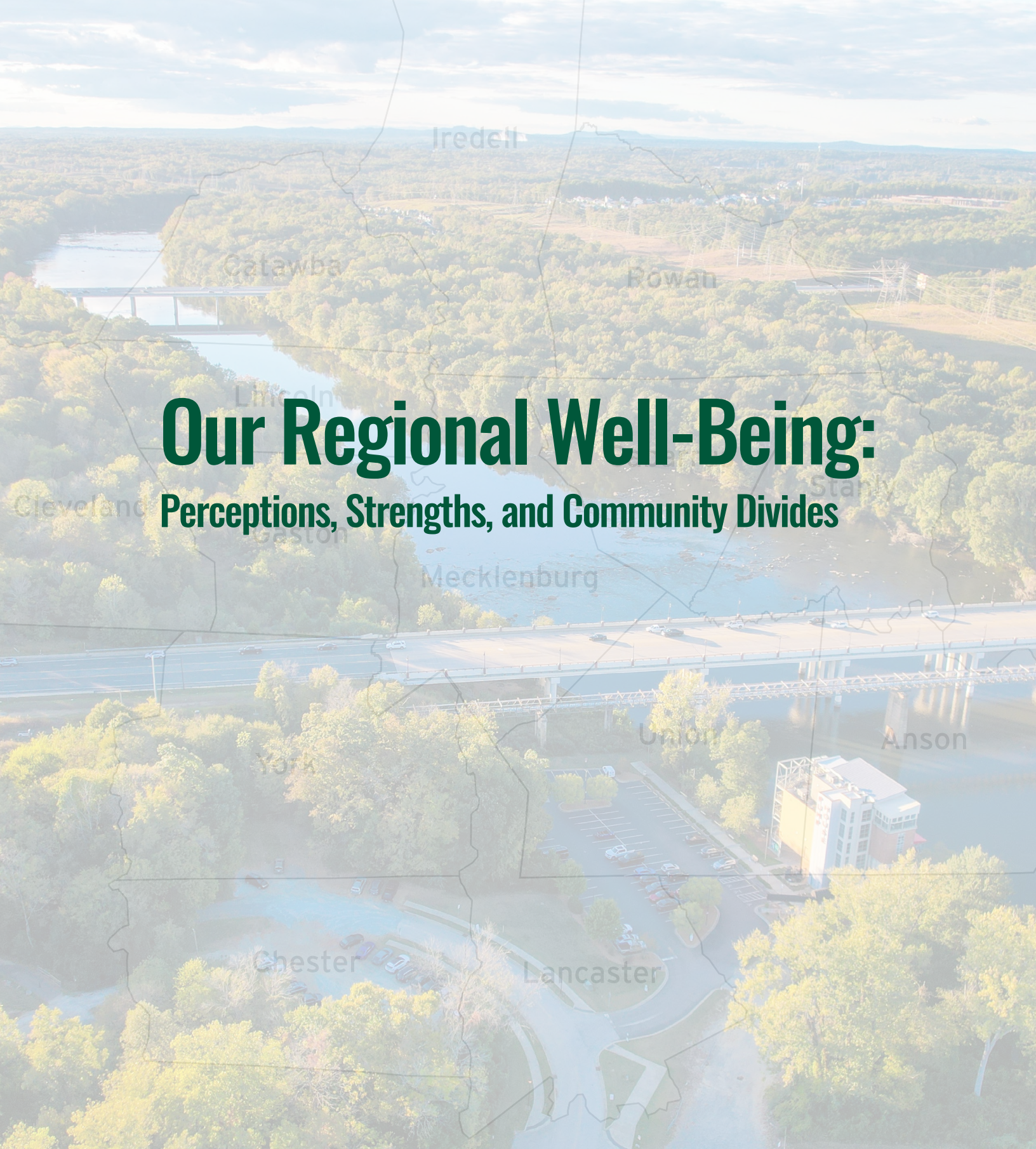




Our Regional Well-Being:

Perceptions, Strengths, and Community Divides



UNIVERSITY OF NORTH CAROLINA
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REGIONAL DATA TRUST



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Introduction

Well-being represents a cornerstone within social science and public policy research. A society's well-being can predict "the extent to which it [the country] is resilient, builds capacity for action, and is prepared to transcend challenges", and researchers, organizations, and governments are increasingly interested in better understanding it.¹

This concept has been studied in the United States, but it has often relied on static measures such as job counts, income, and/or Gross Domestic Product (GDP). While these measures provide critical information for researchers and policymakers alike, an increasing body of evidence demonstrates the shortcomings of using these measures to capture quality of life and subjective well-being effectively.² As the Stiglitz-Sen-Fitoussi commission concluded when examining societal measures of well-being and their limitations, well-being should be "...captured by asking people [about] themselves".³ This, however, raises two additional questions. First, what does well-being entail, and how can we measure it effectively? Second, how does understanding the well-being of citizens and residents inform or shape policy outcomes?

Moving to a Subjective Approach

This first question is not as straightforward as it may seem. Beyond a broad consensus that well-being is a multidimensional concept informed by an individual's physical, social, economic, and environmental circumstances,

there is significant variation in the dimensions that researchers include in their frameworks and how questions are worded to respondents.⁴ That said, there is agreement that well-being often involves three domains: evaluative (how satisfied people are with life overall and whether life feels worthwhile), affective (the balance of positive and negative emotions in everyday experience), and eudaimonic (a sense of meaning and purpose).⁵

Using these domains and leveraging work from organizations such as the Happiness Research Institute and the Organisation for Economic Co-operation and Development (OECD), we also include thirteen measures related to:

- The level of connection we share with our network and community (social capital)⁶
- Financial resiliency and the ability to absorb an unexpected shock (economic security)⁷
- The safety and satisfaction one has from residing in their community (place)⁸
- Optimism about the future of the region (outlook)⁹

Why Studying Well-being Matters

This brings us to the second question from earlier: how does the well-being of citizens and residents matter, or shape, policy outcomes? Put another way, why should policymakers, researchers, practitioners, or residents in our region care about understanding well-being in the multidimensional way we are striving to create?

¹ "Promoting Well-Being," accessed August 3, 2026, <https://www.who.int/activities/promoting-well-being>.

² Andre Perry and Jonathan Rothwell, "We Need to Talk about Well-Being: Why the Study of Well-Being Is Crucial for Race Relations and Advancing Prosperity," *Brookings*, April 28, 2023, <https://www.brookings.edu/articles/we-need-to-talk-about-well-being-why-the-study-of-well-being-is-crucial-for-race-relations-and-advancing-prosperity/>; European Union, "Quality of Life Indicators," Eurostat, accessed July 3, 2026, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Quality_of_life_indicators.

³ Joseph E. Stiglitz et al., "Report by the Commission on the Measurement of Economic Performance and Social Progress," 2009.

⁴ Aaron Jarden and Annalise Roache, "What Is Wellbeing?," *International Journal of Environmental Research and Public Health* 20, no. 6 (2023): 5006, <https://doi.org/10.3390/ijerph20065006>; Antonella Delle Fave et al., "The Eudaimonic and Hedonic Components of Happiness: Qualitative and Quantitative Findings," *Social Indicators Research* 100, no. 2 (2011): 185-207, <https://doi.org/10.1007/s11205-010-9632-5>.

⁵ Carol D. Ryff, "Psychological Well-Being Revisited: Advances in the Science and Practice of Eudaimonia," *Psychotherapy and Psychosomatics* 83, no. 1 (2014): 10-28, <https://doi.org/10.1159/000353263>; OECD, "OECD Guidelines on Measuring Subjective Well-being," OECD, OECD Publishing, March 20, 2013, <https://doi.org/10.1787/9789264191655-en>; Ed Diener et al., "Subjective Well-Being: Three Decades of Progress," *Psychological Bulletin* 125, no. 2 (1999): 276-302, <https://doi.org/10.1037/0033-2909.125.2.276>.

⁶ Robert D. Putnam, *Bowling Alone: The Collapse and Revival of American Community*, Revised and updated (Simon & Schuster Paperbacks, 2020); Sheldon Cohen, "Social Relationships and Health," *American Psychologist* 59, no. 8 (2004): 676-84, <https://doi.org/10.1037/0003-066X.59.8.676>.

⁷ Sendhil Mullainathan and Eldar Shafir, *Scarcity: Why Having Too Little Means so Much* (Times Books Henry Holt and Company, 2013).

⁸ Martha Craven Nussbaum, *Creating Capabilities: The Human Development Approach*, First Harvard University Press paperback edition (The Belknap Press of Harvard University Press, 2013).

⁹ Charles S. Carver et al., "Optimism," *Clinical Psychology Review* 30, no. 7 (2010): 879-89, <https://doi.org/10.1016/j.cpr.2010.01.006>.

To start with, individual-level well-being can directly influence other outcomes. Researchers have found a causal link between well-being and health outcomes, as well as overall mortality rates. Individuals with higher levels of subjective well-being and strong social relationships are found to live longer, on average, while communities with higher levels of optimism display lower rates of substance abuse.¹⁰ Other researchers have focused on the relationship between well-being and crime, with scholars finding evidence that generalized trust and community cohesion (the latter being a component of social capital) resulted in lower levels of violent crime at the neighborhood level.¹¹

Another branch in the literature demonstrates how well-being can serve as a predictive (leading) indicator of future structural transformations. This contrasts with traditional metrics like GDP, which inherently reflect past performance (lagging). Higher levels of social connectedness and community cohesion have been associated with allowing communities to recover more quickly from natural disasters (Hurricane Katrina) or other exogenous shocks (the 2008 financial crisis).¹² On the other hand, satisfaction with the local community and its perceived trajectory plays a critical role in residential mobility choices, with researchers noting the possibility of an eventual “brain drain” of residents (particularly younger ones) increases as belief in the community’s future outlook becomes more pessimistic.¹³

Survey Design

The UNC Charlotte Urban Institute (hereafter the Institute) partnered with the Happiness Research Institute and The Gambrell Foundation to ask a representative sample of residents to complete validated measures of subjective well-being, social capital, and financial resilience.

To effectively execute a representative survey over a 14-county region with a diverse demographic profile distributed across two states (North Carolina and South Carolina) and spanning a wide range of population sizes, from over 1 million in Mecklenburg to under 50,000

in Chester (SC) and Anson (NC) counties, the Institute employed American Directions Research Group (ADRG) to administer a multi-modal survey of:

- 1,700 interviews from non-probability online panelists;
- 2,300 live telephone interviews from listed samples. The live telephone sampling frame consists of a list of telephone numbers obtained from a commercial source and uses a systematic selection technique that selects every *n*th number from the list to generate a representative sample.

