community.

Family formation decisions, including when and where to have children, offer a distinct lens on how households signal local quality of life. Residential stability is a key prerequisite for family formation (Kulu & Milewski, 2007; Vignoli et al., 2013), so quality-of-life advantages that drive up housing prices can sometimes constrain intended fertility (Dettling & Kearney, 2014). As families grow, they commonly adjust both their housing and residential environments to meet children's needs, including seeking larger homes, proximity to childcare, better schools, and proximity to workplaces (Hank, 2001; Holme, 2002; Ratcliffe, 2015; Vidal et al., 2017; Wood & Neels, 2019). Together, this evidence shows how family formation decisions are associated with quality-of-life considerations.

In sum, although location choice and migration have received the greatest attention in the quality of life and regional economics literature, a broader set of behaviors also reveals how people value and engage with places. Decisions about residential tenure, homeownership, commuting, entrepreneurship, and family formation reflect longer-term evaluations of local conditions and trade-offs that extend well beyond the initial decision to move. These behaviors capture how individuals and households adapt to places over time, balancing quality of life against costs, constraints, and life-cycle needs.

2.2 Measurement of Revealed-preference Variables

We use eight revealed-preference variables organized into three behavioral dimensions: **move** (in-migration and out-migration), **stay** (residential retention and out-of-county commuting), and **commit** (homeownership, business startups, birth rates, and share of families with school-age children). Together, these manifest variables reflect the underlying latent factor of quality of life. Unless otherwise noted, data are drawn from the American Community Survey (ACS) 2019 5-year estimates for U.S. counties. We select counties as our research units because they provide the most granular data for those eight revealed-preference indicators. Also, counties cover a diverse spectrum from rural to urban environments, which allows for deeper insights into rural quality of life compared to urban-focused hedonic studies. In addition, counties cover the entire geographic area of the U.S. and provide the most complete ranking, unlike Metropolitan Statistical Areas (MSA) which exclude more remote rural areas. Our sample includes 3,100 counties in the continental U.S. Descriptive statistics are provided in Table 1.

In-migration and out-migration rates together directly capture population dynamics. We expect high-quality-of-life places to exhibit both high in- and out-migration. These measures are constructed using ACS county-to-county migration inflows and outflows per 1,000 residents. Residential retention provides insight into post-move satisfaction. We measure retention using recent housing tenure: the share of households residing in the same dwelling

Table 1 Descriptive summary statistics of manifest variables

Variable	Mean	Min	Max	S.D
In-Migration (per 1,000)	66.2	0	402.3	29.6
Out-Migration (per 1,000)	63.6	0	552.7	28.8
Residential retention (%)	21.6	6.8	52.3	5.4
Commuting out of county to work (%)	35.6	0.8	87.8	18
Homeownership (%)	71.7	19.7	93.1	8.2
Business startup (%)	7.9	0	42.1	2.6
Birth rate (%)	5.8	0	100	2.9
Family with children 6–17 (%)	30.4	0	50.2	5.1

We include 3,100 counties in the continental U.S. and exclude county equivalents in Connecticut. These zero (minimum) and 100 (maximum) values might arise from limitations of point estimates for a few very small rural counties

since 2014 (five years prior to 2019). [1] This retention measure captures dwelling stability rather than county-level population retention; because roughly half of movers relocate within the same county, this measure may understate place attachment, but it remains the best available contemporaneous proxy. Commuting is measured as the share of workers commuting outside their county of residence using ACS county-to-county commuting flows. Although aggregate-level analysis cannot distinguish the "pull" from "push" association between quality of life and commuting, given the prevailing commuting pattern driven by housing costs in the literature, we expect lower out-of-county commuting rates in locations with higher quality of life.

Beyond moving and staying, long-term investments like homeownership and family formation indicate a strong commitment to places. We calculate homeownership as the ratio of owned units to total housing units in a county. Business startups, birth rates, and families with school-age (6–17) children further indicate dedication to places. We measure business startup rates by the share of new businesses using data from 2019 BDS, birth rates as the share of women aged 15–50 who gave birth in the past 12 months, and the share of households with children aged 6–17 compared to total households.

