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Housing Livability Index and County Demographic Change*

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Abstract: Housing conditions both affect and are affected by population dynamics in important ways. This paper develops a novel county-level housing livability index (HLI) based on three dimensions: housing cost burden, new construction activity, and housing adequacy. Using 2019–2023 American Community Survey five-year estimates and county demographic and economic changes measured between the 2009–2013 and 2019–2023 ACS periods, we examine associations between the index and population in-migration, growth in the early prime-working-age population, and growth in incomes and housing values. Results based on this index show substantial rural-urban disparities in housing livability and consistent associations with county demographic trajectories across multiple index specifications.

Keywords: Housing Livability, Affordability–Availability–Adequacy Framework, Rural-Urban Disparities, Composite Indicators

JEL Codes: R21, R31, R58, O18

1. INTRODUCTION

Housing policy debates often center on affordability, with empirical studies mostly limited to metropolitan areas of the U.S., especially high-cost markets such as San Francisco and

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New York. This leaves housing conditions in non-metropolitan areas comparatively understudied.[1] Evidence from rural housing research indicates that affordability pressures were already evident before the recent escalation in housing costs, as housing values outpaced income growth, pushing an increasing number of rural households into high housing cost burdens (Albrecht et al., 2018). Moreover, many non-metro counties face growing pressure from multiple directions: remote work has broadened location choices, retirees continue to move into high-amenity rural areas, insurance and property tax burdens are rising, and high construction costs and labor shortages limit new housing production. In some high-demand and metro-adjacent markets, land-use regulations may further constrain supply.

Recent literature suggests that these pressures reflect multiple interacting constraints rather than isolated price shocks. Housing affordability follows heterogeneous trajectories associated with demographic change and population aging (Brooks, 2022), while affordability dynamics also vary with construction constraints and the responsiveness of housing supply (Molloy, 2020; Baum-Snow and Duranton, 2025). Furthermore, housing challenges take different forms across rural America (Kordel and Naumann, 2024). Some counties combine relatively low housing costs with favorable supply and housing-stock conditions, while others face high cost burdens, aging homes, and little new construction (Council of Economic Advisers, 2025). In places with limited construction and population decline, the durability of the existing housing stock may deepen housing challenges beyond affordability alone (Glaeser and Gyourko, 2005).

Despite extensive research on housing affordability, comprehensive county-level measures of housing conditions remain limited. Most studies examine affordability in isolation, leaving unclear how availability and adequacy contribute to housing livability and relate to county demographic and economic trajectories. Differences between metro and non-metro counties and across county economic typologies also remain insufficiently understood. This paper addresses these gaps by developing a transparent and replicable county-level Housing Livability Index (HLI) based on affordability, availability, and adequacy. Using the 2019–2023 five-year American Community Survey estimates, we compare housing livability between metropolitan and non-metropolitan counties and across county economic typologies, and examine its associations with the growth in in-migration, household income, the early prime-working-age population (defined as persons aged 25-44), and home values over 2013–2023.

The contribution is primarily methodological and descriptive. By moving beyond a one-dimensional affordability measure, the HLI provides a parsimonious diagnostic tool for identifying whether local housing constraints are concentrated in affordability, availability, or adequacy. We assess the sensitivity of the findings to alternative variable specifications and PCA-based measures and evaluate their robustness using spatial models. We also consider how the resulting diagnostics can inform targeted, place-based housing policies. From this multidimensional perspective, we expect higher housing livability scores to be positively associated with in-migration, household income growth, the early prime-working-age population growth, and home-value appreciation. We also expect metro and non-metro counties to exhibit different profiles across the three dimensions of housing livability. Because the

[1]We use "rural" and "non-metropolitan" (or "non-metro") interchangeably, and likewise "urban" and "metropolitan" (or "metro"), because our classification includes all non-metro counties, grouped as metro-adjacent or non-adjacent, across varying degrees of rurality.

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2019–2023 HLI measurement period overlaps with the 2013–2023 demographic and economic change period, these expectations concern associations between recent housing conditions and longer-term county trajectories rather than causal relationships.

2. LITERATURE REVIEW

2.1. Conceptualizing Housing Livability

"Livability" is widely used in planning and geography, yet it has long been criticized for conceptual vagueness. Part of the problem is that researchers often treat the term as interchangeable with related concepts such as "quality of life" or "well-being" (Ruth and Franklin, 2014; Dsouza et al., 2023), obscuring key differences in analytical scope. "Quality of life" typically functions as a broad evaluation of the human experience, while "well-being," by contrast, focuses more directly on individual capabilities and development (Sen, 1993). Blurring these concepts makes it easy to conflate environmental conditions, personal perceptions, and resource access (van Kamp et al., 2003). By reviewing rural well-being metrics, Veréb et al. (2024) identify a loosely assembled set of indicators rather than a clearly delimited framework, thereby what is actually being measured remains uncertain.

Livability, we argue, is narrower than these constructs by design. While "well-being" stretches to cover social relations and institutional performance, livability targets the immediate material conditions of everyday life. This is the distinction Veenhoven (2000) draws in his taxonomy of "the good life," which separates the external "livability of the environment" from the internal "life-ability of the person." Environmental livability can, in principle, span transportation, energy burdens, and tenure security. In this study, we restrict attention to the housing market specifically. Treating "housing livability" as a distinct, bounded subdomain lets us isolate factors tied directly to the home, and this narrower focus is what makes systematic comparison across the rural–urban continuum possible, linking housing quality to broader demographic and economic trajectories.

Setting clear boundaries matters if livability is to function as a rigorous analytical concept rather than a catch-all. Riepl and Grabow (2025), in developing a broader foundational livability indicator, distinguish the availability of essential services from households' financial affordability for basic necessities. We adapt this availability–affordability distinction to the housing market and add a third dimension: adequacy. Housing can be affordable and available and still fail to provide sufficient space or meet basic standards of physical habitability. We therefore define housing livability as the capacity of a local housing system to provide housing that is affordable, available, and adequate.

2.2. The Affordability–Availability–Adequacy Framework

We conceptualize housing livability along three dimensions, namely affordability, availability, and adequacy, which together form what we call the Affordability–Availability–Adequacy (AAA) framework. These dimensions are conceptually distinct, but they interact, and improvement in one does not guarantee improvement in the others. New construction expands the housing stock, for instance, but may initially consist of higher-priced units (Asquith

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et al., 2023); low housing costs in stagnant markets, conversely, can coexist with limited construction and a deteriorating existing stock. No single dimension captures the condition of a local housing market on its own, which is why we take up each in turn below.

Housing affordability is the financial burden of housing costs relative to household income (Stone, 2006; Bogdon and Can, 1997). It captures whether households can secure adequate housing without sacrificing other necessities, and for that reason cannot be inferred from nominal prices alone (Kutty, 2005; Gan and Hill, 2009). When housing costs outpace income growth, households confront difficult financial trade-offs along with heightened risks to physical and mental health (Deller et al., 2026). Because nominal prices also reflect amenity premiums and spatial income sorting, we focus conceptually on housing costs relative to local household resources rather than on price levels per se (Bieri and Dawkins, 2019; Winke, 2021).

Housing availability concerns physical supply access and the elasticity of local housing markets. Geographic constraints and land-use regulations limit the supply of developable land at a broader scale, restricting housing expansion and pushing up costs (Saiz, 2010; Glaeser and Gyourko, 2025; Molloy, 2020). Supply bottlenecks of this kind operate at highly localized geographies, fragmenting markets even within a single metro area (Baum-Snow and Duranton, 2025; Baum-Snow and Han, 2024). In non-metro counties, low supply responsiveness more often reflects thin developer markets, high mobilization costs, and financing barriers. These constraints persist even where nominal housing prices are comparatively low (Kordel and Naumann, 2024; Council of Economic Advisers, 2025; Shucksmith et al., 2009).

Housing adequacy, finally, encompasses both the physical condition of the dwelling and the amount of living space available to its occupants. Physical inadequacy includes deficiencies such as incomplete plumbing or kitchen facilities, heating problems, damaged roofing or exterior materials, and utility interruptions (Yam et al., 2024). Spatial inadequacy is typically measured through overcrowding indicators, such as persons per room, persons per bedroom, or floor area per person (U.S. Department of Housing and Urban Development, 2007), and overcrowding itself can raise exposure to adverse health outcomes, including contagious disease (Ellen et al., 2022). Structural deficiencies and overcrowding often coexist in rural areas, particularly in farmworker housing and other settings where households have limited housing options (Housing Assistance Council, 2001).

2.3. Demographic Trajectories and the Rural Housing Gap

Migration decisions are shaped jointly by employment opportunities, amenities, housing costs, and household characteristics, with effects that vary by tenure, age, and destination (Leishman and Goel, 2025). Rural residents move at relatively high rates, yet rural destinations are less likely than suburban ones to attract homeowners (Xu, 2024). At the same time, lower housing costs, natural amenities, and community ties continue to draw migrants to selected rural counties (Zhang, 2022), producing uneven demand: metro-adjacent and amenity-rich counties can experience migration-driven price pressure, while remote and economically distressed counties more often face population loss and weak housing investment (Brooks, 2022; Kordel and Naumann, 2024).

Housing costs can also reshape the socioeconomic composition of migration. Rising prices

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in prosperous, supply-constrained regions push some households toward less expensive places (Howard and Liebersohn, 2025), and middle-income households in particular tend to leave high-cost cities as homeownership becomes less attainable (Parkhomenko, 2026). These studies focus largely on urban systems, but the underlying mechanisms are relevant to how housing demand redistributes toward smaller and non-metro markets. Affordability may shape household formation as well. Renters in less affordable markets tend to delay childbearing, with implications for fertility and population age structure over the longer term (Japaridze and Sayour, 2024). Such demographic shifts may further accelerate population aging and the decline of working-age populations in many rural counties.