Weighting the Survey

In addition to using regional quotas, the Institute weighted the final sample by county of residence, race, ethnicity, gender, age, reported household income, and homeowner status. Economic stability (as measured by income) is an important driver of sentiment, particularly regarding quality of life and well-being. In addition, renters are traditionally underrepresented in survey research yet remain an ever-growing segment of the region’s population.

After testing multiple iterations of different weighting methodologies, our chosen method reduced the sample by just under 600 respondents (final sample size ~3300). Still, it kept our margin of error below 3% for the overall region. Interested readers can refer to **Appendix A for more detailed information on how the survey weights were calculated.**

Analysis and Methodology

To provide a clear and practical summary of our findings, we present weighted frequency distributions of the outcomes of interest, based on the survey weights. This ensures each overall metric reflects the true composition and demographic diversity of our target population, not just the raw respondent pool, providing a reliable, representative baseline for top-line decision-making.

After establishing these overall results, we disaggregate responses using weighted cross-tabulations to reveal how opinions, priorities, and behaviors vary across key socio-demographic and political groups. To keep these

¹⁰ Julianne Holt-Lunstad et al., “Social Relationships and Mortality Risk: A Meta-Analytic Review,” *PLoS Medicine* 7, no. 7 (2010): e1000316, <https://doi.org/10.1371/journal.pmed.1000316>; Bruno S. Frey, “Happy People Live Longer,” *Science* 331, no. 6017 (2011): 542-43, <https://doi.org/10.1126/science.1201060>; Carol Graham and Redzo Mujcic, “Hope and the Life Course: Results From a Longitudinal Study of 25,000 Adults,” *Health Economics* 35, no. 1 (2026): 90-101, <https://doi.org/10.1002/hec.70041>.

¹¹ Susybel Roxana Kallsen et al., “Collective Efficacy and Crime: Time-Variant Analyses of Los Angeles Neighborhoods, 2000 to 2008,” *Justice Quarterly* 43, no. 2 (2026): 420-42, <https://doi.org/10.1080/07418825.2025.2529354>; Robert J. Sampson et al., “Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy,” *Science* 277, no. 5328 (1997): 918-24, <https://doi.org/10.1126/science.277.5328.918>.

¹² Stefan Partelow, “Social Capital and Community Disaster Resilience: Post-Earthquake Tourism Recovery on Gili Trawangan, Indonesia,” *Sustainability Science* 16, no. 1 (2021): 203-20, <https://doi.org/10.1007/s11625-020-00854-2>; Daniel P. Aldrich, *Building Resilience: Social Capital in Post-Disaster Recovery* (The University of Chicago press, 2012).

¹³ Carol Graham and Sergio Pinto, “Unequal Hopes and Lives in the USA: Optimism, Race, Place, and Premature Mortality,” *Journal of Population Economics* 32, no. 2 (2019): 665-733, <https://doi.org/10.1007/s00148-018-0687-y>; Charlotta Mellander et al., “Here to Stay—The Effects of Community Satisfaction on the Decision to Stay,” *Spatial Economic Analysis* 6, no. 1 (2011): 5-24, <https://doi.org/10.1080/17421772.2010.540031>.

subgroup analyses substantively meaningful and statistically robust, we recoded select demographic variables before disaggregation. This consolidation serves two primary analytical objectives: aligning granular categories with theoretical frameworks (such as grouping income into distinct economic tiers) and addressing small sample sizes in underrepresented sub-populations to prevent sparse cell counts from inflating standard errors. Ultimately, this methodology safeguards statistical power while preserving clear, actionable categories for analysis.

When disaggregating to the county level, relying on raw county estimates can be problematic because sample sizes vary widely across counties, leading to large and uneven margins of error. In some counties, small sample sizes mean that reported percentages can fluctuate significantly due to chance, making it difficult to distinguish real differences from random noise. This can result in misleading conclusions and unreliable comparisons between counties.

Small-area estimation offers a solution by using statistical modeling to combine information from all counties and relevant demographic data. This approach stabilizes estimates for counties with small samples, reducing the impact of random variation and providing more accurate, reliable figures. By drawing on the broader dataset, small-area estimation ensures that county-level results more accurately reflect the true population, supporting more confident decision-making and targeted action. Interested readers can find a more detailed explanation of **how we used Bayesian methods to estimate county-level estimates in Appendix B.**

The Psychological Components of Well-Being

Life satisfaction, also referred to as subjective well-being (SWB), is a fundamental concept in the study of happiness and well-being.¹⁴ Asking about life satisfaction allows respondents to provide a relative self-assessment of their well-being within the context of other contributing factors and circumstances, and provides researchers with an invaluable baseline of how an individual appraises their current life situation.¹⁵

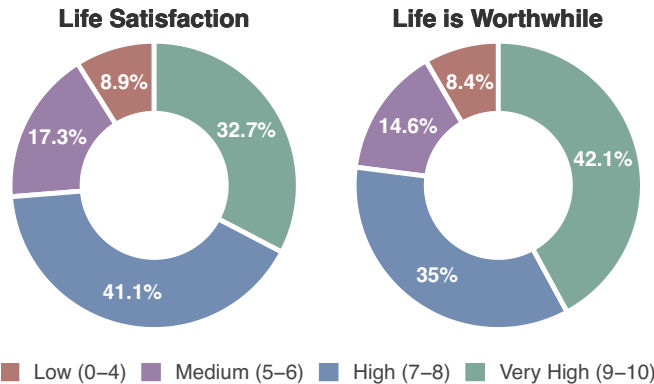
Purposeful well-being (PWB), or the sense that life is worthwhile, represents another facet of well-being. Research shows that *eudaimonic* tendencies, the belief that one's activities are worthwhile and that life has direction, are distinctly important to seeing higher levels of life satisfaction and more stable well-being over time, sometimes with a greater impact compared to the subjective orientations mentioned above.¹⁶

Given the importance of these dimensions to understanding the region's well-being, we asked respondents two questions:

- On a scale of 0 to 10, where 0 is "not at all" and 10 is "completely", how satisfied are you with your life nowadays?
- On a scale of 0 to 10, where 0 is "not at all" and 10 is "completely", overall, to what extent do you feel the things you do in your life are worthwhile?

Residents in our region report an average life satisfaction of 7.4 and an average score of 7.7 when determining if their life is worthwhile, demonstrating that our region appears to have a higher life satisfaction than the national average of 6.82.¹⁷ As there is only so much that can be gleaned from the weighted average, we recategorize the two respective variables into Low (0-4), Medium (5-6), High (7-8), and Very High (9-10) levels and look at the distribution of the data in Figure 1 below.

FIGURE 1 Residents report high levels of subjective and purposeful well-being



¹⁴ Ed Diener, "Guidelines for National Indicators of Subjective Well-Being and Ill-Being," *Applied Research in Quality of Life* 1, no. 2 (2007): 151-57, <https://doi.org/10.1007/s11482-006-9007-x>; Ulrich Schimmack, *Subjective Indicators of Well-Being: Life Satisfaction, Positive Affect, Negative Affect - Replicability-Index*, April 17, 2025, <https://replicationindex.com/2025/04/17/whatisswb/>.

¹⁵ Rosemarie Kobau et al., "Well-Being Assessment: An Evaluation of Well-Being Scales for Public Health and Population Estimates of Well-Being among US Adults," *Applied Psychology: Health and Well-Being* 2, no. 3 (2010): 272-97, <https://doi.org/10.1111/j.1758-0854.2010.01035.x>.

¹⁶ Alan S. Waterman et al., "The Questionnaire for Eudaimonic Well-Being: Psychometric Properties, Demographic Comparisons, and Evidence of Validity," *The Journal of Positive Psychology* 5, no. 1 (2010): 41-61, <https://doi.org/10.1080/17439760903435208>; Carol D. Ryff, "Psychological Well-Being Revisited: Advances in the Science and Practice of Eudaimonia," *Psychotherapy and Psychosomatics* 83, no. 1 (2014): 10-28, <https://doi.org/10.1159/000353263>.

¹⁷ Esteban Ortiz-Ospina et al., "Happiness and Life Satisfaction," *Our World in Data*, May 1, 2017, <https://ourworldindata.org/happiness-and-life-satisfaction>.

Figure 1 further emphasizes that respondents in the region, overall, report high levels of well-being, with around 33% reporting a very high level of life satisfaction and 42% strongly agreeing that their lives are worthwhile. Taken together, 67% of residents in the region have at least a high level of life satisfaction and a sense that their lives are worthwhile (scoring at least 7 on both questions).¹⁸

Granted, research has shown that well-being and happiness are not often evenly distributed amongst the population, often demonstrating disparities in well-being across individuals and social/structural determinants.¹⁹ Therefore, we examined the distribution of this level of well-being across the 14-county region shown in Figure 2 and across various demographic groups shown in Figure 3.

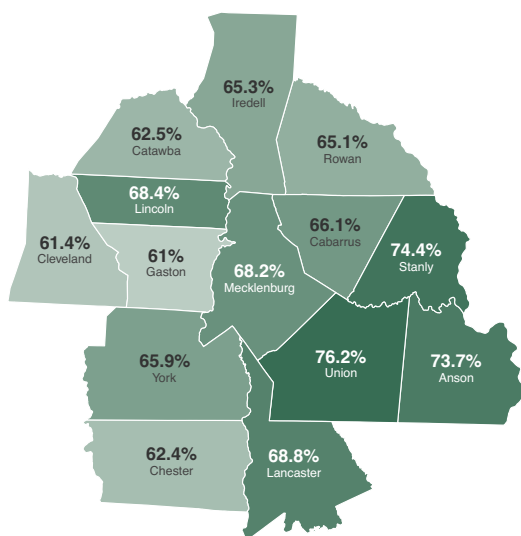


FIGURE 2 Residents in Anson, Stanly, and Union counties report highest levels of well-being

While most counties have around 65%-69% of residents with high levels of both personal life satisfaction and worth, a few notable exceptions stand out across the region. Cleveland, Chester, Gaston, and Catawba counties all have rates on this combined measure that are lower than the regional average. Conversely, Anson, Stanly, and Union counties show the strongest relative levels, placing them in the region's top group for high life satisfaction and purposefulness.

Turning to Figure 3, homeowners are about 23 percentage points more likely than renters to report a high level of well-being. Age and income are positively related to this metric, with both groups experiencing increased well-being as they grow older (age) or earn more (household income). This finding on income remains consistent with findings in the literature, while the relationship between age and well-being varies significantly between countries.²⁰ A similar trend appears in employment status, with those employed full-time reporting higher levels of well-being than those employed (but not full-time) and those currently out of work.