One additional concern arising from the revealed-preference variables is that observed behavior may reflect preferences under certain constraints. One such constraint is economic conditions. Poor economic conditions can leave people "stuck" in their current circumstances and unable to move or start a business, even when they would prefer to do so, which may bias revealed-preference measures. Although aggregate revealed preferences in our study have the advantage of reducing some sources of random noise relevant to individual revealed preferences (Beshears et al., 2008), such as short-term income fluctuations, systematically binding economic constraints should not be treated as noise. Instead, when such constraints operate consistently across people and behaviors, they represent a structural factor that should be explicitly considered. To ensure our revealed-preference indicators capture aggregated revealed preferences independently of economic effects, we adjust each manifest variable by removing income-related influences by regressing each variable on per capita median income and its squared term and extracting the residuals to obtain income-

[1] We chose the 2014 threshold to capture the most recent retention behavior. We acknowledge that respondents surveyed in 2015 are more vulnerable to this threshold due to the short time window, so we conducted a sensitivity analysis using an alternative 2010 cutoff. The resulting quality-of-life index is highly correlated with the original index at 0.72.

adjusted indicators. Subsequent analysis uses these adjusted variables. We also normalize our indicators by deriving z-scores to create unitless variables for comparison. Figure A1 in Appendix A displays correlations among these adjusted variables.

2.3 Spatial Factor Analysis Model

We conceptualize quality of life as a latent, unobservable construct that shapes individuals' location-related decisions. Observable behaviors, such as the choice to relocate to a place and the decision to remain there, in part reflect underlying evaluations of that location's quality of life. In this framework, each revealed-preference indicator, or *manifest variable*, is influenced by the same latent quality-of-life factor.[2] By jointly analyzing these observable choices, we can infer and quantify this latent construct, thereby rendering quality-of-life measurable at specific locations. To do so, we employ a Spatial Bayesian Factor Analysis (SBFA) model that explicitly accounts for spatial dependence in the data, following prior applications of this approach to the study of material deprivation (Hogan & Tchernis, 2004), human development (Qiu et al., 2018), and well-being (Montorsi & Gigliarano, 2024).

SBFA addresses several common limitations in place-based quality-of-life measurement. Its primary advantage is that it does not require subjective priors, such as expert judgment (or opinions), to construct a composite index. Instead, SBFA exploits the correlation structure among observed variables to determine their relative contributions to quality of life. It also allows for insights across multiple revealed-preference variables rather than migration alone. These contributions are captured by factor loadings, which indicate the strength and direction of each manifest variable's relationship to the latent quality-of-life construct, thereby reducing subjectivity in measurement. Moreover, the Bayesian framework yields a full posterior distribution for quality-of-life estimates, allowing uncertainty to be explicitly quantified through credible intervals rather than relying on deterministic rankings. SBFA is also well suited to this application because it accommodates spatial dependence across counties and accounts for variation in the precision of the manifest variables arising from differences in population size, features that are discussed in greater detail below.

Our basic factor analysis model without spatial dependency is specified as follows:

$$Y_{ij} = \mu_j + \lambda_j \delta_i + \varepsilon_{ij},$$

Where Y_{ij} represents one of the manifest variables $j = 1, \ldots, 8$, for the county $i = 1, \ldots, 3{,}100$; μ_j is the corresponding intercept; δ_i is quality of life, the latent factor, in county i; λ_j is the factor loading for the manifest variable j that represents the correlation coefficient between latent factor quality of life, δ_i, and the revealed-preference indicator, Y_{ij}; ε_{ij} is the error term of the revealed-preference indicator j in county i. Under a reasonable set of statistical assumptions and based on existing literature, this method is reasonable in assuming that the