Availability introduces a different set of constraints. New construction generally moderates regional rent growth in broader housing markets and can expand housing choices by triggering a sequence of moves through the existing stock (Been et al., 2025). McClure and Schwartz (2025) show that national housing-unit growth outpaced household growth between 2000 and 2020, and argue that many local affordability problems instead reflect a mismatch between household incomes and the prices of available units. That distinction matters especially in rural markets. A declining county may contain inexpensive or vacant homes but still offer few rentals, starter homes, or units suited to incoming workers (Kang et al., 2024). Recreation, retirement, and metro-adjacent counties, meanwhile, can face persistent demand for long-term housing even where construction remains active. In both settings, thin developer markets, high construction costs, limited builder capacity, and financing barriers slow how quickly supply adjusts (Kordel and Naumann, 2024). Rural housing shortages reach beyond the housing market itself by impeding firm entry, limiting local capacity to accommodate workers, and thereby linking housing conditions to broader economic and demographic trajectories (Silva, 2026).

The condition and composition of the housing stock add a further layer to the rural housing gap. Rural homes are older on average and show elevated rates of heating problems, utility interruptions, damaged roofing or exterior materials, and other structural deficiencies (Yam et al., 2024). These conditions weigh especially heavily in aging communities, where residents may need repairs, accessibility modifications, and better connections to health care, transportation, and other services simply to remain in their homes (Halseth et al., 2024). In some agricultural areas, limited housing options also contribute to shared housing and overcrowding (Housing Assistance Council, 2001). These mismatches matter because housing provides not just shelter but access to location-specific services, institutions, and economic opportunity (Ioannides and Ngai, 2025).

2.4. Research Gap and Contribution

The literature reveals three areas where existing measures leave room to improve. Housing livability itself remains conceptually underdeveloped and is often subsumed within broader notions of quality of life or well-being, even though housing research typically treats affordability, availability, and physical condition as separate concerns (Ruth and Franklin, 2014; Veréb et al., 2024). Few measures integrate these dimensions in a way that supports consistent county-level comparison across the rural–urban continuum, a limitation that matters particularly for rural research given that low housing prices can coexist with weak construc-

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tion, an aging or unsuitable housing stock, and sharp differences among growing, declining, and amenity-based counties. Existing data resources, while detailed on housing needs, generally stop short of offering a readily interpretable summary of local housing conditions. This study takes up these gaps by examining housing livability through three complementary dimensions: affordability, availability, and adequacy. Because each dimension captures a distinct aspect of housing conditions, change in one does not necessarily imply change in the others. Together, they provide a more complete account of spatial variation in housing challenges than affordability measures alone.

3. DATA AND METHODS

3.1. Data Sources

The empirical analysis draws on county-level data from the U.S. Census Bureau's 2019–2023 5-year American Community Survey (ACS) estimates to construct the baseline Housing Livability Index (HLI). We also use the 2009–2013 ACS estimates as the base year for calculating county demographic and socioeconomic changes over the last decade. In addition, we use county classifications from the U.S. Department of Agriculture Economic Research Service (USDA ERS) Rural-Urban Continuum Codes and County Typology Codes to examine variation in housing livability across geographic and economic contexts (U.S. Department of Agriculture, Economic Research Service, 2023, 2015). The analysis includes nearly all U.S. counties and county equivalents.[2] Appendix A provides the complete data dictionary, definitions, and sources for all variables (Table A1).

The temporal window captured by the 2019–2023 5-year ACS represents a unique transition period in the U.S. housing market. The five-year pool includes the height of the COVID-19 pandemic (2020–2021), during which the average 30-year fixed mortgage rate reached a historic low of 2.65% in early 2021, and tenants received unprecedented federal safety net support, such as eviction moratoria and Emergency Rental Assistance (ERA) programs (Joint Center for Housing Studies of Harvard University, 2024). Conversely, the latter portion of this period (2022–2023) saw an aggressive monetary tightening cycle (Federal Reserve Bank of St. Louis, 2024b), causing mortgage rates to rise sharply, peaking at nearly 8% in late 2023 (Federal Reserve Bank of St. Louis, 2024a), while rent inflation escalated and pandemic-era assistance programs expired. Because the 5-year ACS estimates report a rolling average, they partially smooth out these distinct phases. Consequently, the HLI reflects a transitional state of housing conditions rather than the peak of the post-2023 housing cost burdens and interest rate surges, which only fully manifest in later data, e.g., late 2023 and 2024 (Joint Center for Housing Studies of Harvard University, 2024).

Following the conceptual framework and the procedural guidelines outlined in the OECD handbook on composite indicators (OECD, 2008), we construct the HLI through a three-stage process: indicator selection, index construction, and validation.

[2]Counties in Connecticut (CT) are excluded from the calculation of demographic changes because Connecticut transitioned from standard counties to Planning Regions as county equivalents starting with the 2019–2023 ACS release, making direct longitudinal comparison at the county level impossible.

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3.2. Indicator Selection

Given the conceptual AAA framework developed in Section 2.2, this section operationalizes each dimension into empirical indicators using the 2019–2023 5-year ACS estimates. To construct a parsimonious yet comprehensive index of housing livability, we select three baseline indicators, each corresponding to a distinct dimension of the AAA constraint.

Housing Cost Burden (Affordability): Operationalized as the percentage of occupied housing units where selected monthly owner costs (for owner-occupied units) or gross rent (for renter-occupied units) exceed 30% of household income. The 30% threshold represents the standard U.S. Department of Housing and Urban Development (HUD) policy benchmark for housing affordability (U.S. Department of Housing and Urban Development, 2013), capturing the population-level prevalence of severe financial constraints by scaling nominal housing costs to local household purchasing power. Consistent with the conceptual concerns outlined in Section 2.2, absolute price measures (nominal home values or rents) are intentionally excluded. Relying on absolute dollar values would introduce scaling bias by masking relative affordability (e.g., a nominally cheap $100,000 rural home can be just as financially out of reach for a low-income household as a $500,000 suburban home is for a middle-income family) and capitalize localized amenity premiums that reflect spatial sorting rather than housing stress (Bogdon and Can, 1997). A key limitation of this ratio-based metric is its inability to distinguish voluntary "strategic overspending" by high-income households from involuntary, resource-constrained shelter burdens (Gan and Hill, 2009).

Housing Supply (Availability): Operationalized as the percentage of total housing units (both occupied and vacant) constructed in the year 2020 or later. Because absolute housing construction varies by orders of magnitude between populous metropolitan counties and rural areas, this proportion scales recent residential construction to the existing housing stock, capturing recent construction activity relative to the existing housing stock. A technical limitation of this indicator is that it relies on new permits and construction, omitting informal supply channels such as manufactured housing placements, accessory units, major rehabilitations, and unit conversions. In rural areas, where manufactured housing constitutes a substantial portion of the new supply, this indicator may represent a conservative estimate and undercount actual housing additions.

Overcrowding (Adequacy): Operationalized as the percentage of occupied housing units with 1.5 or more occupants per room (excluding bathrooms, hallways, and utility rooms). Following HUD standards, this threshold isolates severe overcrowding to serve as an empirical proxy for spatial inadequacy, capturing situations where households must double up due to extreme economic shocks or physical supply deficits. However, a major limitation of overcrowding as an adequacy proxy is that it focuses on spatial density and fails to capture physical and structural deficiencies (such as lack of complete plumbing or kitchen facilities, roofing decay, or heating issues), which are critical quality components in rural areas (Housing Assistance Council, 2001). We address this limitation and validate the parsimonious baseline by testing it against a broader 12-variable Hierarchical PCA (H-PCA) specification in Appendix D that incorporates these structural variables.

The choice of this parsimonious three-variable benchmark with one representative variable per dimension is guided by three critical methodological considerations. First, it maxi-

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mizes interpretability, avoiding the "black box" complexity of high-dimensional indices and ensuring that the driving factor behind any county's score remains transparent. Second, it prevents redundancy and collinearity distortions. Although the three dimensions are conceptually related, they exhibit very low empirical correlation in our sample ($r = 0.15$ between cost burden and overcrowding, and new construction correlates weakly with both; see Appendix C). This low correlation and the resulting near-zero Cronbach's alpha ($\alpha = -0.016$) are theoretically expected for a composite index, confirming that the three pillars capture distinct, non-redundant housing market constraints rather than converging on a single reflective construct (OECD, 2008). Third, the selected indicators provide unambiguous directional interpretations for housing conditions: unlike alternative variables (e.g., vacancy rates or median prices, which carry context-dependent meanings), lower cost burdens, higher construction rates, and lower overcrowding consistently signal better housing conditions.

3.3. Index Construction

Following the OECD composite-indicator practice (OECD, 2008), the process of constructing the HLI consists of normalization, orientation, aggregation, rescaling, and robustness assessment.

Step 1: Standardization. Each raw indicator $X_{i,c}$ in county c is standardized using county-level z-scores: $Z_{i,c} = (X_{i,c} - \mu_i)/\sigma_i$, where μ_i and σ_i are the mean and standard deviation of indicator i across all U.S. counties.

Step 2: Code inversely for cost burden and overcrowding. To ensure higher index values indicate better housing livability, we reverse the direction for negative indicators (cost burden and overcrowding): $Z^*_{\text{cost},c} = -Z_{\text{cost},c}$, $Z^*_{\text{adequacy},c} = -Z_{\text{adequacy},c}$. The new construction indicator, $Z_{\text{new const},c}$, maintains its direction.

Step 3: Equal-weight combination:

$$\text{HLI}_c = \frac{1}{3}\left(Z^*_{\text{cost},c} + Z_{\text{new const},c} + Z^*_{\text{adequacy},c}\right) \tag{1}$$

We choose equal weights for three reasons. First, equal weighting maximizes interpretability and transparency, ensuring that each dimension contributes equally and that the index composition remains intuitive for users. Second, it facilitates comparability by establishing a stable reference specification that makes county-level comparisons and regression outputs straightforward to interpret. Third, it aligns with our conceptual framework: in the absence of a strong prior theory suggesting that housing cost burden, construction activity, or spatial adequacy is substantively more critical, they should receive equal baseline importance.