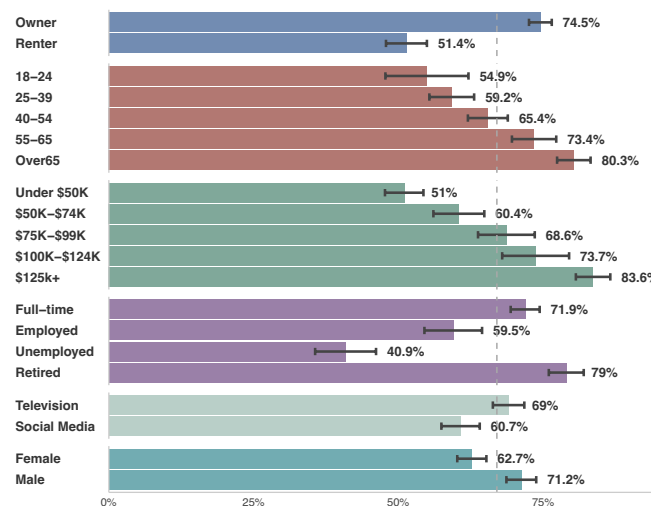


FIGURE 3 Homeowners, older residents, and households with higher income enjoy significantly higher levels of well-being

Another interesting divide is where residents get their information about local issues. Just under 70% of residents who obtain their information from more traditional sources, i.e., television, report a high sense of well-being. In comparison, just under 61% of residents who get their information from social media sources report the same level. Although not statistically significant, a slightly higher proportion of Hispanic residents (70%) report high levels of well-being than White (67%) and Black/African American (63%) residents.

¹⁸ Gallup Inc, "Indicator: Life Evaluation Index," Gallup.com, Accessed July 27, 2026, <https://www.gallup.com/394505/indicator-life-evaluation-index.aspx>.

¹⁹ Andrew Steptoe et al., "Subjective Wellbeing, Health, and Ageing," *The Lancet* 385, no. 9968 (2015): 640-48, [https://doi.org/10.1016/S0140-6736\(13\)61489-0](https://doi.org/10.1016/S0140-6736(13)61489-0); Ellen J. Thompson et al., "Psychological Distress, Depression, Anxiety, and Life Satisfaction Following COVID-19 Infection: Evidence from 11 UK Longitudinal Population Studies," *The Lancet Psychiatry* 9, no. 11 (2022): 894-906, [https://doi.org/10.1016/S2215-0366\(22\)00307-8](https://doi.org/10.1016/S2215-0366(22)00307-8).

²⁰ Michael Gurven et al., "Subjective Well-Being across the Life Course among Non-Industrialized Populations," *Science Advances* 10, no. 43 (2024): eado0952, <https://doi.org/10.1126/sciadv.ado0952>; Matthew A. Killingsworth, "Experienced Well-Being Rises with Income, Even above \$75,000 per Year," *Proceedings of the National Academy of Sciences* 118, no. 4 (2021): e2016976118, <https://doi.org/10.1073/pnas.2016976118>.

Understanding Social Connectedness

Well-being is not confined to just the personal. Research has found that the level of social connectedness, e.g., community trust, social networks, and perceived support, remains an important determinant of an individual's and population's quality of life.²¹ The importance of the connection, reciprocity, and trust between individuals and their social networks on an individual's well-being has remained a consistent source of interest since Putnam's seminal work nearly 30 years ago, as individuals in communities with higher levels of social capital report higher levels of subjective and purposeful well-being.²²

To assess the importance of social networks and relationships within the region, we began by asking residents how often they came into contact with friends, family, neighbors, and colleagues. For each group, respondents indicated how often they came into contact with it and could select from the following options: Never, Less than once a month, 1-3 times a month, Weekly, Daily, or Not relevant.

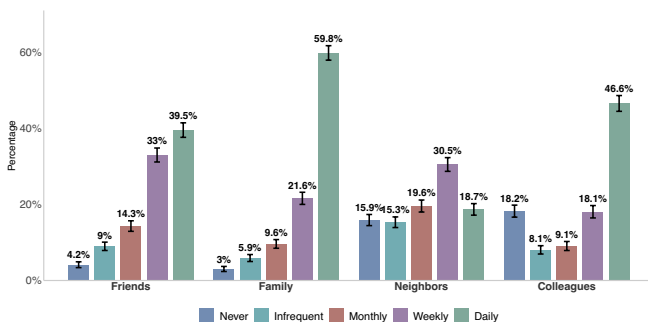


FIGURE 4 Residents have more frequent contact with their immediate networks

Figure 4 shows that over 70% of residents interact with or come into contact with their friends and family at least once a week. This number drops when we examine relationships beyond one's immediate circle, with fewer than 50% of residents reporting similar contact with their neighbors.

This discrepancy also appears in two related questions we asked about social connectedness. The first question asks "How would you describe your sense of belonging to your

local community?", while the second question asks "On a scale from 0 to 10, where 0 means you completely disagree and 10 means you completely agree: How much do you agree or disagree that if you were in trouble, you have relatives or friends you could count on?"

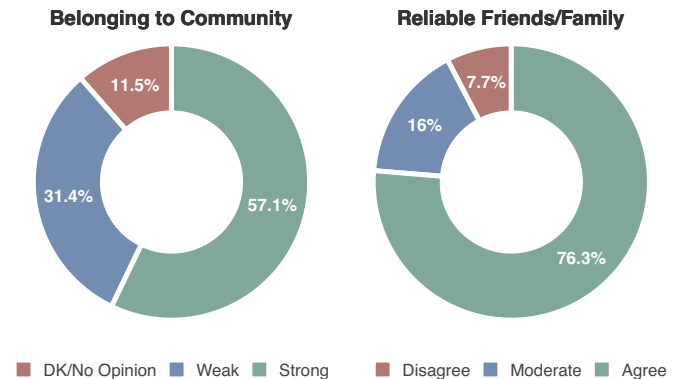


FIGURE 5 Residents express greater confidence in their support from immediate networks than connection to wider community

While 76% of residents strongly agree that they have relatives or friends they could count on if they were in trouble (score of at least 8 out of 10), just 57% of residents felt a strong sense of belonging to their local community.

While trying to understand these items separately may be difficult, research has shown that questions around the frequency of social contact, perceived availability of support, and sense of belonging to the community all map onto a multidimensional construct of social connection.²³ We therefore calculated a composite social connectedness score using the previous questions (seven in total, as the social contact question is split into the four categories) to provide a more robust overview of the level of social connectedness, or lack thereof, across the region. Confirmatory factor analysis (CFA) demonstrates the unidimensionality of these items and, consequently, supports treating them as indicators of a common underlying construct.

The composite variable ranges from -1.92 to 1.12. A higher score implies a higher level of social connectedness, with an individual having more regular contact with friends/family/neighbors/colleagues, a stronger sense of belonging to their local community, and a belief that they have friends/family they can count on in a crisis. Conversely, a lower score implies an individual is less likely to have regular contact

²¹ John F. Helliwell and Robert D. Putnam, "The Social Context of Well-Being," *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences* 359, no. 1449 (2004): 1435-46, <https://doi.org/10.1098/rstb.2004.1522>; Julianne Holt-Lunstad, "Social Connection as a Critical Factor for Mental and Physical Health: Evidence, Trends, Challenges, and Future Implications," *World Psychiatry* 23, no. 3 (2024): 312-32, <https://doi.org/10.1002/wps.21224>.

²² John F. Helliwell et al., "Social Capital and Well-Being in Times of Crisis," *Journal of Happiness Studies* 15, no. 1 (2014): 145-62, <https://doi.org/10.1007/s10902-013-9441-z>.

²³ "World Happiness, Trust and Social Connections in Times of Crisis," accessed July 2, 2026, <https://worldhappiness.report/ed/2023/world-happiness-trust-and-social-connections-in-times-of-crisis/>.

with these four groups, a weaker sense of belonging, and does not believe they have people they can count on.

We now turn our attention to this latter group. We begin by calculating the county-level estimates of residents with low levels of social connectedness (**social disconnection**) using our small-area estimation framework. These estimates are provided in Figure 6 below:

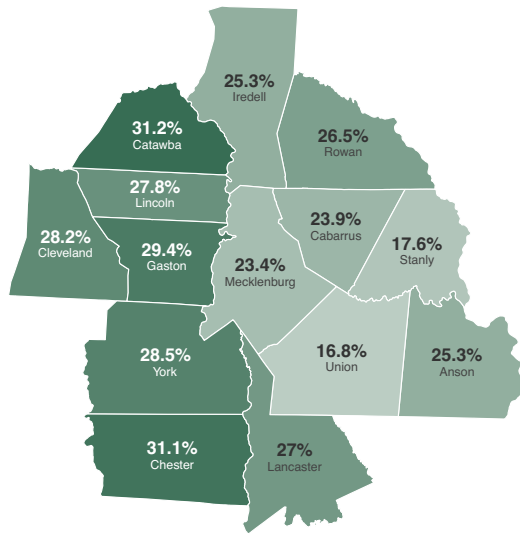


FIGURE 6 Residents in Gaston, Chester, and Catawba experience higher levels of social disconnection

Union, Stanly, and Mecklenburg counties have the smallest percentage of residents experiencing social disconnection. This suggests residents in these counties lead more socially active lives, with more regular social interactions and a stronger sense of community. Gaston, Chester, and Catawba counties cluster at the opposite end of this spectrum, implying that residents in these counties have much lower levels of interaction with their social networks and engage with their communities less frequently than the regional average.

Figure 7 plots the weighted percentage of residents experiencing social disconnection across select groups. Similar to other researchers, we find that renters are significantly more likely than homeowners to have weak social connections and support: approximately 38% of renters experience social disconnection compared to just 19% of homeowners, a difference of 18 percentage points.²⁴ Household income shows a linear trend: households earning under \$75,000 a year are significantly more likely to experience social marginalization than those earning at least \$125,000.