[2] Of note, each revealed-preference indicator is affected by many factors, among which we assume there is a common latent factor that we refer to as quality of life. This common latent factor is identified through the variance shared across manifest variables, while the variance unique to each indicator, reflecting the influence of indicator-specific factors, is estimated separately and falls beyond the scope of this study.

shared covariance among revealed-preference indicators can be used to estimate quality of life.[3]

Following Cheng et al. (2026), we adopt a regional approach to quality of life as determined not only by an individual county itself but also by its neighbors. To model this spatial spillover or dependency, we employ a Conditional Autoregressive model, which specifies the relationship between the quality-of-life latent factor of a county i and those of its neighboring counties.[4] Neighbors are defined as those counties that share a border or a vertex, identified using queen contiguity. This approach improves estimation precision by borrowing information across space. Specifically, incorporating spatial dependency reduces the variability in the posterior parameter distribution of the factor loadings (Hogan & Tchernis, 2004, p. 320).

In addition to spatial dependency, the larger variance of revealed preferences in smaller places necessitates adjustment for population size in the modeling process. Counties with smaller populations often show greater noise in revealed-preference indicators and the latent quality-of-life factor. For example, migration rates can fluctuate significantly from year to year, in sparsely populated counties, where larger population areas are less prone to this problem. Ignoring population size simply assumes observations from both highly populous urban and remote rural areas have equal precision in data. This assumption does not always hold given the higher uncertainty of reported data in less populous counties.[5] To address these issues, our model explicitly introduces population (matrix $\boldsymbol{M}$ defined below) in both the inverse variance of the error terms and the latent factor scores following Hogan and Tchernis (2004) and Qiu et al. (2018).

The final spatial Bayesian factor model is presented in vector form as follows:

$$\boldsymbol{Y}|\boldsymbol{\delta} \sim N(\boldsymbol{\mu} + \boldsymbol{\Lambda\delta}, M^{-1} \otimes \boldsymbol{\Sigma})$$

[3] We assume error terms ε_{ij} are independently and identically normally distributed (IID) $\varepsilon_{ij} \sim N\left(0, \sigma_j^2\right)$, meaning ε_{ij} have a mean of zero $\mathrm{E}(\varepsilon_{ij}) = 0$ and are uncorrelated with other revealed-preference indicators' error terms $\mathrm{Cov}(\varepsilon_{ij}, \varepsilon_{ij\prime}) = 0$, $j \neq j\prime$. If the IID assumption holds, it implies that all the revealed-preference indicators correlate only through the quality-of-life latent factor.

[4] We specify the conditional distribution of the county's quality-of-life latent factor as follows:

$$\delta_i|\delta_k \sim \mathcal{N}\left(\sum\nolimits_k \omega\delta_k, \nu\right),$$

where k indicates its neighbor county, $$\omega $$ measures the degree of spatial dependency, and the conditional variance $$v$$ captures any residual variation. By setting the conditional variance $$\nu = 1$$, our conditional specification results in a simple marginal distribution for latent factor scores of quality of life:

$$\boldsymbol{\delta} \sim \mathcal{N}\left(0, (\boldsymbol{I} - \omega\boldsymbol{W})^{-1}\right)$$

where $\mathbf{W}$ is a 3100×3100 neighbor matrix with elements equal 1 if two counties are adjacent to one another and 0 otherwise and $\boldsymbol{W_{ii}} = 0$. $\boldsymbol{I}$ is a 3100×3100 identity matrix. Setting $\mathbf{Y}$ and $\boldsymbol{\delta}$ as normally distributed, the expected latent factor for a county is a linear combination of its own information Y_i and that of its neighbors Y_k, where $k \neq i$.

[5] The literature about small-area estimation state that sparsely populated areas often have greater variance due to small sample sizes and require adjustment to reduce sampling variability (Fay & Herriot, 1979; Ghosh & Rao, 1994).