This choice is consistent with the composite-indicator literature, which cautions against treating statistically derived weights as if they automatically reveal substantive importance (OECD, 2008; Becker et al., 2017). Data-driven weighting schemes are valuable as robustness checks, but they should not replace theory and interpretability when the conceptual case for differential weights is weak. As a sensitivity check, we construct a hierarchical principal component analysis (H-PCA) index that incorporates multiple indicators within each housing-livability dimension. The H-PCA index is strongly correlated with the equal-weight HLI ($r = 0.82$), indicating substantial correspondence between the two specifications.

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We retain the equal-weight HLI as the baseline because it is transparent and readily interpretable, while using the H-PCA specification to assess the sensitivity of the findings to broader indicator selection and data-driven weighting (Appendix D).

Step 4: Rescale. To improve interpretability, we rescale the raw composite scores to a 0–100 range using min-max standardization:

$$\text{HLI}_{100,c} = \frac{\text{HLI}_c - \min(\text{HLI})}{\max(\text{HLI}) - \min(\text{HLI})} \times 100 \tag{2}$$

where min(HLI) and max(HLI) represent the minimum and maximum values of the raw index across all counties.

3.4. Validation Strategy

The empirical analysis evaluates whether cross-county variation in the HLI and its component dimensions is associated with longer-run demographic and economic conditions. We examine four correlates measured between the 2009–2013 and 2019–2023 ACS five-year estimates: growth in in-migration, real median household income, the early prime-working-age population (ages 25–44), and real median home values. Together, these indicators capture demographic change, labor-force and household formation dynamics, local economic conditions, and housing-market performance. We focus on the early prime-working-age population because this cohort is commonly associated with household formation, residential mobility, and entry into homeownership, making it especially relevant to housing-market conditions. The purpose of this analysis is to assess whether counties with stronger demographic and economic trajectories tend to exhibit higher current housing livability scores.

To establish these associations, we estimate ordinary least squares (OLS) regressions of the HLI on each demographic correlate:

$$\text{HLI}_c = \alpha + \beta X_c + \gamma_{s(c)} + \epsilon_c$$

where HLI_c is the 0–100 scaled index for county c, X_c is the percentage change between the 2009–2013 and 2019–2023 ACS five-year estimates of demographic or economic correlates, $\gamma_{s(c)}$ represents state-level fixed effects, and ϵ_c is the error term. To ensure that the composite index's associations are not driven by a single dominant component, we also estimate separate regression models replacing the composite HLI with each of the three individual AAA dimensions (cost burden, new construction, and overcrowding) as the dependent variable.

To evaluate structural variations in housing conditions across diverse economic and geographic environments, we expand this regression framework to analyze heterogeneity. First, we regress the HLI on county metropolitan status using the RUCC classification, comparing metropolitan counties (RUCC 1–3), metro-adjacent non-metropolitan counties (RUCC 4, 6, and 8), and non-adjacent non-metropolitan counties (RUCC 5, 7, and 9). Second, we regress the HLI on county economic typology indicators (farming-dependent, manufacturing-dependent, recreation-dependent, retirement-destination, and persistent-poverty counties) to analyze how housing constraints systematically covary with local economic specializations.

Several methodological issues merit attention when interpreting these empirical associations. First, because housing conditions and population dynamics are endogenously related,

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these regressions estimate conditional correlations rather than causal effects. Second, spatial spillovers, including housing demand and construction spillovers from adjacent metropolitan areas, could bias cross-sectional estimates if not explicitly modeled. We address this potential limitation by estimating spatial econometric models (specifically, a Spatial Durbin Model) as a robustness check in Appendix G, validating that our baseline OLS results remain robust when accounting for spatial lag and spatial error dependencies. Third, the HLI is deliberately narrow in scope and excludes other critical housing quality measures (e.g., energy burden, transport accessibility, and tenure security) due to the lack of uniform county-level data.

4. RESULTS

4.1. Descriptive Statistics and Index Distribution

Table 1 presents summary statistics for the three index components, the equal-weight HLI, and the four demographic and economic correlates. On its 0–100 scale, the HLI has a mean of 58.2 and a standard deviation of 5.60. Its distribution is approximately symmetric and bell-shaped (Figure 1). Before aggregation, each component is standardized as a z-score, eliminating differences in measurement scale and assigning the same coefficient to each dimension in the equal-weight index. Consequently, the index is not mechanically dominated by the higher percentage values of housing cost burden, which has a mean of 23.7%, relative to new construction and overcrowding.

Table 1: Descriptive Statistics for Index Components, HLI, and Demographic Variables

Variable	N	Mean	SD	Min	Max
Panel A. HLI Component					
Cost burden (%)	3,135	23.65	5.86	0.00	52.24
New construction (%)	3,135	0.88	0.88	0.00	9.02
Overcrowding (%)	3,135	0.71	1.07	0.00	20.47
Equal-weight HLI (0–100 scale)	3,135	58.17	5.60	0.00	100.00
Panel B. Demographic and Economic Correlates					
In-migration growth (%)	3,131	4.80	43.22	-100.00	500.00
Income growth (%)	3,135	14.88	11.89	-54.06	95.30
Early prime-working-age pop. growth (%)	3,135	2.42	14.52	-100.00	155.73
Home value growth (%)	3,135	27.77	21.97	-66.51	153.81

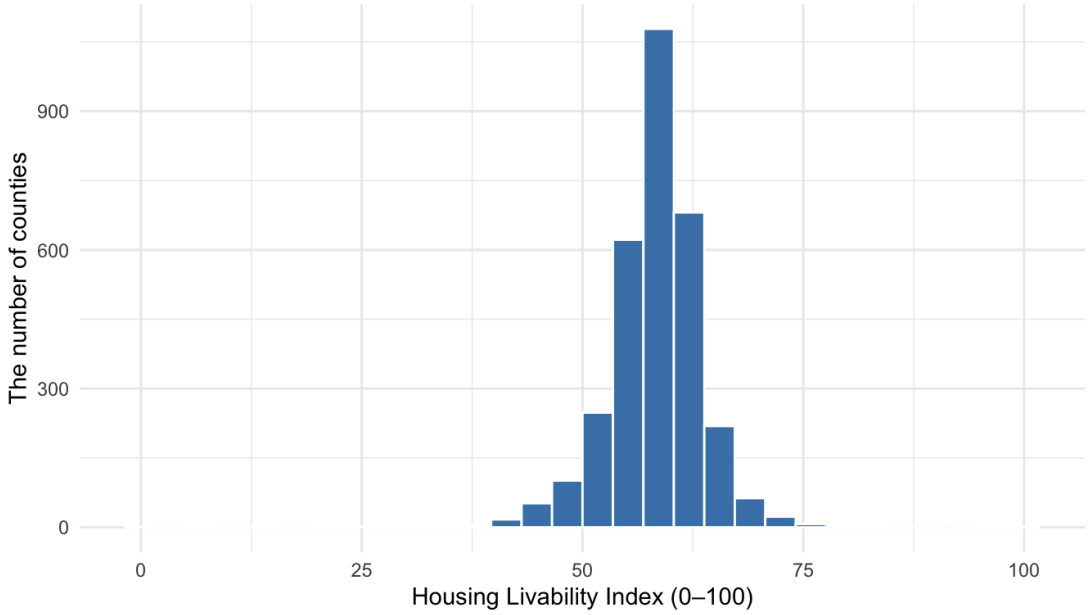
Notes: Index components are expressed as percentages (0–100%). Demographic and economic variables are calculated as percentage changes between the 2009–2013 and 2019–2023 ACS five-year estimates. Sample size is 3,131 for in-migration growth because the growth measure could not be calculated for four counties; all other demographic and economic variables have $N = 3,135$.

The HLI components exhibit substantial cross-county variation, particularly in new construction and overcrowding. Although their county medians are low—0.66% for housing built in 2020 or later and 0.46% for overcrowded occupied units—both variables are strongly

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right-skewed and display considerable relative dispersion. As reported in Appendix C, the coefficients of variation are 99.8% for new construction and 150.2% for overcrowding, compared with 24.8% for housing cost burden. Counties in the bottom decile report minimal new construction, with no more than 0.08% of their housing stock built in 2020 or later, and no measured overcrowding. At the 90th percentile, new construction rises to 1.86% and overcrowding to 1.51%; the maximum overcrowding rate is 20.47%. These distributions indicate that low national medians conceal substantial concentration of new construction and overcrowding in a relatively small number of counties.

Figure 1: Distribution of the Equal-Weight Housing Livability Index (2023)

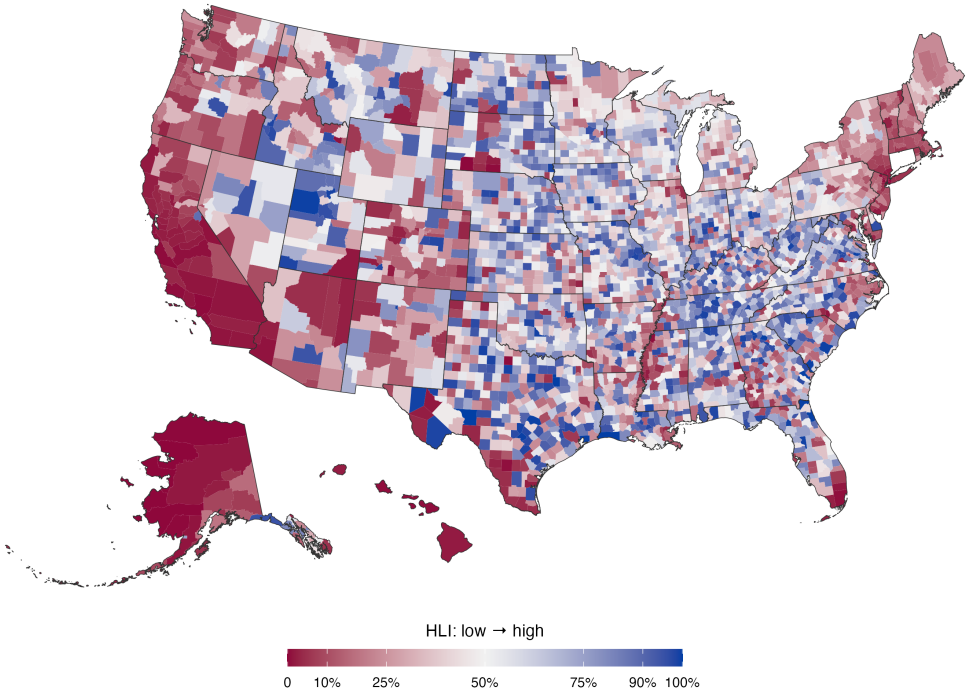


Note: The figure displays the distribution of the 0–100 scaled equal-weight Housing Livability Index across 3,135 U.S. counties for the 2019–2023 ACS period.