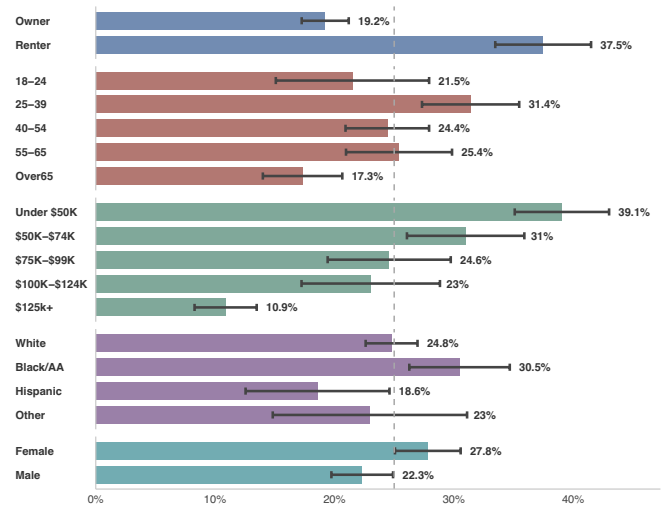


FIGURE 7 Renters, households with lower income, and residents between 25-39 years old are more likely to experience social disconnection

While slightly weaker than income, age also has a significant impact, but in a different way. Here we see a U-shaped relationship, with social disconnection peaking among residents aged 25-39, then dropping back to around the regional average. While middle-aged residents don't quite drop to the level of those under 25, it is interesting given the expected linear trend highlighted in the literature, and one that could warrant further exploration.²⁵ Hispanic residents experience the lowest rates of social disconnection, while Black/African American residents are more likely to experience this issue compared to White residents.

Moving from Connection to Trust

Generalized trust in others represented another facet of the social context of well-being, i.e., social capital. While the previous section discussed the importance of social connections to an individual's overall life satisfaction, research also points to a similar importance of generalized trust (the ability to trust others outside one's immediate network) for stable life evaluation and satisfaction.

Figure 8 shows that around 48% of residents in the region have a high level of trust in the general public, indicating strong agreement with the statement that "most people can be trusted". This is particularly interesting given recent national trends showing that around 25% of Americans

²⁴ Denise DiPasquale and Edward L. Glaeser, "Incentives and Social Capital: Are Homeowners Better Citizens?," *Journal of Urban Economics* 45, no. 2 (1999): 354-84, <https://doi.org/10.1006/juec.1998.2098>.

²⁵ Shannon Ang, "Life Course Social Connectedness: Age-Cohort Trends in Social Participation," *Advances in Life Course Research* 39 (March 2019): 13-22, <https://doi.org/10.1016/j.alcr.2019.02.002>.

believe that most people can be trusted.²⁶ While that GSS question is closed-ended rather than on a 0-10 scale, it suggests our region appears more trusting than the national average.

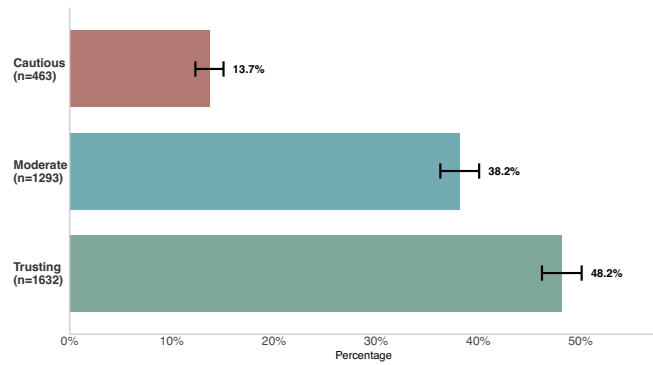


FIGURE 8 Less than half of residents believe people can be trusted, in general

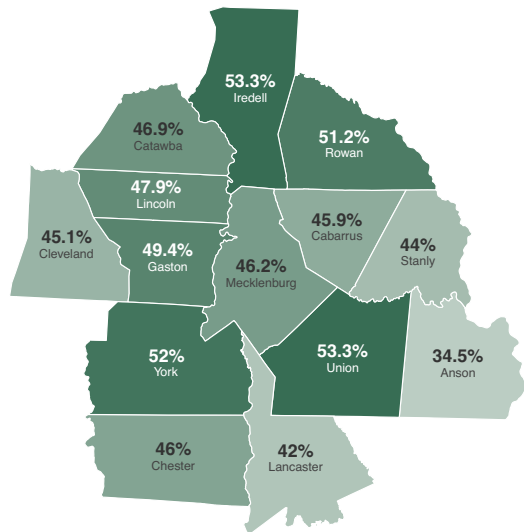


FIGURE 9 Residents in Iredell and Union counties express the highest levels of generalized trust

Figure 9 shows that a majority of counties cluster around the expected average level of generalized trust (48%), a finding that is consistent with research in the US.²⁷ The only outliers of interest are Anson and Lancaster, where residents express lower levels of social trust compared to the regional average, while Iredell and Union counties have residents

expressing higher levels of social trust compared to the regional average.

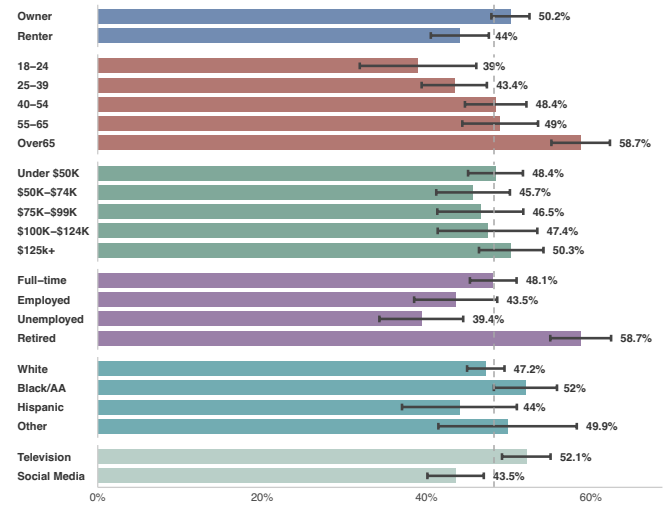


FIGURE 10 Homeowners, older residents and those getting information on local issues from television have higher levels of generalized trust

Homeowners express higher levels of social trust than renters, while residents across the region appear to report greater social trust as they get older. Residents who get local news on television report higher levels of social trust than those who get their news from social media (about a 9-percentage-point difference). No significant differences emerge across household income levels or race/ethnicity. While this finding is contrary to expectations, there may be other factors influencing this (null) relationship and could be of interest to explore further.²⁸

Economic and Financial Situation

It is impossible to discuss well-being and quality of life without discussing an individual's financial status/situation. Specifically, research shows that perceived financial trajectory (how have your finances changed over the past year) and financial resilience (the capacity to absorb an unanticipated expense without borrowing) remain core indicators of economic well-being and, by extension, overall quality of life.

²⁶ NORC at the University of Chicago, "General Social Survey, 1972-2024 Cumulative File," GSS Data Explorer, 2025.

²⁷ Laura Silver et al., "Americans' Trust in One Another," Pew Research Center, May 8, 2025, <https://www.pewresearch.org/2025/05/08/americans-trust-in-one-another/#h-geography>.

²⁸ Andrea Albertazzi et al., "Income Inequality and Social Trust," *Economics Letters* 257 (December 2025): 112675, <https://doi.org/10.1016/j.econlet.2025.112675>.

The first item, which asks about perceived changes over the past year, is drawn from behavioral economics, where research shows that an individual's self-evaluation of their financial situation can significantly affect their understanding of well-being.²⁹ The economics literature also informs the importance of using the "unexpected expense" or "financial fragility" item. Often defined as the inability to cope with a modest, unanticipated financial shock using readily available resources, this measure remains an integral part not only of the literature but also of the work of both the Federal Reserve and the United States Consumer Financial Protection Bureau.³⁰

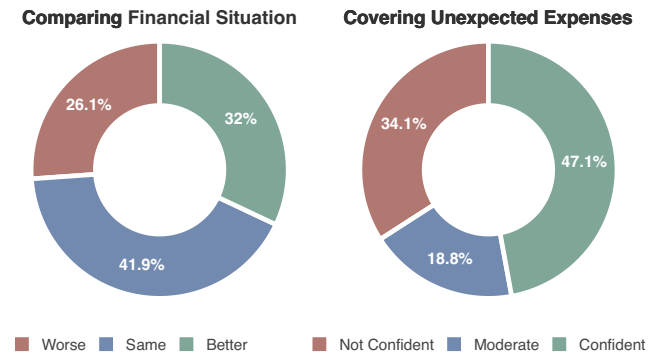


FIGURE 11 While a majority of residents state their financial situation is either the same or improved from a year ago, more than one-third are not confident in dealing with an unexpected expense

Figure 11 examines these two questions at the regional level. For the first question (perceived changes to one's financial situation), a plurality of residents say their finances are about the same as they were a year ago (as of April 2026). This is similar to findings from the same month from the Federal Reserve of New York, which reported that around 40% of respondents estimated their financial situation to be about the same as it was one year ago.³¹

This same study found that 42% of national respondents stated their financial situation has worsened in the last year. Interestingly, only a quarter of residents in our region say their finances are worse today than they were at this time last year. This could indicate relative economic resilience in our region compared to the country as a whole,

though it is difficult to state definitively without more advanced analyses.

The picture of our region's financial well-being does not improve when residents report their financial fragility. 34% of residents across the region say they are not confident they can handle an unexpected expense without asking for assistance. This is in line with recent data from the Federal Reserve, which found that a similar proportion of national respondents would have to borrow or rely on others to help pay for an unexpected expense.³² Given how many residents are concerned about this type of expense, we examine potential differences across groups and within our region.

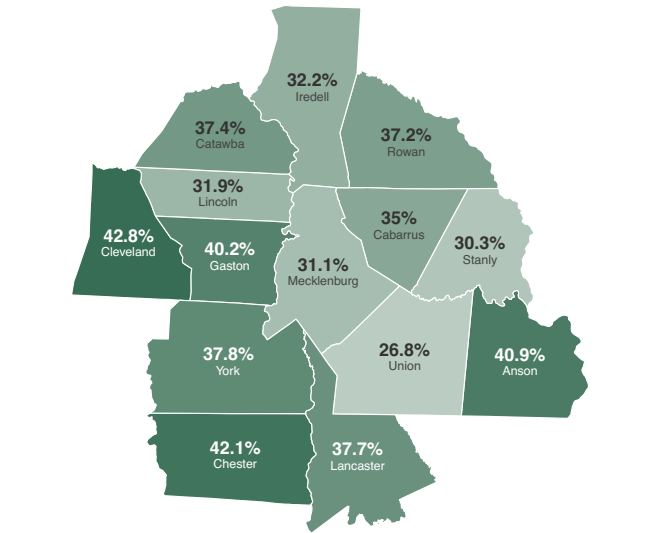


FIGURE 12 Residents in Gaston, Anson, Cleveland, and Chester counties report the highest levels of financial uncertainty

Union County stands out with the lowest relative rate of financial fragility across the region. A central group of counties, including Stanly, Mecklenburg, Iredell, and Lincoln, tracks close to the regional baseline. On the other end of the scale, Gaston, Anson, Cleveland, and Chester counties form a distinct cluster with elevated relative levels of financial vulnerability, illustrating that residents face greater difficulty handling an unexpected bill.