Table 2 Normalized squared correlation coefficients and factor loadings for manifest variables

	P^2		λ	
Variable	Mean	95% CI	Mean	St
In-migration (per 1 000)	14.2%	(13.8%, 14.4%)	7.1	0.2
Out-migration (per 1 000)	5.4%	(4.7%, 6.0%)	3.3	0.2
Residential retention (%)	46.3%	(43.5%, 49.3%)	15.7	0.2
Commuting out of county to work (%)	7.6%	(6.9%, 8.2%)	−6.2	0.3
Homeownership (%)	18.6%	(18.6%, 18.6%)	−11.1	0.3
Business startup (%)	3.2%	(2.6%, 3.8%)	4.6	0.2
Birth rate (%)	0.0%	(0.0%, 0.1%)	−0.5	0.2
Family with children 6–17 (%)	4.7%	(4.0%, 5.3%)	3.5	0.2

P² is the normalized squared correlation coefficient. 95% CI is 95 percent credible interval. **λ** is the factor loading

$$\boldsymbol{\delta} \sim \mathcal{N}\left(0, M^{-\frac{1}{2}}\boldsymbol{\psi}\boldsymbol{M}^{-\frac{1}{2}}\right)$$

where $\boldsymbol{Y}$ is the vector of$\mathrm{Y_{ij}}$'s stack over revealed-preference indicators $j = 1,2,\ldots,8$ and then county $i = 1,2,\ldots,3100$; $\boldsymbol{\mu} = (\mu_1,\ldots,\mu_8)\prime$ is the intercept vector for the manifest variable$j$;$\boldsymbol{\Lambda} = I_{3100} \otimes \boldsymbol{\lambda}$, with I_{3100} as a 3100×3100 identity matrix; $\boldsymbol{\lambda} = (\lambda_1,\ldots,\lambda_8)\prime$, and $\otimes$ denotes a Kronecker product; $\boldsymbol{\Sigma}$ is a diagonal matrix with σ_j^2 as the diagonal elements, and 0's elsewhere; $\boldsymbol{\psi} = (\boldsymbol{I} - \omega\boldsymbol{W})^{-1}$ indicates the spatial correlation of latent factor of quality of life, and $\boldsymbol{M}$ is a 3100×3100 matrix with county populations $m_1, m_2, \ldots, m_{3100}$ along the diagonal and 0's elsewhere. Estimating this model provides factor loadings and "contribution" for each of our revealed-preference variables as well as a distribution of the quality-of-life index for each county from which we use the mean for our primary analysis.[6]

3 Results

3.1 Manifest Variables' Contribution to Quality of Life

Before discussing the latent factor of quality of life, we first compare the contribution of each manifest variable in the quality-of-life index. The contribution is measured by normalized squared correlation coefficients, which are analogous to variable weights.[7] The normalized squared correlation coefficients (P^2) for each revealed-preference indicator, along with their 95% credible intervals, are provided in Table 2. We also present factor loadings (λ) and

[6] We use the Metropolis–Hastings algorithm within a Gibbs Sampler to estimate the posterior. We specify a set of non-informative priors for our parameters, $\boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\delta}, \boldsymbol{\sigma}^2,$ andω. The posterior distribution is updated mainly through the data. In all the 4,500 iterations of the sampler, we burn in the first 500 draws, and we draw the posterior distribution of the latent factor scores of quality of life. The details of our main result's prior specifications are available more formally in Qiu et al. (2018).

[7] We use normalized squared correlation coefficients by $\frac{\mathrm{P}_j^2}{\sum_{j\in J}\mathrm{P}_j^2}$ to understand the contribution of the revealed-preference indicators to the quality-of-life latent factor following Qiu et al. (2018). P_j^2 is squared correlation coefficients metric which explains the proportion of a manifest variable's variance explained by the latent factor, formulated as $\mathrm{P}_j^2 = \frac{\lambda_j^2}{\lambda_j^2+\sigma_j^2}, j = 1,\ldots,8$.

their standard deviation, which show both the correlation between the latent variable and, more importantly, the direction of the correlation.