Figure 2 presents the geographic distribution of county HLI percentile ranks. Low-scoring counties are concentrated in California and appear in parts of the Southwest, Pacific Northwest, Northeast, Mississippi Delta, and Rio Grande Valley. Higher-scoring counties are more geographically dispersed, with clusters in portions of the interior West, Great Plains, Midwest, Appalachia, and Southeast. The map also shows substantial variation within regions and states, indicating that housing livability does not follow a uniform rural–urban pattern. Some higher-scoring counties appear near metropolitan areas, but both metro and non-metro regions contain considerable internal variation. Because the HLI combines affordability, availability, and adequacy, similar composite scores may result from different combinations of component conditions. Appendix B maps the individual components underlying these patterns.

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Figure 2: Geographic Distribution of Equal-Weight HLI (2023)



Note: Geographic distribution with percentile-rank color scheme from dark red (lowest livability, ≤10th percentile) to dark blue (highest livability, ≥90th percentile).

4.2. Results of Regression Analyses

Table 2 reports associations between county demographic and economic trajectories and the equal-weight HLI, controlling for state fixed effects. The HLI is positively and statistically significantly associated with all four correlates. Among the components, availability has the most consistent associations with all four variables. This pattern accords with the reciprocal relationship between housing production and local demand discussed in the supply literature (Been et al., 2025; Howard and Liebersohn, 2025). Affordability displays mixed associations, while the adequacy measure is not significantly related to any of the four correlates, potentially reflecting the narrow focus of the baseline adequacy indicator on overcrowding rather than broader housing quality.

Panel A of Table 3 compares metro and non-metro counties. Relative to metro counties, metro-adjacent and non-adjacent non-metro counties have modestly lower HLI scores. The component estimates show that the difference is concentrated in availability: both non-metro groups have substantially lower new-construction scores, with a larger shortfall among non-adjacent counties. By contrast, both groups have more favorable affordability scores, and neither differs significantly from metropolitan counties in baseline adequacy. The composite rural–urban difference therefore reflects a pronounced availability disadvantage that is only partly offset by lower cost burdens.

Panel B shows substantial variation across county economic typologies. Persistent-poverty counties have the largest HLI deficit and score significantly lower on affordability,

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Table 2: Association between Demographic Correlates and Equal-Weight HLI

Demographic or economic correlate	Equal-weight HLI	Affordability	Availability	Adequacy
In-migration growth (%)	0.010*	-0.006	0.032**	0.002
	(0.004)	(0.005)	(0.007)	(0.003)
Household income growth (%)	0.059**	0.071*	0.123**	-0.004
	(0.009)	(0.030)	(0.025)	(0.008)
Early prime-working-age pop. growth (%)	0.057**	-0.110**	0.286**	-0.011
	(0.014)	(0.032)	(0.047)	(0.010)
Home-value growth (%)	0.043**	-0.060*	0.171**	0.005
	(0.011)	(0.023)	(0.021)	(0.012)

Notes: Each cell reports the coefficient from a separate OLS regression. Columns indicate dependent variables; rows indicate explanatory variables. All models include state fixed effects, with standard errors clustered by state. Standard errors are in parentheses. Higher HLI and component scores indicate more favorable housing conditions. The HLI and component measures use the 2019–2023 ACS estimates; demographic and economic correlates measure changes between the 2009–2013 and 2019–2023 ACS periods. $^{+}$ $p < .10$. * $p < .05$. ** $p < .01$.

availability, and adequacy. Retirement-destination counties have substantially higher HLI scores, driven mainly by new construction, while their affordability score does not differ significantly from the reference group. Farming-dependent counties combine more favorable affordability and adequacy with lower availability, producing a positive composite score. Manufacturing-dependent and recreation-dependent counties differ little in their overall HLI scores, although both show some evidence of weaker availability. These patterns reinforce the value of examining the component profile rather than interpreting the composite score alone.

4.3. Robustness: Hierarchical PCA and Sensitivity Analysis

To assess specification sensitivity, we implement a broader robustness analysis that varies the indicators within each dimension and applies a hierarchical principal component analysis (H-PCA) approach. H-PCA organizes variables into conceptually meaningful groups before estimating their shared variation, thereby preserving the structure of the underlying dimensions (Avellaneda and Serur, 2020). In our application, we apply PCA separately within the affordability, availability, and adequacy dimensions, retain the first principal component from each dimension, adjust its sign so that higher values indicate more favorable housing conditions, and combine the resulting dimension scores with equal weights. This approach preserves the AAA structure while allowing the indicator loadings within each dimension to reflect their covariance. Tables 4 and 5 report the H-PCA results. Appendix D details the construction procedure, Appendix E presents the alternative indicator-composition scenarios, and Appendix F reports sensitivity regressions restricted to non-metropolitan counties (Table F1).

As shown in Table 4, the H-PCA HLI remains positively and statistically significantly associated with all four correlates, closely matching the equal-weight results in Table 2.

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Table 3: Equal-Weight HLI and Component Differences by County Classification

County classification	Equal-weight HLI	Affordability	Availability	Adequacy
Panel A. Metropolitan status				
Non-metro, metro-adjacent	-0.746*	4.249**	-5.973**	0.034
	(0.361)	(0.593)	(0.820)	(0.240)
Non-metro, non-adjacent	-0.886*	5.978**	-7.998**	0.092
	(0.377)	(0.920)	(0.971)	(0.266)
Panel B. County economic typology				
Farming-dependent	1.757**	8.373**	-4.048**	1.096*
	(0.231)	(0.818)	(0.920)	(0.420)
Manufacturing-dependent	0.409^{+}	2.957**	-0.974^{+}	-0.196
	(0.206)	(0.446)	(0.493)	(0.159)
Recreation-dependent	-0.121	0.240	-1.124^{+}	0.298
	(0.297)	(0.755)	(0.638)	(0.226)
Retirement-destination	3.167**	-0.027	8.998**	0.261*
	(0.330)	(0.940)	(1.263)	(0.126)
Persistent-poverty	-3.319**	-3.021**	-3.387**	-2.100**
	(0.552)	(0.937)	(0.586)	(0.675)

Notes: Panel A uses metropolitan counties as the reference group. Panel B uses non-specialized counties as the reference group. County economic typology indicators are entered jointly; categories may overlap. All models include state fixed effects, with standard errors clustered by state. Standard errors are in parentheses. Higher HLI and component scores indicate more favorable housing conditions. $^{+}$ $p < .10$. * $p < .05$. ** $p < .01$.

Availability again exhibits the most consistent pattern, with positive associations across all four models. Affordability is positively associated with income growth but negatively associated with in-migration, the early prime-working-age population growth, and home-value growth. Unlike the baseline overcrowding measure, the broader H-PCA adequacy component is positively associated with the early prime-working-age population growth and home-value growth. Overall, the similarity of the composite results indicates that the main associations are reasonably stable across the equal-weight and H-PCA specifications, although some component results differ.

Table 5 replicates the county-classification analysis in Table 3 using the H-PCA HLI and its broader component measures. Non-metro counties continue to have lower composite scores, with larger deficits among non-adjacent counties; more favorable affordability is outweighed by lower availability and adequacy. Persistent-poverty counties score lower on all three dimensions, while retirement-destination counties score higher overall, primarily because of greater availability. Farming-dependent counties combine stronger affordability with weaker availability, and recreation-dependent counties have lower composite scores because of weaker affordability.

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Table 4: Robustness Check: Association between Demographic Correlates and Hierarchical PCA HLI

Demographic or economic correlate	H-PCA HLI	Affordability	Availability	Adequacy
In-migration growth (%)	0.007*	-0.013*	0.029**	0.002
	(0.003)	(0.005)	(0.005)	(0.001)
Household income growth (%)	0.072**	0.097**	0.091**	0.009
	(0.013)	(0.021)	(0.027)	(0.009)
Early prime-working-age pop. growth (%)	0.076**	-0.101**	0.268**	0.030**
	(0.014)	(0.018)	(0.040)	(0.009)
Home-value growth (%)	0.045**	-0.081**	0.157**	0.028*
	(0.011)	(0.014)	(0.017)	(0.011)

Notes: Each cell reports the coefficient from a separate OLS regression in which the equal-weight HLI or indicated component is the dependent variable and the row variable is the explanatory variable. All models include state fixed effects, with standard errors clustered by state. Standard errors are in parentheses. Higher HLI and component scores indicate more favorable housing conditions. The HLI and component measures use the 2019–2023 ACS estimates; demographic and economic correlates measure changes between the 2009–2013 and 2019–2023 ACS periods. $^{+}$ $p < .10$. * $p < .05$. ** $p < .01$.