²⁹ Nishant Garg et al., "Financial Well-being: An Integrated Framework, Operationalization, and Future Research Agenda," *Journal of Consumer Behaviour* 23, no. 6 (2024): 3194-212, <https://doi.org/10.1002/cb.2372>.
³⁰ Annamaria Lusardi et al., *Financially Fragile Households: Evidence and Implications*, no. w17072 (National Bureau of Economic Research, 2011), w17072, <https://doi.org/10.3386/w17072>; Jacob S. Hacker et al., "The Economic Security Index: A New Measure for Research and Policy Analysis," *Review of Income and Wealth* 60, no. S1 (2014), <https://doi.org/10.1111/roiw.12053>.
³¹ Federal Reserve Bank of New York., "June Survey: Inflation Expectations Up at Short- and Medium-Term Horizons; Gas Price Growth Expectations Fall," 2026, <https://www.newyorkfed.org/microeconomics/sce>.
³² Federal Reserve Board, "Economic Well-Being of U.S. Households in 2025 - May 2026," 2026, <https://www.federalreserve.gov/publications/2026-economic-well-being-of-us-households-in-2025-executive-summary.htm>.

Given the variation across counties, it is unsurprising that groups within the region also differ significantly.

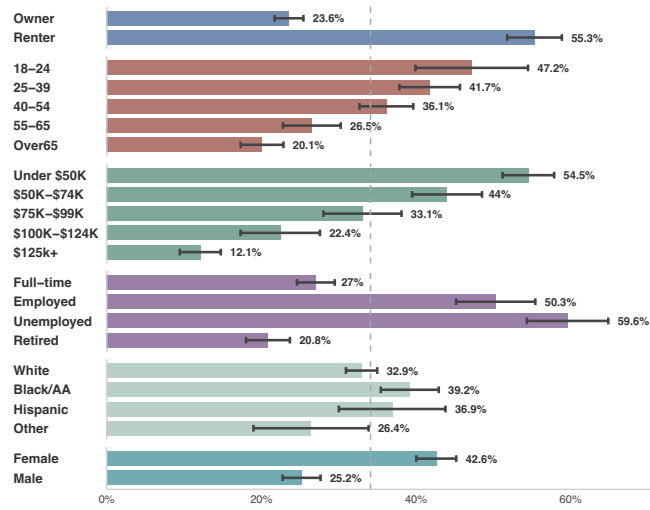


FIGURE 13 Renters, younger residents, households with lower income, females, Black and Hispanic residents are significantly more likely to be uncertain about their ability to deal with an unexpected expense

Renters report financial fragility at a rate just under 32 percentage points higher than homeowners, with age and income showing the expected linear decrease (older and higher-income residents have significantly lower levels of financial uncertainty). Gender also shows a significant difference: just under 43% of females have no confidence in dealing with an unexpected expense, compared to just over 25% of males (a difference of 18 percentage points). Race/Ethnicity also sees significant differences, with Black/African American (39%) and Hispanic (37%) residents experiencing greater uncertainty than White (33%) or other (26%) residents.

Regional Outlook

While previous sections of this report evaluate residents' immediate, daily realities—such as personal finances and social networks—this final section shifts to the broader regional picture. An individual's quality of life is heavily shaped by the community conditions around them, which can also have the impact of attracting and/or retaining residents; therefore, understanding how residents across our 14-county region feel about the region itself remains an important component not only to understanding well-

being but also for economic development considerations.³³ In this portion of the survey, respondents answered questions about regional strengths, challenges, and potential future outcomes.

Strengths of the Region

We begin by examining what residents consider the region's top assets (strengths). Among the many strengths residents listed, **food/restaurants** was cited most often (40.9% of residents), followed by **climate/weather** (35.8%), **job opportunities** (33.6%), **diversity** (31.2%), and **community/culture** (28.4%).

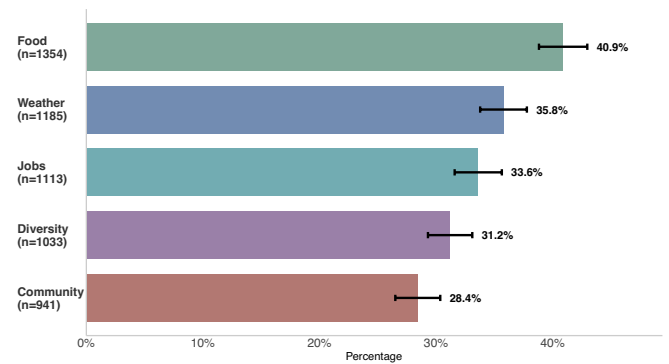


FIGURE 14 The Food and Restaurant scene was the most commonly selected strength of the region

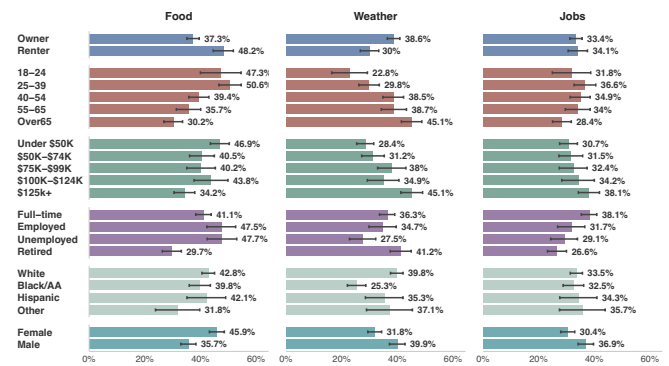


FIGURE 15 Gender, Household Income, and Employment Status show the largest differences in the expressed strengths of the region

Younger residents, renters, and females all ranked food and restaurants among the region's top strengths. More than half of adults aged 25-39 cited this as the region's top strength (50.6%, compared with 30.2% of seniors), while nearly half (48.2%) of renters cited it as the region's top strength, compared with 37.3% of homeowners.

³³ Edward L. Glaeser et al., "Consumer City," *Journal of Economic Geography* 1, no. 1 (2001): 27-50, <http://www.jstor.org/stable/26160399>; Carol Graham et al., "Monitoring Wellbeing as a Warning Indicator: The U.S. Crisis of Deaths of Despair," *Applied Research in Quality of Life*, November 15, 2025, <https://doi.org/10.1007/s11482-025-10517-y>; Johannes Emmerling et al., "Subjective Well-Being at the Macro Level—Empirics and Future Scenarios," *Social Indicators Research* 157, no. 3 (2021): 899-928, <https://doi.org/10.1007/s11205-021-02670-2>.

Climate/weather, on the other hand, was more likely to be cited as a strength by older respondents (45.1% of seniors compared with only 22.8% of adults aged 18-24), homeowners (38.6% of homeowners compared with 30% of renters), and males (39.9% compared to 31.8% for females).

Interestingly, job opportunities as a regional strength showed little variation across most socio-demographic groups, but were more likely to be identified as a strength among full-time workers (38.1%) and men (36.9% compared with 30.4% of women).

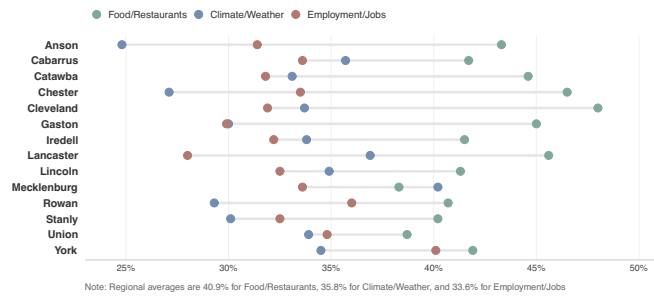


FIGURE 16 Agreement on the strengths of the region appears divided across a rural-urban divide

Geographically, strengths are sorted along a rural-urban divide, with appreciation for the region's food scene highest in peripheral counties such as Cleveland, Chester, and Lancaster. In comparison, only 38.3% of Mecklenburg County residents selected this as a strength. The idea that job opportunities are a regional strength is strongest in York and Rowan counties, while Lancaster residents were least likely to share this view.

Issues of the Region

Housing affordability was identified as a top-three concern for the region by nearly 60% of respondents, 13 percentage points higher than the second-highest concern (**crime and public safety**, with 46.3% of residents citing concern) and nearly double the other concerns (**transportation/traffic** at 29.4%, **taxes** at 27.4%, and **public education** at 27.2%).

The survey data on housing represents a curious paradox: many residents rate their own housing situation highly (mean of 7.7 on a 10-point scale), yet roughly 75% name housing affordability as a significant challenge in their community. At first glance, these two findings may seem in conflict, but they answer different questions. Satisfaction measures how residents feel about the housing they already hold, while the affordability question concerns the broader market as it stands today. The second question better informs policy because it reflects current rather than legacy conditions, and it is compelling because, in every county, at

every income level, and for both major political parties, residents describe the market as difficult.

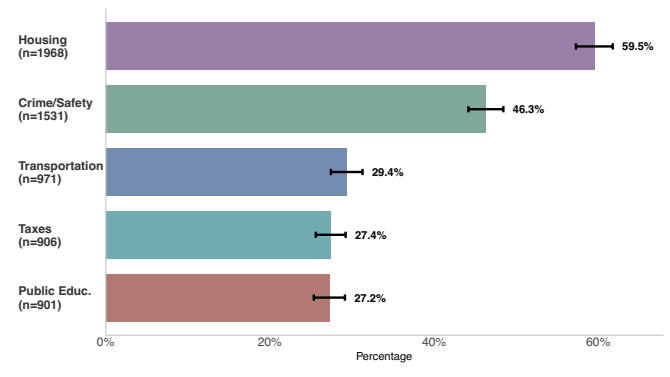


FIGURE 17 Housing affordability is the biggest concern for residents in our region by a significant margin

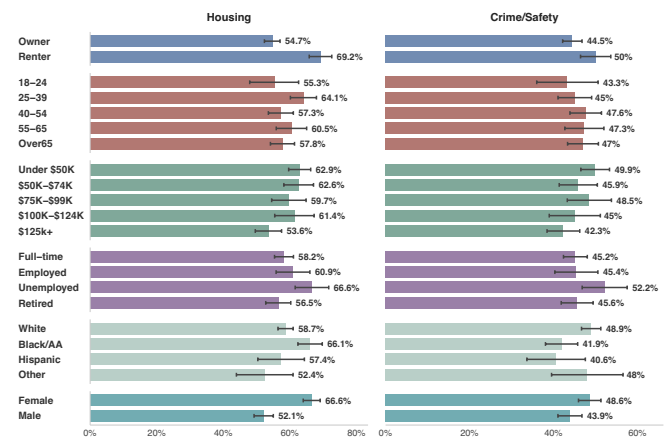


FIGURE 18 Renters, females, and household income see the greatest differences in their selection of housing affordability and crime/safety as issues of regional concern

Beyond this broad consensus around housing affordability are notable stratifications by social group. Concerns about housing affordability are highest among renters (69.2% compared with 54.7% of homeowners), women (66.6% compared with 52.1% of men), and Black/African American residents (66.1% compared to 58.7% of White and 57.4% of Hispanic/Latino residents).