The estimate of the spatial parameter ω, loosely interpretable as a spatial lag coefficient, is 0.15, with a very small standard deviation (0.0002), indicating statistically significant spatial spillovers. This result supports treating quality of life as a regional phenomenon rather than a purely local one. In addition, this result suggests that earlier studies that fail to take spatial spillover effects into consideration are missing important attributes of regional quality of life.

The factor loadings (λ) in Table 2 show that higher quality of life is indicated by greater residential retention, lower homeownership rates, stronger migration flows, lower out-of-county commuting, more active business formation, and a higher concentration of families with school-age children. Grouping contributions (P^2) into three behavioral dimensions–*move* (in- and out-migration), *stay* (residential retention and commuting), and *commit* (homeownership, entrepreneurship, and family formation), these dimensions account for approximately 20 percent, 53 percent, and 27 percent of the quality-of-life latent factor, respectively.

Indicator by indicator, residential retention is by far the dominant contributor to the latent quality-of-life factor, accounting for 46.3 percent of its explanatory power. Homeownership follows at 18.6 percent. Together, these two housing-related dimensions, housing tenure stability and tenure type, account for roughly two-thirds of the total weight, underscoring the central role of housing-related behavior in indicating quality of life. Mobility-related indicators also contribute meaningfully. In-migration explains 14.2 percent of the latent factor, while out-of-county commuting accounts for 7.6 percent, reflecting the importance of both longer-term and daily spatial adjustment choices. The remaining indicators carry smaller weights: out-migration (5.4 percent), the share of families with children ages 6–17 (4.7 percent), and the business startup rate (3.2 percent). The birth rate contributes negligibly to the latent construct.

Taken together, high quality of life is indicated by large flows of in- and out-migration, and by people choosing to stay after moving in, being less likely to own homes, being more likely to live and work within the same county, and, lastly, showing sustained commitment through business formation and raising families. Across these revealed-preference indicators, although housing-related choices play a dominant role in shaping quality of life, other behaviors still contribute additional meaningful, though smaller, information. By incorporating behaviors often overlooked in studies, this hybrid approach provides a more comprehensive understanding of how people interact with places and, in turn, how quality of life is revealed.

3.2 Quality-of-life Estimates

Under the Bayesian framework, the county-level latent factor of quality of life is estimated as a posterior distribution. For mapping and comparison purposes, we show the posterior mean of the quality-of-life latent factor. To aid interpretation, we convert these means into an ordinal ranking from 1 (highest quality of life) to 3,100 (lowest quality of life).

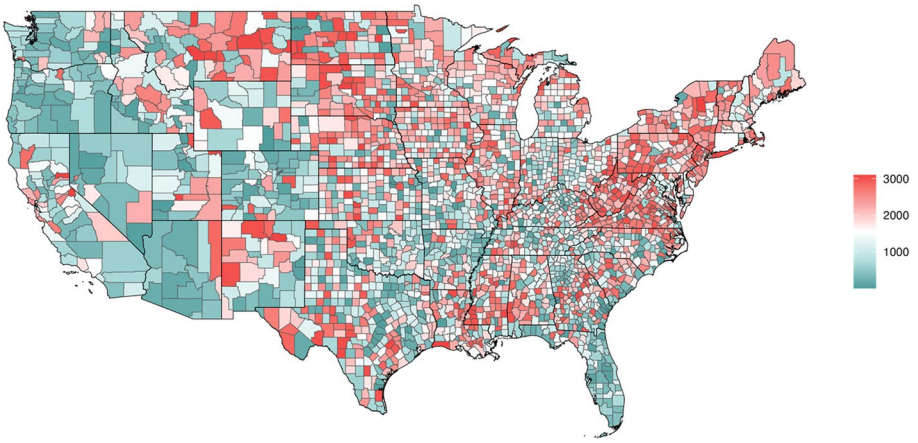


Fig. 1 Ranking of quality of life across counties in the U.S. Notes: We present ordinal ranks of quality of life with the highest quality of life ranked "1" and the lowest quality of life ranked "3,100"

The ordinal quality-of-life rankings of counties are provided in Fig. 1.[8] Clear regional patterns emerge: the Midwest and parts of the Northeast generally have the lowest-ranking counties, along with some areas in the national interior such as North Dakota, South Dakota, Nebraska, and Kansas, as well as historically disadvantaged regions like the Southern Delta and Appalachia. In contrast, the Far West, the Southwest, and the Rocky Mountain region tend to have higher quality-of-life rankings, with mild weather, natural amenities, and proximity to coastal areas being contributing factors.