Table 5: Robustness Check: H-PCA HLI and Component Differences by County Classification

County classification	H-PCA HLI	Affordability	Availability	Adequacy
Panel A. Metropolitan status				
Non-metro, metro-adjacent	-1.784**	3.667**	-6.925**	-1.018**
	(0.283)	(0.510)	(0.596)	(0.169)
Non-metro, non-adjacent	-2.290**	4.826**	-9.030**	-1.304**
	(0.309)	(0.706)	(1.020)	(0.200)
Panel B. County economic typology				
Farming-dependent	-0.195	7.364**	-8.507**	-0.185
	(0.251)	(0.550)	(0.886)	(0.213)
Manufacturing-dependent	0.343^{+}	2.368**	-1.065*	-0.208
	(0.190)	(0.349)	(0.506)	(0.135)
Recreation-dependent	-0.765*	-2.476**	0.531	-0.029
	(0.345)	(0.881)	(0.446)	(0.204)
Retirement-destination	3.027**	-1.058	9.067**	0.563**
	(0.255)	(0.831)	(0.995)	(0.106)
Persistent-poverty	-3.948**	-2.423**	-1.898*	-2.753**
	(0.490)	(0.853)	(0.776)	(0.543)

Notes: Each cell reports the coefficient from an OLS regression comparing the indicated county type to metropolitan counties (Panel A) or non-specialized counties (Panel B), with state fixed effects and standard errors clustered by state. Component scores are multiplied by 10 for readability. Standard errors are in parentheses. $^{+}$ $p < .10$. * $p < .05$. ** $p < .01$.

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5. DISCUSSION

Our analysis indicates consistent cross-sectional associations between the Housing Livability Index and county demographic trajectories. Counties scoring higher on the index are more likely to be associated with stronger in-migration, higher income growth, faster early prime-age population growth, and greater home-value appreciation over 2013–2023. These findings, along with the systematic rural-urban and economic typology differences revealed in the HLI, have important policy implications. In analyzing the landscape of affordable housing interventions, Hilber and Schöni (2022) propose a conceptual taxonomy that distinguishes between demand-side policies (e.g., housing vouchers, mortgage subsidies, government equity loans) and supply-side policies (e.g., social/public housing development, land-use deregulation, construction subsidies). The key argument in their framework is that the welfare effects, distributional consequences, and overall effectiveness of any housing policy are highly context-dependent, relying heavily on local market conditions and on the price elasticity of housing supply. In markets where housing supply is highly inelastic due to natural conditions or regulatory restrictions, demand-side subsidies tend to be capitalized into higher house prices and rents, primarily benefiting existing landlords and homeowners rather than the targeted low- and moderate- income households (Collinson and Ganong, 2018; Eriksen and Ross, 2015). Conversely, in highly supply-elastic markets, demand-side interventions can successfully expand access and lower housing costs without inflating local prices, while supply-side policies may be redundant or inefficient (Sinai and Waldfogel, 2005).

This framework provides a powerful lens for translating the HLI's diagnostics into place-based policy interventions across different county economic typologies. In metro-adjacent non-metro counties and fast-growing retirement-destination counties, strong housing demand drives distinct market pressures. However, for non-metro counties, new construction is generally constrained (reflected in the large negative HLI availability coefficients), suggesting weaker construction activity in these areas. This pattern may reflect a combination of housing demand conditions, development constraints, limited builder capacity, financing barriers, or other factors discussed in the housing literature (Saiz, 2010). In retirement-destination counties, high amenity-driven demand is met with substantial new construction (reflected in the large positive availability coefficient of 8.998), yet relative affordability remains under pressure (the neutral affordability coefficient of -0.027) as incoming demand outpaces supply. In both supply-constrained and high-demand environments, standard demand-side vouchers or mortgage subsidies are highly susceptible to price capitalization (Hilber and Turner, 2014; Agarwal et al., 2017). Policies in these counties could focus on expanding housing production and improving affordability. This includes structural land-use reforms (e.g., easing municipal zoning regulations to allow accessory dwelling units, duplexes, and infill density), creating community land trusts to remove parcels from speculative markets (Lee et al., 2024; Schneider et al., 2023), and implementing inclusionary zoning mandates (Wang et al., 2024) or workforce housing set-asides (Stacy et al., 2021) to ensure new developments accommodate moderate-income workers.

In persistent-poverty and remote rural counties, our HLI findings reveal severe deficits across all three dimensions. This pattern suggests that these counties face challenges, such as chronically low incomes, a lack of private development interest, and deteriorated housing

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stock (Brooks, 2022; Kordel and Naumann, 2024). Because land in those areas is usually abundant and regulatory barriers are typically minimal, housing supply may be more responsive to demand than in highly constrained markets (Glaeser and Gyourko, 2005). As a result, demand-side subsidies, such as USDA Section 502 Direct Home Loans for low-income homebuyers and Section 504 home repair grants for elderly homeowners (Petach, 2024), may improve affordability without the risk of inflating prices. Furthermore, since thin rural markets often fail to attract private developers due to low profit margins, direct public intervention may be warranted. This includes public funding for weatherization through programs like the Weatherization Assistance Program (WAP) (Fowlie et al., 2018), structural rehabilitation of aging homes, and public investments in basic utilities and infrastructure to lower developer costs.

In agricultural and industrial areas characterized by stagnant population growth and older housing stock, the primary challenge is the quality and preservation of existing homes (Brooks, 2022). As reflected in our HLI results, these counties demonstrate significant deficits in new housing availability (with strongly negative construction coefficients for farming and manufacturing counties) while maintaining relatively neutral or positive adequacy scores compared to persistent-poverty areas. Because thin population growth and economic stagnation limit economies of scale and make new speculative home-building a risky gamble for private developers (Brooks, 2022; Kordel and Naumann, 2024), housing preservation may be an important policy consideration. Furthermore, as industrial restructuring has left these areas with an aging housing stock poorly suited for their increasingly older populations (Halseth et al., 2024), interventions should focus on rehabilitation tax credits, municipal low-interest renovation loans, and targeted code enforcement. These tools help prevent the loss of naturally occurring affordable housing and rehabilitate substandard housing before it falls into complete disrepair.

Two concerns limit how the results should be interpreted. First, several index components are endogenously related to local market conditions. Construction activity, for example, may reflect responses to prior population growth or expectations of future demand. Similarly, cost burden differences may arise from income dynamics or local shocks unrelated to housing supply. Second, unobserved factors such as amenities, public-service quality, or regional labor-market opportunities likely influence both housing and demographic conditions, generating omitted-variable bias in cross-sectional comparisons. Within these limits, the patterns align with the view that the interaction of affordability, supply responsiveness, and adequacy correlates with broader indicators of county vitality. Counties with relatively stronger livability conditions appear systematically different from those facing higher burdens, weaker construction pipelines, or more overcrowding. This does not imply that changes in housing conditions causally generate demographic or economic outcomes, but it suggests that county housing environments reflect broader market and institutional characteristics associated with long-run performance.

6. CONCLUSION

This paper develops a parsimonious county-level measure of housing livability combining three dimensions: cost burden, new construction activity, and housing adequacy. When

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examined against four demographic correlates, including in-migration, income growth, early prime-working-age population growth, and housing value appreciation, the HLI is consistently and significantly associated with more favorable demographic trajectories. Large and systematic rural-urban gaps in livability scores point to a multidimensional rural housing problem that aggregate affordability metrics alone do not capture. The hierarchical PCA, scenario sensitivity analyses, and spatial robustness checks confirm that these patterns are robust to reasonable variation in index construction choices and spatial dependence.

For policymakers, the index serves as a diagnostic tool to align housing strategies with local market conditions rather than applying policies uniformly. The constraints facing a persistent-poverty county, where stagnant demand and thin developer markets require direct public investment and demand-side support, require fundamentally different interventions than those facing a fast-growing retirement destination characterized by intense price capitalization, or an agricultural county struggling with the preservation of its aging housing stock. By identifying whether housing challenges are concentrated in affordability, availability, or adequacy, housing policy paired with broader economic development is more likely to move the needle than uniform interventions pursued in isolation.

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Appendix A. Data Dictionary

Table A1: Definition and Data Sources of Variables

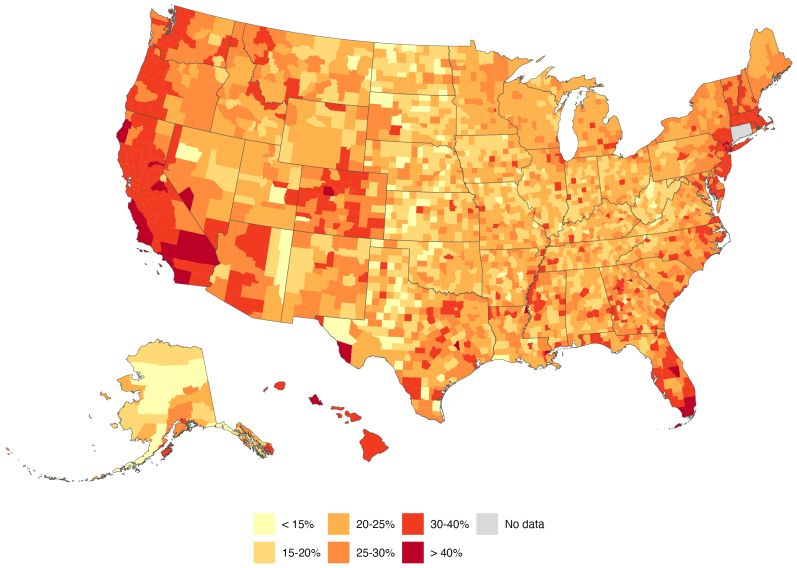
Variable	Definition	Source	Units
Cost Burden	Share of households spending >30% of income on housing	ACS 2019–2023 5-year estimates	%
New Construction	Share of housing stock built 2020 or later	ACS 2019–2023 5-year estimates	%
Overcrowding	Share of occupied units with ≥1.5 persons per room	ACS 2019–2023 5-year estimates	%
In-Migration Growth	% change in in-migration count (residents moving from different county, state, or abroad)	ACS 2009–2013 and 2019–2023	%
Income Growth	% change in real median household income (deflated to 2017 dollars)	ACS 2009–2013 and 2019–2023	%
Early Prime-Working-Age Pop. Growth	% change in early prime-working-age population (25–44)	ACS 2009–2013 and 2019–2023	%
Home Value Growth	% change in real median home value (deflated to 2017 dollars)	ACS 2009–2013 and 2019–2023	%

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Appendix B. Component and Demographic Variable Maps

This appendix presents county-level geographic distributions for the baseline HLI components and the four demographic and economic growth correlates across the contiguous United States.