Concerns about crime and safety show similar trends. Low-income households (49.9% compared to 42.3% for those earning at least \$125k), females (48.6% as opposed to 43.9% of males), and renters (50% compared to 44.5% of homeowners) are all more likely to be concerned about crime and safety across the region, none of which are necessarily surprising given the groups of individuals who are statistically the most likely to be victims of violent

crime.³⁴ What is interesting is that the trend for race/ethnicity flips from what we see with housing affordability. Here, White residents (48.9%) are statistically more likely to select crime/safety as a top regional concern compared to Black/African American (41.9%) or Hispanic/Latino (40.6%) residents.

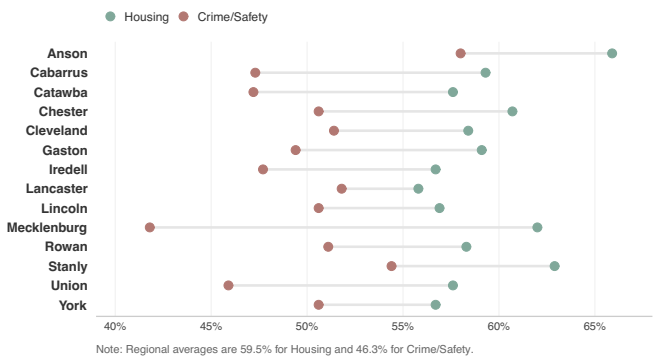


FIGURE 19 While concern about affordability is (largely) universal, concern about crime is concentrated in the peripheral counties

Geography tells a two-part story in the survey’s findings. On the one hand, housing affordability is a majority concern in all 14 counties. Concern about crime, by contrast, is concentrated in peripheral counties such as Anson and Stanly, compared with a regional low in Mecklenburg. This loose coupling of perceived vulnerability and actual recorded crime is a well-documented pattern.³⁵ Researchers have uncovered potential causal mechanisms behind this, including the effect of media coverage in rural areas.³⁶

It is also worth considering that respondents were asked about problems facing the entire region and thus may have answered with the entire 14-county region in mind, not just their home county.

Our Region in the next 3-4 years

Survey respondents were asked whether living conditions in their communities will be better, worse, or about the same in three to four years. Excluding those who were unable to say, 25% expected improvement, 43% expected stability, and 31% expected decline.

Group-based differences in outlook are apparent by age, housing tenure, and where respondents obtain their news about their local communities. Residents aged 25-55 expressed the highest rates of pessimism about the region’s

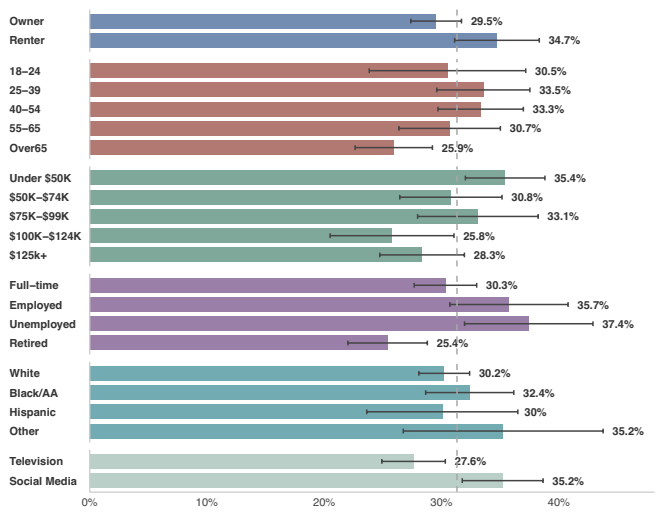


FIGURE 20 Renters and those getting their news from social media are significantly more likely to be pessimistic about their community’s future

future (~33%), renters (34.7%) were more likely to be pessimistic compared to homeowners (29.5%), and those who rely on social media as their primary news source (35.2%) are significantly more likely to be pessimistic compared to those relying on more traditional sources (27.6%).

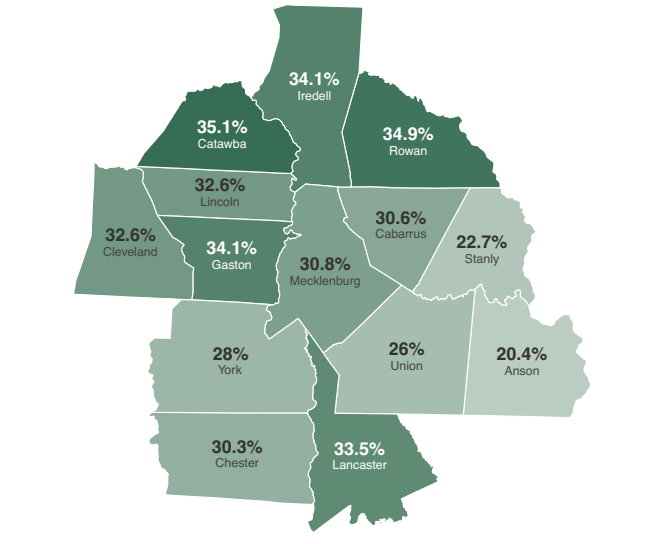


FIGURE 21 Pessimism regarding change in living conditions is highest in the northern part of the region

³⁴Erika Harrell et al., *Household Poverty and Nonfatal Violent Victimization, 2008-2012*, NCJ 248469 (U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics, 2014), <https://bjs.ojp.gov/content/pub/pdf/hpnnv0812.pdf>.

³⁵C. Hale, “Fear of Crime: A Review of the Literature,” *International Review of Victimology* 4, no. 2 (1996): 79-150, <https://doi.org/10.1177/026975809600400201>.

³⁶Ted Chiricos et al., “Crime, News and Fear of Crime: Toward an Identification of Audience Effects,” *Social Problems* 44, no. 3 (1997): 342-57, <https://doi.org/10.2307/3097181>.

Community pessimism shows a clear geographic pattern, clustering primarily across the northern part of the region. Catawba, Rowan, and Iredell counties exhibit elevated relative rates of residents expecting local conditions to decline in the next 3-4 years, while pessimism sits at the lower end of the regional scale in Union, Stanly, and Anson counties. However, this may reflect smaller sample sizes (which increases uncertainty around the estimates) or some of these counties already being in lower socio-economic areas and therefore more likely to feel that things will stay the same.

For most measures of well-being, suburban Union and Lincoln Counties rank near the top among the 14 counties, while a set of smaller, more rural counties (Anson, Cleveland, Chester) rank near the bottom. Urban Mecklenburg County is close to the regional average on most measures, except for concern for the environment (higher than average) and concern about crime (lower than average). However, responses to the question about future outlooks complicate this pattern, with both Cleveland and Anson counties showing above-average levels of hope for the future despite low current well-being scores. In contrast, some comparatively prosperous counties, such as Lincoln and Iredell, expect a decline.

Conclusions and Discussion

Findings from the 14-county survey indicate a robust overall baseline well-being. Regional averages for life satisfaction (7.4) and purposeful well-being (7.7) exceed a comparable national benchmark for life satisfaction (6.82), and 67% of residents score high (at least 7) in both dimensions.

These regional averages and totals, however, mask disparities across geographic and socioeconomic boundaries:

- Anson, Stanly, and Union counties show the highest well-being levels, reaching 74% or higher, whereas Cleveland, Chester, Gaston, and Catawba counties trail the regional average by at least 4.5 percentage points.
- Homeowners are 23 percentage points more likely than renters to report high well-being. Similarly, higher income, full-time employment, older age, and primary reliance on traditional news outlets strongly align with higher reported well-being.

A significant disparity exists between private networks and broader social trust. While three-quarters (76%) of residents cite dependable immediate networks, only 57% feel a strong sense of belonging to their local community, pointing to a marked split between broad civic integration and personal support systems. As with the combined

measure of well-being, a factor analysis of our composite index shows distinct demographic and geographic gaps.

Rates of social disconnection reach 30% or more in Catawba, Chester, and Gaston counties, whereas Union, Stanly, and Mecklenburg exhibit much lower levels. From a demographic perspective, disconnection affects Black residents, adults between 25 and 39 years old, households with annual incomes below \$75,000, and renters (38% versus 19% for homeowners) at disproportionately higher rates.

On a related note, regional metrics show that 48% of residents agree that “most people can be trusted”. While this figure exceeds national benchmarks (~25%), it remains well below the trust and support residents feel for their primary circles.

However, generalized trust varies by geography: Iredell and Union see at least 53% of residents agreeing that most people can be trusted, while this sentiment falls below 43% in Anson and Lancaster counties. Demographically, older residents, homeowners, and people who rely on traditional television news rather than social media show higher levels of generalized trust (a 9-percentage-point difference).

A large share of residents report financial fragility.

Turning to economic well-being highlights a pronounced dichotomy between positive short-term trends and widespread systemic vulnerability: although just 25% of respondents say their personal financial position deteriorated over the preceding year, over a third (34%) express little or no confidence in handling a sudden emergency cost independently. This vulnerability exhibits sharp geographic and demographic concentration:

- Geographically, financial fragility rises to 40% or more across Gaston, Anson, Cleveland, and Chester counties, whereas Union County stands at a regional low of 27%.
- High levels of fragility disproportionately burden renters (exceeding homeowners by nearly 32 percentage points), female respondents (43% compared to 25% for males), lower-income and younger demographics, as well as Black (39%) and Hispanic (37%) community members.