It would be tedious to discuss the rankings of all counties individually, but counties that rank high align with our expectation that high-quality-of-life places are those where people move, stay, and commit. There are many factors explaining those revealed preferences and corresponding quality of life, including the presence of higher education, critical institutions, dominant industries, a rich natural environment, and other local amenities. A casual review of the top-ranking counties reveals a few shared features of counties with high quality of life. For example, there appears to be a role for critical institutions. Chattahoochee County, Georgia, for example, ranks highly partly due to a major military base, while Madison County, Idaho, and Whitman County, Washington, are affected by large university populations. Notably, in the top 20 counties,[9] more than half contain a major university, whose presence significantly shapes migration patterns. Although such institutions might seem to skew the index toward these areas, they also directly enhance local quality of life by providing a skilled workforce, economic opportunities, and a sense of community that people may

[8] As noted throughout the study, one of the challenges is the "correct" set of variables to include in the analysis (e.g., Tomaselli et al., 2021; Veréb et al., 2024) and to explore the robustness of our final measures we conducted a series of sensitivity analyses. These included exploring alternative variables and combinations, different scaling, non-income adjusted measures, and different spatial weight matrices. We found that our final quality-of-life index is largely stable across a range of alternatives. The results of this sensitivity analysis are available from the authors upon request.

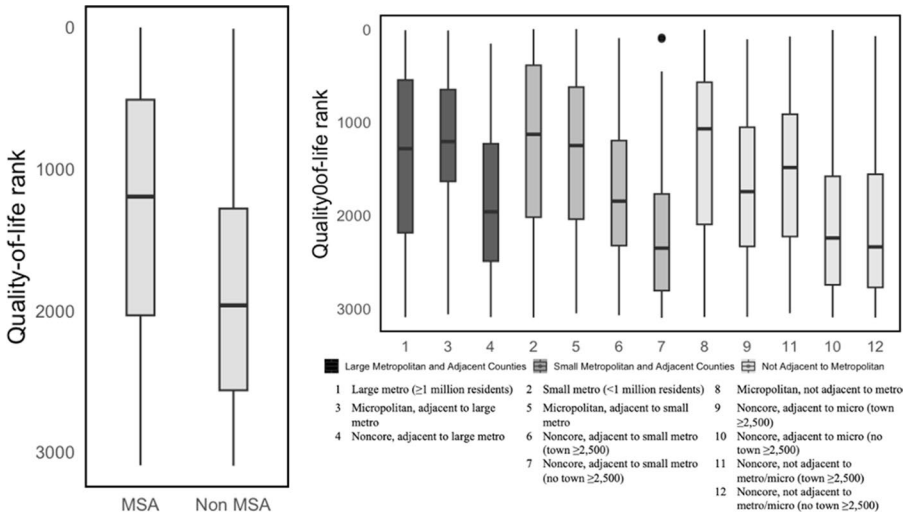
[9] Data is available upon request.

value. Not surprisingly, those top high-quality-of-life places have higher educational attainment, and a higher-than-average share of STEM and creative class workers emphasized for their role in regional development (Florida, 2002, 2005; Mellander & Florida, 2011). Similarly, a growing body of work argues that human capital and higher education institutions and their associated amenities play a key role in shaping local quality of life (Glaeser et al., 2001; Shapiro, 2006; Winters, 2011).