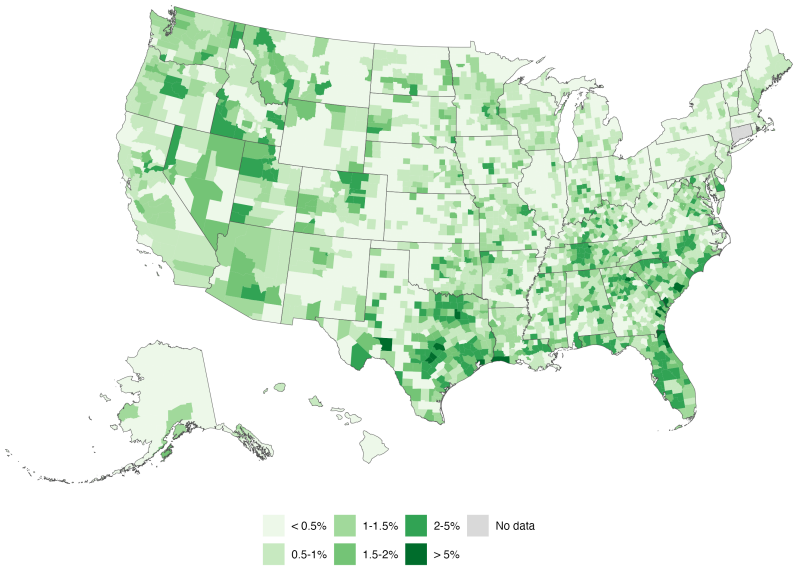
Figure B1: Geographic Distribution of Housing Cost Burden Rate (2023)



Note: County map showing the share of households paying >30% of income on housing. Light gray indicates counties with no data (e.g., Connecticut due to Census planning region reclassification).

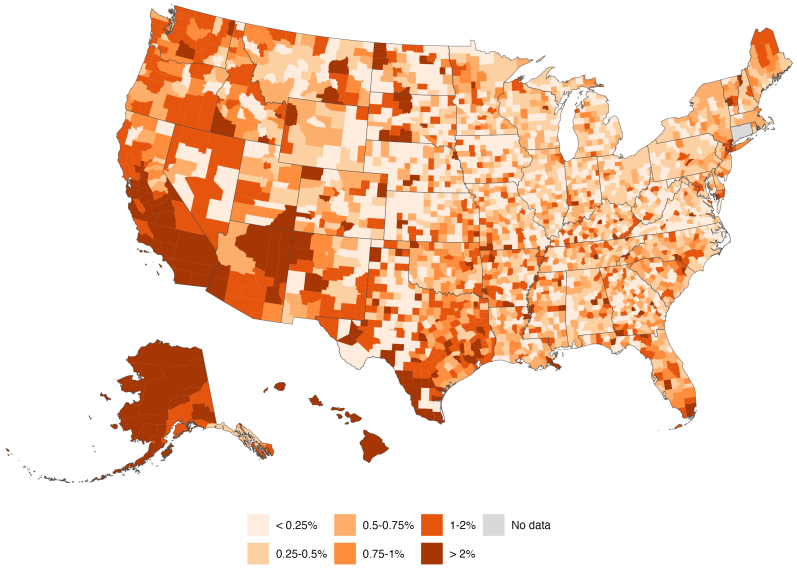
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Figure B2: Geographic Distribution of New Construction Share (2023)



Note: County map showing the share of housing units built in 2020 or later. Light gray indicates counties with no data.

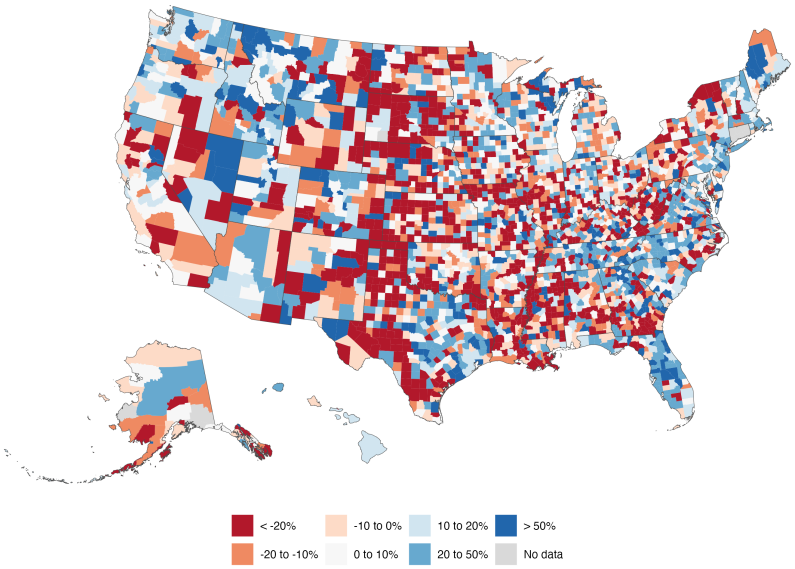
Figure B3: Geographic Distribution of Overcrowding Rate (2023)



Note: County map showing the share of occupied housing units with ≥1.5 persons per room. Light gray indicates counties with no data.

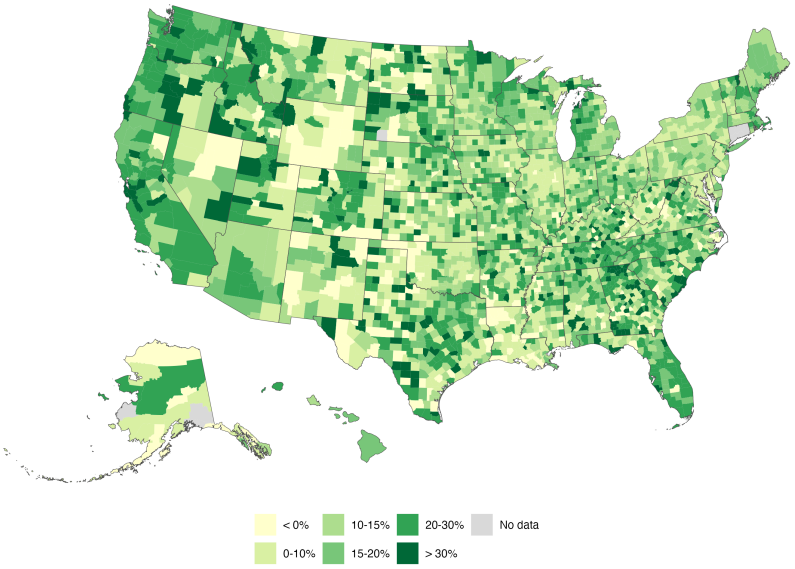
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Figure B4: County In-migration Growth Rate (2013–2023)



Note: Percentage change in net in-migration between 2009–2013 and 2019–2023 ACS periods. Light gray indicates counties with no data.

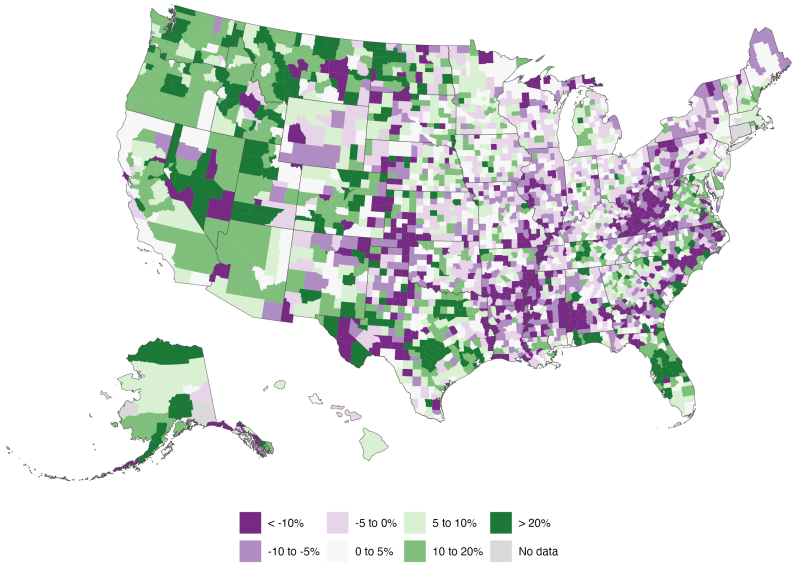
Figure B5: Real Median Household Income Growth (2013–2023)



Note: Percentage growth in inflation-adjusted median household income (2023 dollars). Light gray indicates counties with no data.

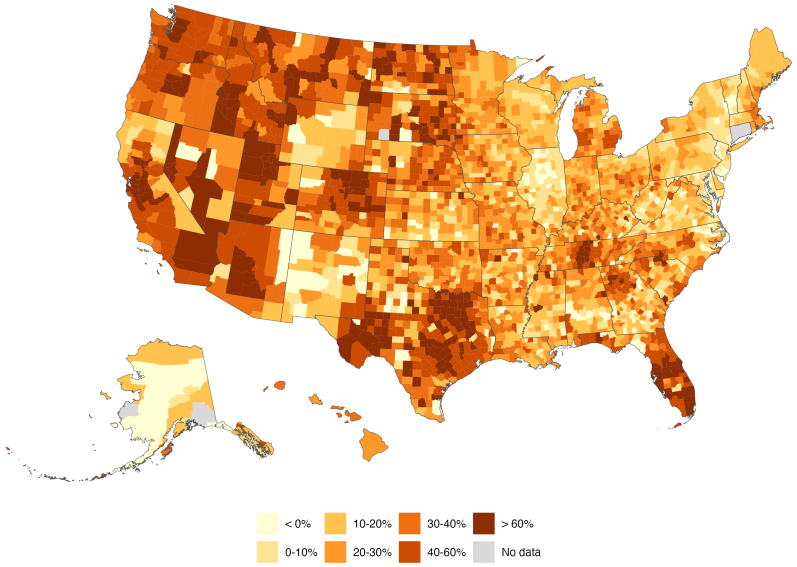
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Figure B6: Early Prime-working-age Population Growth (2013–2023)



Note: Percentage growth in population aged 25–44 between 2009–2013 and 2019–2023. Light gray indicates counties with no data.