Residents express some concern about the future. Just under one-third (31%) of community members expect local living conditions to deteriorate over the next three to four years; this pessimism is most pronounced among renters, middle-aged adults, social media news consumers, and residents in northern counties, even as certain economically challenged rural communities remain remarkably optimistic.

Taken together, these findings reveal a region with aggregate prosperity masking disparities and challenges in housing, financial security, and social cohesion. While regional baselines for life satisfaction, generalized trust, and short-

term economic trajectory consistently outperform similar national averages, they obscure vulnerabilities concentrated along clear socioeconomic, geographic, and racial lines.

- Homeownership emerges as the single most critical anchor of overall well-being, with renters experiencing starkly elevated rates of financial fragility, social disconnection, and pessimism about the region's future.
- Peripheral counties—most notably Gaston, Chester, Cleveland, and Catawba—repeatedly exhibit compounded disadvantages across multiple metrics.
- Universal alarm over housing affordability underscores a regional housing market that increasingly threatens long-term stability.

These findings paint a picture of a region where overall well-being is unevenly shared across groups and areas. That said, the findings are not meant to offer all the answers. They provide a solid foundation for further work, raising important questions about why these disparities exist and what underlying factors might be at play. The next step is for researchers and local leaders to dig deeper, using more advanced statistical modeling and integrated spatial tools such as the Carolinas Regional Explorer to better understand the root causes of these inequalities.

Appendices

Appendix A: Survey Weights

While we worked with ADRG to consider regional quotas when conducting the survey, several issues ensured the resulting sample would deviate from standard population metrics. First, quotas were focused on county of residence, race, Hispanic origin, gender, and age. In addition, because the quotas were somewhat relaxed, we generated them using straightforward marginal totals (i.e., how many Whites, how many Females, etc.) rather than a joint distribution.

Second, we purposely oversampled lower-density counties such as Anson and Chester. This was done to ensure that the final sample had an adequate number of respondents from every county in our region, with the knowing trade-off that it would consequently skew metrics for other variables.¹

In addition to these issues, we know that survey data often suffers from certain groups, e.g., younger individuals or renters, who are shown to be significantly less likely to participate than others (non-response bias), while the modality of the survey (phone or online) can also skew the final sample a survey provides.² This means that while the final quota counts remain within the acceptable deviation range (ADRG language), we still feel it is necessary to adjust each respondent's contribution to statistically match known Census population totals.

Variable Selection and Harmonization

We expanded the variables in our weighting strategy to include income and homeownership, in addition to those used to meet regional quotas: County, Race, Hispanic Ethnicity, Gender, and Age. We have included this expanded version of statistical weighting for the following reasons:

1. Studies have shown that economic stability is a primary driver of sentiment, particularly regarding quality of life and well-being. By weighting to Income targets, we ensure our findings on “well-being” aren’t artificially inflated by a sample that is wealthier than the actual population.³
2. Homeownership is a critical variable in local policy and quality-of-life questions, but renters are traditionally underrepresented in survey research; by including this variable, we ensure their unique perspectives on housing and community stability are given their proper proportional “voice”.⁴

¹ Richard Valliant et al., *Practical Tools for Designing and Weighting Survey Samples*, Statistics for Social and Behavioral Sciences (Springer International Publishing, 2018), <https://doi.org/10.1007/978-3-319-93632-1>.

² Richard Valliant et al., *Practical Tools for Designing and Weighting Survey Samples*, Statistics for Social and Behavioral Sciences (Springer International Publishing, 2018), <https://doi.org/10.1007/978-3-319-93632-1>.

³ Daniel Kahneman and Angus Deaton, “High Income Improves Evaluation of Life but Not Emotional Well-Being,” *Proceedings of the National Academy of Sciences* 107, no. 38 (2010): 16489–93, <https://doi.org/10.1073/pnas.1011492107>; Matthew A. Killingsworth et al., “Income and Emotional Well-Being: A Conflict Resolved,” *Proceedings of the National Academy of Sciences* 120, no. 10 (2023): e2208661120, <https://doi.org/10.1073/pnas.2208661120>.

⁴ Barry Steinberg et al., “A Nonresponse Bias Study of the Consumer Expenditure Survey for the Ten-Year Period 2010–2019,” Consumer Expenditure Surveys Program Report Series, U.S. Bureau of Labor Statistics, 2022, https://www.bls.gov/cex/research_papers/pdf/steinberg-et-al-a-nonresponse-bias-study-of-the-consumer-expenditure-survey-for-the-ten-year-period-2010-2019.pdf; Denise DiPasquale and Edward L. Glaeser, “Incentives and Social Capital: Are Homeowners Better Citizens?,” *Journal of Urban Economics* 45, no. 2 (1999): 354–84, <https://doi.org/10.1006/juec.1998.2098>.

We begin by aligning the survey data with Census targets, starting by collapsing the Race categories. As noted in Table A1, certain groups have extremely small counts and, consequently, can produce issues within the various weighting algorithms, creating unstable response propensity estimates and extreme weight variance.⁵

Responses of Online and Telephone Respondents, Unweighted Percentages (Column)

	Phone (%)	Web (%)	Total (%)
White	64.44	68.84	66.33
Black or African American	22.75	23.17	22.93
Asian	1.82	1.97	1.88
American Indian or Alaskan Native	1.56	2.25	1.86
Middle Eastern or North African	0.25	0.62	0.41
Native Hawaiian or other Pacific Islander	0.34	0.62	0.46
Other	5.37	1.91	3.89
Respondent hung up	0.17	0	0
DK/Refused	3.3	0.62	2.15

To avoid these issues and increase the likelihood that the weighting specifications converge, we merged the smaller categories of "AIAN" and "NAPI" into the "Other" category. We also manually reviewed the values and levels for each demographic variable in the survey data to ensure they matched the target list exactly, preventing errors during iterative processing.

Different Weighting Models

Traditional raking, also known as *Iterative Proportional Fitting (IPF)*, is the classic method to adjust survey samples to reflect population totals.⁶ The model works iteratively: it adjusts the weights for one demographic variable, checks how that shifts the others, and makes small course corrections. It cycles through every variable again and again until all demographic targets match their Census marginals.

Calibration differs from the traditional IPF specification in that it is a model-based technique that uses a distance function to solve for all demographic targets simultaneously and is designed to find the smallest possible adjustment to the raw weights that will satisfy all population constraints.⁷ To ensure methodological rigor, our process evaluated three distinct functional forms of calibration to determine which provided the most stable and representative results:

⁵ David Haziza and Jean-François Beaumont, "Construction of Weights in Surveys: A Review," *Statistical Science* 32, no. 2 (2017), <https://doi.org/10.1214/16-STS608>; Michael P. Battaglia et al., "Practical Considerations in Raking Survey Data," *Survey Practice* 2, no. 5 (2009): 1-10, <https://doi.org/10.29115/SP-2009-0019>.

⁶ W. Edwards Deming and Frederick F. Stephan, "On a Least Squares Adjustment of a Sampled Frequency Table When the Expected Marginal Totals Are Known," *The Annals of Mathematical Statistics* 11, no. 4 (1940): 427-44, <https://doi.org/10.1214/aoms/1177731829>.

⁷ Jean-Claude Deville and Carl-Erik Särndal, "Calibration Estimators in Survey Sampling," *Journal of the American Statistical Association* 87, no. 418 (1992): 376-82, <https://doi.org/10.1080/01621459.1992.10475217>.

- **Linear:** This method utilizes a squared-distance function to minimize the difference between raw and adjusted weights. It is the mathematical foundation for most large-scale government surveys. While highly efficient, it can produce negative weights if the sample requires extreme adjustments to meet population targets.
- **Raking:** This functional form replicates traditional raking within the calibration framework. It uses a multiplicative distance function to ensure that all final weights remain positive. It is often used as a more robust alternative to linear calibration when the survey sample is significantly skewed.
- **Logit (Bounded):** This is an advanced optimization technique that allows the researcher to set “hard bounds” (a floor and a ceiling) directly within the algorithm. It forces the computer to find a valid solution while strictly adhering to a predefined weight cap (e.g., 3.0), preventing any single respondent from becoming a statistical outlier during calculation.

While weighting corrects for demographic bias, it can also create “outliers”, i.e., respondents with very high weights. This raises the theoretical argument for weight truncation as extreme weights, whether caused by deliberate oversampling or nonresponse adjustments, can drastically inflate sampling variance and destabilize survey estimates.⁸ To evaluate the tradeoffs inherent within weight trimming, we run multiple iterations with different combinations of upper and lower bounds.⁹

Weighting Model Diagnostics

We compare the different weighting models using three standard metrics to gauge the most effective and appropriate methodology:

- **Design Effect:** This measure (DEFF) measures the “cost” of weighting. It quantifies how much the variance of our estimates increases as we move away from a simple unweighted sample using Kish’s formula.¹⁰
- **“Effective” Sample Size:** A calculation that estimates the accuracy and precision of our data by comparing it to a hypothetical perfect random sample. While theoretical, the metric remains critical for researchers as it indicates how much confidence we can place in our statistical tests after applying weighting.
- **Max Bias:** Another measure of accuracy that identifies the largest gaps between the weighted sample and the census targets for all weighted variables.

Table A2 evaluates the multiple weighting philosophies against three core criteria discussed above on our expanded weighting criteria (the ones the ADRG used in their quota counts in addition to our economic factors). We’ve also included the maximum weight (Max) to show the variation among the outliers for each method.

⁸ Frank Potter and Yuhong Zheng, “Methods and Issues in Trimming Extreme Weights in Sample Surveys,” paper presented at American Statistical Association, *American Statistical Association, Section on Survey Research Methods*, 2015.

⁹ Matthew DeBell and Jon A. Krosnick, *Computing Weights for American National Election Study Survey Data*, no. nes012427, ANES Technical Report Series (American National Election Studies, 2009), <http://www.electionstudies.org/>.

¹⁰ Leslie Kish, “Weighting for Unequal Pi,” *Journal of Official Statistics* 8 (1992): 183-200.

Survey Weighting Diagnostics and Efficiency Metrics (Expanded Models)

	Max Weight	Design Effect	Max Bias
Raking	5	1.414	0.027
Calibrate LM (Standard)	7.06	1.426	0
Calibrate LM (Truncated)	4.09	1.382	0
Calibrate Logit	2.99	1.4	0
Raking (T3)	3.07	1.312	0.023
Raking (T5)	5	1.413	0.027
Calibrate Ridge (0.1)	3.07	1.308	0.014
Calibrate Ridge (0.5)	5.01	1.405	0.002
Calibrate LM Bound (A)	2.99	1.347	0.005
Calibrate LM Bound (B)	4.06	1.365	0.003

After removing methods that failed to meet the accuracy threshold and those with extreme outliers in max weight and excessively high design effect, we selected the linear calibration with a weight truncation of 3 (L3) as the final weight for this project. By using the linear form and subsequently applying a conservative trim to an increasingly used methodology, we achieved a high-precision model that remains within 0.5% of all Census targets while maintaining a superior ESS. This dual-layer approach ensures that the final data is both demographically accurate and statistically powerful for regional analysis.