A second shared feature is that many of the top-ranking counties are located outside urban centers and are largely rural in character. For example, Chattahoochee County, while part of the Columbus, Georgia metropolitan statistical area, offers a rural lifestyle with access to outdoor recreation, including the Chattahoochee River along its western boundary. Madison County, Idaho, which ranked the highest, likely benefits from its proximity to natural amenities such as Yellowstone National Park. Whitman County, Washington, provides another illustration of a rural setting, in contrast to two earlier more urban examples. It ranked fourth for quality of life. Located in the Palouse region, Whitman County is characterized by rolling hills formed from wind-blown silt, providing productive dryland agriculture and striking scenic landscapes.

Another notable characteristic of these top counties is strong civic engagement. Beyond high census response rates, they experience more peaceful protests than average and higher levels of political contributions from both individuals and organizations. Several top counties have also made deliberate efforts to improve government transparency. For example, Albany County, Wyoming, ranked tenth in quality of life, has streamed county council meetings since 2016. Other counties, including Laramie County, Wyoming; Onslow County, North Carolina; Payne County, Oklahoma; and Oktibbeha County, Mississippi, also provide live public access to county commission meetings. Overall, these patterns suggest that high-quality-of-life counties are characterized by active civic participation and proactive local governance that emphasizes transparency and accessibility.

Rural areas are often characterized as economically disadvantaged with lower standards of living, but a growing body of research challenges this portrayal (e.g., Isserman et al., 2009; Schmidt et al., 2026), raising the question of whether a meaningful rural–urban divide exists in our measure of quality of life. Using Metropolitan Statistical Area (MSA) status, we find that metropolitan counties rank significantly higher than non-MSA counties (Fig. 2). Further categorizing counties by Urban Influence Codes (UICs), quality of life declines within each tier as counties move further from the regional or urban core, yet core counties of any size sshare a similar median rank of around 1,200. A county's position in the regional hierarchy is therefore more important to understanding quality of life than overall population size. Despite these trends, rankings span the full distribution, from highest to lowest, within every category, MSA or UIC, and some remote counties rank among the highest in our measures. Residing in a metropolitan area does not ensure a high quality of life, nor are remote counties uniformly disadvantaged. At a minimum, these findings caution against broad generalizations about urban and rural places, which can lead to ineffective policy design. Explaining why some urban areas exhibit relatively low quality of life while certain rural areas prosper remains an open and important question for future research.



(A) Quality-of-life ranks by MSA status (B) Quality-of-life ranks by UICs

Fig. 2 Quality-of-life ranks across rural–urban continuum. Notes: We present ordinal ranks of quality of life with the highest quality of life ranked "1" and the lowest quality of life ranked "3,100"

4 Discussion and Conclusions

The importance of quality of life in community-level discussions around economic growth and development has become increasingly evident (e.g., Deller, 2021, 2025; Dissart & Deller, 2000). The lack of a consensus definition often pushes measurement toward subjective judgments or long checklists of place attributes (e.g., Cheng et al., 2026; Dsouza et al., 2023; Veréb et al., 2024). In this study, we add to this literature by conceptualizing and developing an indicator of place-based quality of life using revealed preferences: whether people move to, remain in, and invest in a place. We extend both the behavioral scope and time span of revealed preferences and apply Spatial Bayesian Factor Analysis to construct a county-level quality-of-life index that incorporates regional spillovers.

We find that residential retention and homeownership together account for nearly two-thirds of the index weight, and significant spatial spillovers confirm that quality of life operates regionally. Urban counties rank higher on average, yet many rural counties also perform well with untapped potential. Metropolitan status alone does not explain outcomes of quality of life. Instead, regional cores with functioning services, infrastructure, and economic roles tend to perform better, suggesting that agglomeration and regional collaboration sustain quality of life more than isolated, place-by-place efforts. Examination of individual counties reinforces the behavioral lens of our approach. Chattahoochee County, Georgia (anchored by a military installation), and Madison County, Idaho, and Whitman County, Washington (anchored by major universities), post high-quality-of-life scores despite modest traditional economic metrics. Institutional anchors, cultural assets, educational resources, natural amenities, and community cohesion elevate migration and retention, indicating that our index captures livability beyond standard growth measures. While not generalizable to all places, these examples illustrate the value of our approach.