Figure B7: Real Median Housing Value Growth (2013–2023)



Note: Percentage growth in inflation-adjusted median owner-occupied housing value (2023 dollars). Light gray indicates counties with no data.

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Appendix C. Index Component Variation and Reliability

This appendix addresses the statistical variation of the core index components—and their alternative specifications—and evaluates the internal consistency of the multidimensional composite index.

C.1. Relative Dispersion and Decile Variation

Although baseline measures like new construction and overcrowding exhibit low absolute medians across counties, they possess exceptionally high relative dispersion. To evaluate dispersion independent of scale, we utilize the coefficient of variation (CV = $(\sigma/\mu) \times 100$).

As shown in Table C1, the coefficient of variation reveals extreme relative variance for new construction (99.8%) and severe baseline overcrowding (150.2%), compared to cost burden (24.8%). Other alternative indicators, such as lacking plumbing (217.8%) and lacking a complete kitchen (79.9%), show similarly extreme relative variation.

Furthermore, these constrained variables exhibit highly right-skewed distributions with long tails representing localized extremes. For instance, baseline new construction reaches 1.86% at the 90th percentile (a 23-fold increase from the 10th percentile). Because the HLI z-score standardizes all variables prior to aggregation, differences in absolute scale are eliminated, ensuring the index captures the robust relative variation of these constrained components.

Table C1: Relative Variation and Decile Distributions of HLI Components and Alternatives (2023)

Variable	CV (%)	Min	p10	p30	p50	p70	p90	Max
Housing Cost Burden (share)	24.8	0.0	17.1	20.5	23.1	26.0	31.5	52.2
New Construction (share 2020+)	99.8	0.0	0.1	0.4	0.7	1.0	1.9	9.0
Overcrowding (share 1.5+)	150.2	0.0	0.0	0.3	0.5	0.8	1.5	20.5
Value-to-Income Ratio	39.7	0.6	1.9	2.4	2.8	3.3	4.5	12.2
Rent-to-Income Ratio	20.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Median Year Built	0.6	1938	1961	1972	1979	1984	1991	2010
Vacant Occupancy (share)	61.4	1.7	6.4	10.5	14.8	19.7	30.4	77.3
Old Housing (share pre-1940)	77.1	0.0	2.9	6.1	10.6	18.9	30.8	58.3
Adequate Space (share $\leq$1 per rm)	2.3	60.7	95.7	97.4	98.1	98.7	99.3	100.0
Severe Overcrowding (share >2 per rm)	243.2	0.0	0.0	0.0	0.1	0.2	0.5	10.6
Mobile Homes (share)	80.0	0.0	2.0	5.1	8.9	14.5	24.2	51.7
Lacking Plumbing (share)	217.8	0.0	0.0	0.2	0.4	0.6	1.2	33.5
Lacking Kitchen (share)	79.9	0.0	1.2	2.2	3.4	5.0	8.2	44.4

Note: $N = 3,135$ counties. Coefficient of Variation ($CV = (\sigma/\mu) \times 100$) captures relative dispersion independent of absolute indicator scale.

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C.2. Component Reliability and Correlation (Cronbach's Alpha)

We evaluated the internal consistency of the composite index using Cronbach's alpha (see Table C2). For the equal-weighted HLI, the across-dimension alpha is near zero ($\alpha = -0.016$), reflecting weak correlations between the dimensions (affordability and adequacy $r = 0.15$; availability and affordability $r = -0.15$; availability and adequacy $r = -0.017$) as shown in Figure C1. For the H-PCA index, alpha is notably negative ($\alpha = -0.79$), driven by the strong negative correlation between affordability and availability ($r = -0.35$).

As emphasized in composite indicator methodology (OECD, 2008), near-zero or negative across-dimension alphas are expected and appropriate for multidimensional indices. The three pillars of the HLI intentionally capture distinct, often countervailing constraints (e.g., active construction often co-occurs with high cost burdens). High internal consistency across dimensions would imply redundancy, suggesting the index could be collapsed into fewer components.

Conversely, the *within-dimension* indicators demonstrate solid internal consistency. In the H-PCA specification, the three cost measures (affordability) show strong convergence ($\alpha = 0.81$), while the availability and adequacy dimensions show acceptable moderate consistency ($\alpha = 0.68$ respectively). This pattern—strong within-dimension coherence but weak across-dimension correlation—confirms that the HLI successfully aggregates non-redundant facets of housing livability.

Table C2: Cronbach's Alpha Reliability Estimates for HLI Dimensions

Index	Level	Dimension	Cronbach's Alpha
Simple HLI (v1.2a)	Across-dimension	Composite	-0.016
H-PCA HLI (v2.0)	Across-dimension	Composite	-0.786
H-PCA HLI (v2.0)	Within-dimension	Affordability	0.806
H-PCA HLI (v2.0)	Within-dimension	Availability	0.678
H-PCA HLI (v2.0)	Within-dimension	Adequacy	0.680

Appendix D. Hierarchical PCA: Construction and Sign Correction

The H-PCA used as the main robustness check in Tables 4 and 5 applies PCA separately within each housing-livability dimension before combining the resulting dimension scores. The procedure adapts the hierarchical principle of grouping related variables before modeling their shared variation (Avellaneda and Serur, 2020). It does not reproduce the full HPCA correlation model of Avellaneda and Serur (2020), which models both within- and cross-cluster asset correlations. Instead, because our objective is composite-index construction, we use a dimension-first implementation in which the first principal component is retained within each theoretically defined AAA dimension and the three scores are combined with equal weights. This application-specific adaptation preserves the conceptual structure of the HLI while allowing the indicators within each dimension to receive data-driven loadings. We refer to this specification as the H-PCA HLI. The procedure is implemented in five steps.

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Figure C1: Pairwise Correlation Matrix across Dimensions: Equal-weight HLI (left) and H-PCA (right)



Note: Heatmap of pairwise Pearson correlation coefficients across the three housing dimensions for the Equal-weight HLI and the H-PCA HLI across 3,135 U.S. counties.

Step 1: Variable assignment and direction harmonization. Negative indicators are reversed by multiplying by -1 so that higher values consistently indicate more favorable housing conditions. Twelve variables are assigned to three dimensions:

Table D1: Variables Assigned to Dimensions and Direction of Coding in H-PCA

Dimension	Variables	Direction
Affordability	Cost burden rate (share spending >30% on housing)	Higher = worse → reversed
	House-value-to-income ratio	Higher = worse → reversed
	Rent-to-income ratio	Higher = worse → reversed
Availability	Share of units built 2020 or later	Higher = better → kept
	Median year structure built	Higher = better → kept
	Share of vacant occupancy units for all types	Higher = worse → reversed
	Share of units built 1939 or earlier	Higher = worse → reversed
Adequacy	Share of units with ≤1 person per room	Higher = better → kept
	Share of units with >2 persons per room	Higher = worse → reversed
	Share of mobile homes	Higher = worse → reversed
	Share of occupied units lacking complete plumbing	Higher = worse → reversed
	Share of occupied units lacking complete kitchen	Higher = worse → reversed

These variable directions follow the conceptual structure of the AAA framework and established housing research. Higher housing costs relative to income are treated as less

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favorable affordability outcomes. New construction and newer housing stocks are treated as favorable indicators of housing-market renewal, whereas high vacancy rates and large concentrations of very old housing are treated as unfavorable because they are commonly associated with disinvestment or weak housing-market conditions. Adequacy indicators capture both living space and housing quality; severe overcrowding and the absence of complete plumbing or kitchen facilities indicate housing inadequacy. Mobile-home prevalence is included as a housing-stock vulnerability indicator. Although manufactured housing provides an important source of affordable housing in many rural communities, higher concentrations of mobile homes are often associated with broader challenges related to housing quality, financing, replacement, and long-term housing conditions.

Step 2: Standardization. All direction-harmonized variables are z-scored (mean zero, unit standard deviation) across counties, so that differences in natural units do not drive the PCA solution.

Step 3: Dimension-level PCA. PCA is run separately on the correlation matrix of indicators within each dimension $d \in \{\text{affordability}, \text{availability}, \text{adequacy}\}$:

$$F_{d,c} = \sum_{j=1}^{K_d} w_{d,j} \tilde{Z}_{d,j,c} \tag{D1}$$

where $w_{d,j}$ is the first principal component eigenvector loading of variable j in dimension d. The first principal component (PC1) is retained. Because PC1 by construction captures the shared variance between the variables, it serves as a data-driven composite score for that dimension. The variance explained by PC1 within each dimension is 72.2% for affordability, 56.1% for availability, and 47.2% for adequacy.

Step 4: Orienting the dimension scores. Let X denote the centered and standardized county-by-indicator matrix for a given dimension. The first principal-component loading vector, w_1, is the unit eigenvector associated with the largest eigenvalue, λ_1, of the covariance or correlation matrix Σ:

$$\Sigma w_1 = \lambda_1 w_1 \quad \text{subject to} \quad \| w_1 \|_2 = 1$$

The corresponding county scores are $y_1 = X w_1$. A unit eigenvector is defined only up to sign. Specifically, $\Sigma(-w_1) = \lambda_1(-w_1)$. Hence, $-w_1$is an equally valid unit eigenvector with the same eigenvalue, and its corresponding scores are $-y_1$. The two orientations explain the same proportion of variance and differ only in the direction of the component axis.