Appendix B: Small-Area Estimation

Understanding how residents across the fourteen-county region differ in their experiences and perceptions of quality of life and community well-being may not be the sole objective of the stratified analysis; it remains an integral component of the survey. Unfortunately, this ostensibly straightforward objective is more complicated than one might anticipate, compared with other demographic or descriptive variables. When comparing race, household income, gender, partisanship, employment status, and housing tenure, the sample's over 3,300 respondents (post-weighting) provide sufficient statistical power for reliable subgroup analyses.

This means results showing Black residents rate regional life satisfaction differently from white residents, or that renters express distinct opinions on housing affordability compared to homeowners, have sufficient numbers across groups to report descriptive cross-tabulations and weighted means directly. From a more technical perspective, larger sample sizes yield acceptable margins of error, allowing us to be confident these differences exist. This makes the results easy to interpret and provides a solid foundation for policy discussions.

County (of residence) presents a fundamentally different challenge. While the survey strove to achieve representation across all fourteen counties, the practical reality of a fixed sample size distributed across a region of this scale means that individual county samples, and therefore margins of error, vary substantially. A fact that can be seen in Table B1 below:

Total Number of Responses by Modality and Margin of Error

County	Phone	Web	Unwgt. N	Population	MOE (%)
Anson	25	22	47	22,432	14.28
Cabarrus	171	115	286	244,925	5.79
Catawba	104	110	214	167,054	6.69
Chester	23	66	89	32,323	10.37
Cleveland	85	99	184	102,194	7.22
Gaston	179	183	362	242,010	5.15
Iredell	116	93	209	206,361	6.78
Lancaster	73	52	125	111,652	8.76
Lincoln	79	63	142	97,611	8.22
Mecklenburg	957	510	1,467	1,206,285	2.56
Rowan	93	90	183	153,384	7.24
Stanly	58	46	104	67,326	9.6
Union	165	90	255	263,386	6.13
York	172	161	333	303,001	5.37
TOTAL	2,300	1,700	4,000	3,219,944	1.55

Note. MOE represents Margin of Error at the 95% confidence level.

Mecklenburg County, unsurprisingly, has the greatest number of respondents at just over 1300, a sample size that yields a margin of error of just over 2%. At the other end of the distribution, Anson County has just under 50 participants. While a higher number than would be “expected” if we strictly adhered to the region’s representative proportions, it still means the county has a margin of error of over 14%.

Why does this matter? For example, let’s say we were examining a question about overall life satisfaction, and a county estimate found that 60% of residents reported a high level of life satisfaction. A margin of error of 8 percentage points, i.e., roughly the average we theoretically expect from our sample, implies that this estimate could plausibly range from 52% to 68% in the actual population. This variability complicates our ability to distinguish between counties, and presenting raw county-level percentages as comparable to the regional subgroup figures would be methodologically misleading and could lead to actions based on false premises.

This uncertainty around certain geographies does not imply that the data is flawed or completely unreliable. Instead, it means direct estimation is problematic for small county samples, which is why the modeling approach described below aims to address these concerns.

Calculating County-level Estimates

Standard statistical models assume survey respondents are independent draws from a single population. In reality, respondents are nested within counties, sharing a local environmental context—such as housing markets, labor conditions, and public services—that individual demographics alone cannot explain. To generate defensible county-level estimates, we employ a Bayesian Hierarchical Model that explicitly captures this two-level data structure. At the individual level, the model accounts for key respondent demographics, such as race, income, employment status, and housing tenure. At the county level, it captures residual geographic variation using county-level Census covariates, including age structure, median income, racial composition, and homeownership rates.

The primary statistical advantage of this hierarchical framework lies in its use of partial pooling, which allows the model to learn the relationship between county demographics and survey outcomes across the full regional sample, using that baseline to stabilize estimates in counties with sparse data.¹¹ The degree to which a county’s estimate is pulled toward the regional trend—a phenomenon known as shrinkage—is calibrated dynamically by local sample size. Counties with large sample sizes, such as Mecklenburg, possess sufficient local data and remain largely unadjusted. In contrast, counties with small sample sizes, such as Anson, experience greater shrinkage toward the regional mean to prevent extreme sampling noise from skewing the final metrics.

While frequentist multilevel models also perform partial pooling, their reliance on large-sample asymptotic approximations creates significant limitations when working with a small number of geographic units.¹² A Bayesian specification overcomes this limitation by treating county-level random effects as parameters with their own prior distributions, estimating full posterior distributions for all parameters simultaneously so that county-level uncertainty is explicitly quantified rather than approximated. Additionally, the inclusion of weakly informative prior distributions on county-level

¹¹ Andrew Gelman and Jennifer Hill, *Data Analysis Using Regression and Multilevel/Hierarchical Models*, 23rd printing, Analytical Methods for Social Research (Cambridge Univ. Press, 2021).

¹² Daniel Stegmueller, “How Many Countries for Multilevel Modeling? A Comparison of Frequentist and Bayesian Approaches,” *American Journal of Political Science* 57, no. 3 (2013): 748–61, <https://doi.org/10.1111/ajps.12001>.

covariates and variance terms acts as a regularizing mechanism against overfitting.¹³ This ensures that the model's predictions remain appropriately conservative, responding only to genuine, data-supported geographic differences while safeguarding against sampling noise.

In summary, this two-level Bayesian framework provides the analytically rigorous foundation necessary for reliable small-area estimation.¹⁴ By capturing the nested nature of survey data, leveraging partial pooling to balance local signal with regional strength, and using Bayesian priors to fully propagate uncertainty across 14 geographic units, the model maximizes statistical efficiency without overstating precision.

The Difference in Bayesian Estimates

Unlike a traditional regression, Bayesian models treat each parameter as having a probability distribution, or a range of plausible values weighted by their consistency with the observed data and prior knowledge about reasonable parameter ranges. This means the output of a Bayesian model is not a point estimate but a full posterior distribution over all model parameters.

The computational method employed to estimate these posterior distributions is Markov Chain Monte Carlo sampling, implemented via the Stan probabilistic programming platform, which underpins both the *rstanarm* and *brms* packages used in this analysis.¹⁵ The underlying concept is intuitive: just as a survey estimates population tendencies by drawing a representative sample of individuals, MCMC estimates a model's posterior distribution by generating a large representative sample of plausible parameter values. Stan specifically employs Hamiltonian Monte Carlo, a particular form of MCMC that utilizes the derivatives of the posterior density to generate transitions that explore the parameter space more effectively than older approaches. This reduces the number of iterations required to achieve reliable estimates.

The practical difference between the county-level results reported here and those produced by a simpler approach lies in the post-estimation step. Instead of calculating a single county-level predicted probability and attaching a margin of error based on a normal approximation, the process generates 2,000 plausible county-level estimates for each county and outcome category. These estimates are then aggregated at the county level using survey-design weights, increasing the likelihood that the final predictions reflect each county's actual population composition rather than the respondent sample's composition within that county.

Another difference between the Bayesian approach we utilize and a more traditional regression lies in the uncertainty of these estimates. A confidence interval, as one might see in a fixed-effects regression, describes the long-run behavior of the estimator across hypothetical repeated samples. On the flip side, our approach provides a probability that a given estimate contains the true estimate based on the full posterior distribution of plausible values for each county.¹⁶ While it is easy to conflate these

¹³ Andrew Gelman, "Prior Distributions for Variance Parameters in Hierarchical Models (Comment on Article by Browne and Draper)," *Bayesian Analysis* 1, no. 3 (2006), <https://doi.org/10.1214/06-BA117A>.

¹⁴ J. N. K. Rao and Isabel Molina, *Small Area Estimation*, 1st ed. (Wiley, 2015), <https://doi.org/10.1002/9781118735855>.

¹⁵ Bob Carpenter et al., "Stan: A Probabilistic Programming Language," *Journal of Statistical Software* 76, no. 1 (2017), <https://doi.org/10.18637/jss.v076.i01>; Paul-Christian Bürkner, "Brms: An R Package for Bayesian Multilevel Models Using Stan," *Journal of Statistical Software* 80, no. 1 (2017), <https://doi.org/10.18637/jss.v080.i01>.

¹⁶ Andrew Gelman and Sander Greenland, "Are Confidence Intervals Better Termed 'Uncertainty Intervals'?", *BMJ*, September 10, 2019, 15381, <https://doi.org/10.1136/bmj.15381>; Richard D. Morey et al., "The Fallacy of Placing Confidence in Confidence Intervals," *Psychonomic Bulletin & Review* 23, no. 1 (2016): 103-23, <https://doi.org/10.3758/s13423-015-0947-8>; John K. Kruschke and Torrin M. Liddell, "The Bayesian New Statistics: Hypothesis Testing, Estimation, Meta-Analysis, and Power Analysis from a Bayesian Perspective," *Psychonomic Bulletin & Review* 25, no. 1 (2018): 178-206, <https://doi.org/10.3758/s13423-016-1221-4>.

two concepts, the latter allows us to analyze model results more intuitively and better aligns with practitioners' and non-specialists' ability to interpret these findings.

For binary outcome variables, we used a multilevel logistic regression implemented in the `rstanarm` package in R, which models the probability of a respondent falling into the outcome category of interest as a logistic function of individual-level demographic predictors and a county-level random intercept. For ordered categorical outcomes such as the three-category life satisfaction variable, the model used was a multilevel cumulative logistic regression implemented in the `brms` package in R, which extends the binary framework to outcomes with more than two ordered categories by estimating threshold parameters that divide the underlying continuum of the outcome into the observed categorical responses.

In both specifications, individual-level predictors account for compositional differences across counties; county-level Census covariates anchor the geographic variation in outcomes to observable structural features of each county; and post-stratification weights derived from the survey's quota sampling design are incorporated directly into the estimation process to ensure that the results reflect the population. The county-level random intercept in both models is the mechanism through which partial pooling operates, and its posterior distribution, when passed through the post-estimation prediction step, produces the county-level estimates and accompanying credible intervals reported throughout this analysis.



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