From a policy perspective the key takeaway from this research is that policies must be locationally tailored and people-centered. The implication is that a bottom-up approach is required and that top-down "one size fits all" approaches are likely to be ineffective. Given this overall observation, there are general themes that can help inform grassroots initiatives. First, policies should prioritize retention and commitment, not just attraction. Residential retention emerges as the strongest indicator of quality of life, implying that improving conditions for those already living in a place may yield greater returns than recruiting new residents or firms.

Second, amenities and livability investments should be recognized as legitimate development tools. High-quality-of-life counties often succeed not because of superior economic performance, but because they offer attractive living environments that people are willing to pay for. Investments in natural resource protection, recreation, arts and culture, historic preservation, and downtown vitality can enhance local appeal, support retention, and attract footloose households such as entrepreneurs and remote workers. Housing affordability should be addressed alongside amenity enhancement to avoid displacement and ensure that rising quality of life benefits existing residents.

Finally, regional collaboration should be emphasized over isolated local initiatives. The analysis shows that proximity to functional regional cores, rather than county size alone, is correlated with higher quality of life. Small and rural counties benefit when they are integrated into regional labor markets, service networks, and infrastructure systems. Policies that encourage interjurisdictional cooperation in transportation, broadband, healthcare, and economic development can help smaller places capture agglomeration benefits without duplicating expensive investments. Taken together, these recommendations suggest a shift in development practice: from maximizing short-run economic output toward strengthening the conditions that allow people to stay, invest, and flourish in place.

The study is not without its limitations. First, although county-level aggregation reduces individual-level noise, information frictions may cause some high-quality places, especially rural, to be overlooked in migration decisions, biasing our revealed-preference measure downward for informationally "opaque" places. Future work should incorporate place-based amenities and other features to complement insights from observed human behavior. Second, the Spatial Bayesian factor model assumes a single latent factor (quality of life) and spatial dependence only through that factor, unobserved heterogeneity and additional latent dimensions like social ties merit investigation. A third limitation, particularly for rural counties, is the presence of a single large institution, such as a military base or a university, where there is a natural inflow and outflow of people driven by the nature of the institution itself. In these cases, it is difficult to separate the structural impact on our signals of quality of life, such as through migration, from the features of the institutions that influence the latent quality of life itself.

There is one final limitation with the approach outlined in this study: we can provide no insights into the well-being or quality of life of different groups of people within the community. The community is composed of a heterogeneous group of people with different preferences for what defines quality of life. As we discussed earlier with the competing theories of out-migration and the "pull" and "push" forces in commuting, aggregate-level measures essentially disguise these heterogenous preferences and the underlying reasons for the resulting behaviors. Our community-wide measure of quality of life cannot shed light on that heterogeneity. This shortcoming begs the broader question of "quality of life for

whom." But for many community policymakers who are pursuing a 4th wave approach to community economic development, the first and foremost concern is well-being or quality of life of the larger community.

Despite these limitations, our approach provides a behaviorally grounded starting point for measuring quality of life beyond conventional growth metrics and for informing development strategies tailored to place. This study provides a way forward for understanding quality of life by capturing how people interact with places. This approach helps address the longstanding debate of how to identify quality of life, whether as a composite of place-based characteristics or as a distinct construct on its own. It sets the stage for seeking place-based strategies relevant to practitioners and community leaders, with potential applications across a wide range of quality-of-life topics. Future research should explicitly model spatial heterogeneity, which, beyond the spatial spillovers accounted for here, may further improve our ability to capture quality of life across heterogeneous places. While the aggregate nature of this approach does not directly address this question, it offers a practical advantage in that the method can be applied in settings where individual-level data are scarce and extended to other regional contexts beyond the U.S.

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Data Availability All data analyzed in this study are from publicly available sources. The results generated during the current study are available from the corresponding author upon request.

Declarations

Competing 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.
The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

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