Because the sign of a principal component is arbitrary, each dimension score must be oriented consistently with the interpretation of the HLI. For each dimension, we create a reference score by averaging the standardized indicators from Step 1 for each county. If the reference score is negatively correlated with the unadjusted PC1 scores from Step 2, we reverse the signs of the PC1 scores and loadings so that higher component scores indicate more favorable housing conditions. This sign reversal leaves the eigenvalue, variance explained, pairwise distances among counties, and PCA fit unchanged. It only changes the orientation of the component. All three dimension scores required sign reversal in the present application.

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Step 5: Equal-weight combination and rescaling. The three sign-corrected dimension PC1s are combined with equal weights:

$$\mathrm{HLI}_{\text{H-PCA},c} = \frac{1}{3}\widetilde{\mathrm{PC1}}_{\text{afford},c} + \frac{1}{3}\widetilde{\mathrm{PC1}}_{\text{avail},c} + \frac{1}{3}\widetilde{\mathrm{PC1}}_{\text{adequacy},c} \tag{D2}$$

where $\widetilde{\mathrm{PC1}}_{d,c}$ represents the sign-corrected first principal component score of dimension d in county c.

The composite is then linearly rescaled to the 0–100 range for comparability with the equal-weight index. The resulting sign-corrected H-PCA index has a national mean of 79.1 and a standard deviation of 5.9. Under the H-PCA index, the correlation between the equal-weight HLI and the H-PCA index is 0.821. The equal weighting at the cross-dimension combination stage means that the H-PCA and the equal-weight HLI share the same dimensional structure; they differ only in how each dimension's internal variables are aggregated (data-driven PCA weights vs. assumed equal weights).

Appendix E. Sensitivity Analysis – Alternative Variable Compositions

We evaluated seven alternative index specifications (S1–S7) by systematically varying the measurement choice within each of the three housing-livability dimensions while holding the equal-weight aggregation scheme constant. Scenarios S1–S3 replace one dimension at a time, while S4–S7 replace two or all three dimensions simultaneously.

- **Affordability**: The baseline uses the share of households spending >30% of income on housing (cost burden rate). Alternative scenarios substitute the ratio of median house value to median household income, which captures the wealth-building constraint for prospective homeowners rather than the monthly cash-flow constraint for current occupants.

- **Availability**: The baseline uses the share of units built 2020 or later, capturing the most recent supply response. Alternative scenarios substitute median year structure built, a longer-horizon measure that reflects the overall age of the housing stock.

- **Adequacy**: The baseline uses the share of occupied units with 1.5 or more persons per room (overcrowding rate). Alternative scenarios substitute the share with 2.0 or more persons per room, a stricter threshold capturing severe overcrowding.

Across all alternative specifications, the direction and statistical significance of associations with demographic correlates remain stable. The Pearson correlations between each alternative index and the baseline equal-weight specification range from 0.34 to 0.93, confirming that while the indices capture the same broad phenomenon, the specific variable choice does introduce meaningful variation (see Table E1).

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Table E1: Correlations Between Baseline (S0) and Alternative Scenarios (S1–S7)

Scenario	Pearson	Kendall
S1: Adequacy (Severe Overcrowding)	0.93	0.80
S2: Construction (Median Age)	0.85	0.60
S3: Affordability (Value/Income)	0.87	0.61
S4: Adequacy + Availability	0.77	0.53
S5: Adequacy + Affordability	0.80	0.53
S6: Availability + Affordability	0.72	0.42
S7: All Three	0.63	0.34

Appendix F. Non-Metro Counties Housing Sensitivity Analysis

Because rural and non-metropolitan housing markets are structurally distinct from metro cores, characterized by lower developer density, higher construction mobilization costs, and lower average household incomes, we evaluate whether our core findings hold when restricting the analysis to the non-metro counties (comprising both metro-adjacent and non-adjacent non-metro counties). Restricting the sample to non-metro counties (N = 1,976) ensures that the observed associations between the HLI and demographic correlates are not driven by the stark contrasts between urban and rural areas or by metropolitan suburbanization trends.

Table F1: Non-Metropolitan Regression Coefficients

Method	In-Migration Growth	HH Income Growth	Early Prime-Working-Age Pop. Growth	Housing Value Growth
Equal-Weight	0.005	0.046**	0.006	0.026*
	(0.004)	(0.008)	(0.013)	(0.014)
H-PCA (sign-flipped)	0.003	0.046**	−0.001	0.005
	(0.003)	(0.012)	(0.009)	(0.012)

Notes: Standard errors in parentheses. $^{+}$ $p < .10$. * $p < .05$. ** $p < .01$.

F.1. Robustness of Income Growth

As shown in Table F1, the positive relationship between the HLI and household income growth remains highly robust and statistically significant in the non-metropolitan sample. Under the baseline Equal-Weight index (S0), a higher HLI score is a strong positive predictor of real median household income growth ($\beta = 0.046$). Under the sign-flipped H-PCA index, the coefficient remains virtually identical ($\beta = 0.046$). This confirms that higher housing livability is systematically associated with household economic upward mobility in rural America.

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F.2. Divergence in Demographic Correlates

In contrast to the national sample, the associations between the HLI and demographic growth indicators, like in-migration change and early prime-working-age population growth, become statistically non-significant when restricting the analysis to rural counties. This divergence reflects a crucial structural characteristic of rural housing markets:

1. **Economic Primacy in Rural Migration**: In non-metropolitan areas, migration and prime-age worker retention are primarily driven by employment opportunities and regional economic structural factors, rather than housing availability or affordability alone. A county may have highly livable and affordable housing, but it cannot attract or retain working-age households if the local labor market is thin or contracting.

2. **Weak Spatial Commuting Spillovers**: Unlike metropolitan collar counties where housing construction immediately attracts commuters from adjacent job centers, remote non-metropolitan counties do not experience the same residential elasticity. Housing improvements in remote rural areas support local household stabilization (reflected in income growth) but do not trigger automatic demographic expansion.

Appendix G. Spatial Econometric Robustness Check (Spatial Durbin Model)

To address the potential for bias from spatial spillovers and spatial dependency across county boundaries, we estimate a Spatial Durbin Model (SDM) as a robustness check for our validation regressions. The SDM simultaneously models spatial lags in both the dependent variable (the HLI) and the independent variables (the demographic and economic correlates):

$$\mathrm{HLI}_c = \rho \sum_{j \neq c} W_{\mathrm{cj}} \mathrm{HLI}_j + \beta X_c + \theta \sum_{j \neq c} W_{\mathrm{cj}} X_j + \alpha + \epsilon_c$$

where W is a row-standardized Queen contiguity weight matrix constructed over the contiguous United States (excluding Alaska and Hawaii, leaving $N = 3,099$ counties), ρ is the spatial autoregressive parameter, and X_c is the demographic and economic correlates. Due to the feedback loops inherent in spatial autoregressive models, the regression coefficients cannot be interpreted directly. Instead, we calculate the Direct Effect (the impact of a local change in the predictor on local HLI), the Indirect Effect (the spatial spillover effect from changes in neighboring counties), and the Total Effect (the cumulative impact). Standard errors and p-values are computed via 200 simulation runs.

As shown in Table G1, the OLS validation findings remain highly robust when explicitly modeling spatial processes. For all four demographic and economic correlates, the Direct Effect is positive, highly statistically significant, and consistent with the main text's baseline OLS estimates. Specifically, a higher local housing livability index is strongly associated with local household income growth ($\beta_{\mathrm{direct}} = 0.051$), early prime-working-age population growth ($\beta_{\mathrm{direct}} = 0.047$), home value growth ($\beta_{\mathrm{direct}} = 0.030$), and in-migration growth ($\beta_{\mathrm{direct}} = 0.008$).

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The Indirect (Spillover) Effects reveal nuanced regional dynamics: 1. Income Growth Spillovers: Neighboring household income growth has a negative and statistically significant spillover effect on a county's local HLI ($\beta_{\text{indirect}} = -0.065$). This suggests a strong regional sorting and cost pressure effect: when neighboring counties experience income booms, demand pressures spill over, bidding up local housing cost burdens and reducing local affordability without a matching increase in local incomes. 2. Other Spillovers: Spillovers for in-migration, early prime-working-age population growth, and home value growth are statistically non-significant, suggesting that spatial dependencies in these dimensions are largely localized or absorbed by the spatial lag of the HLI itself ($\rho \approx 0.45$, which is positive and extremely significant across all specifications). These findings confirm that the descriptive patterns identified in the main text are not artifacts of spatial autocorrelation, and highlight how regional housing market spillovers shape local housing health.

Table G1: Spatial Durbin Model (SDM) Impacts: Direct, Indirect (Spillover), and Total Effects

Demographic and Economic Correlate	Effect Type	Estimate	Std. Error	P-value
In-Migration Growth (%)	Direct	0.0083**	0.0021	0.0001
	Indirect (Spillover)	0.0039	0.0057	0.5174
	Total	0.0122^{+}	0.0065	0.0708
Income Growth (%)	Direct	0.0509**	0.0071	0.0000
	Indirect (Spillover)	−0.0652**	0.0225	0.0040
	Total	−0.0143	0.0243	0.5788
Early Prime-Working-Age Pop. Growth (%)	Direct	0.0468**	0.0061	0.0000
	Indirect (Spillover)	−0.0242	0.0157	0.1378
	Total	0.0227	0.0172	0.1743
Home Value Growth (%)	Direct	0.0302**	0.0052	0.0000
	Indirect (Spillover)	−0.0068	0.0101	0.4823
	Total	0.0233*	0.0098	0.0227

Notes: SDM estimated via maximum likelihood using a row-standardized Queen contiguity matrix on contiguous U.S. counties ($N = 3,099$). $^{+}$ $p < .10$. * $p < .05$. ** $p < .01$.

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