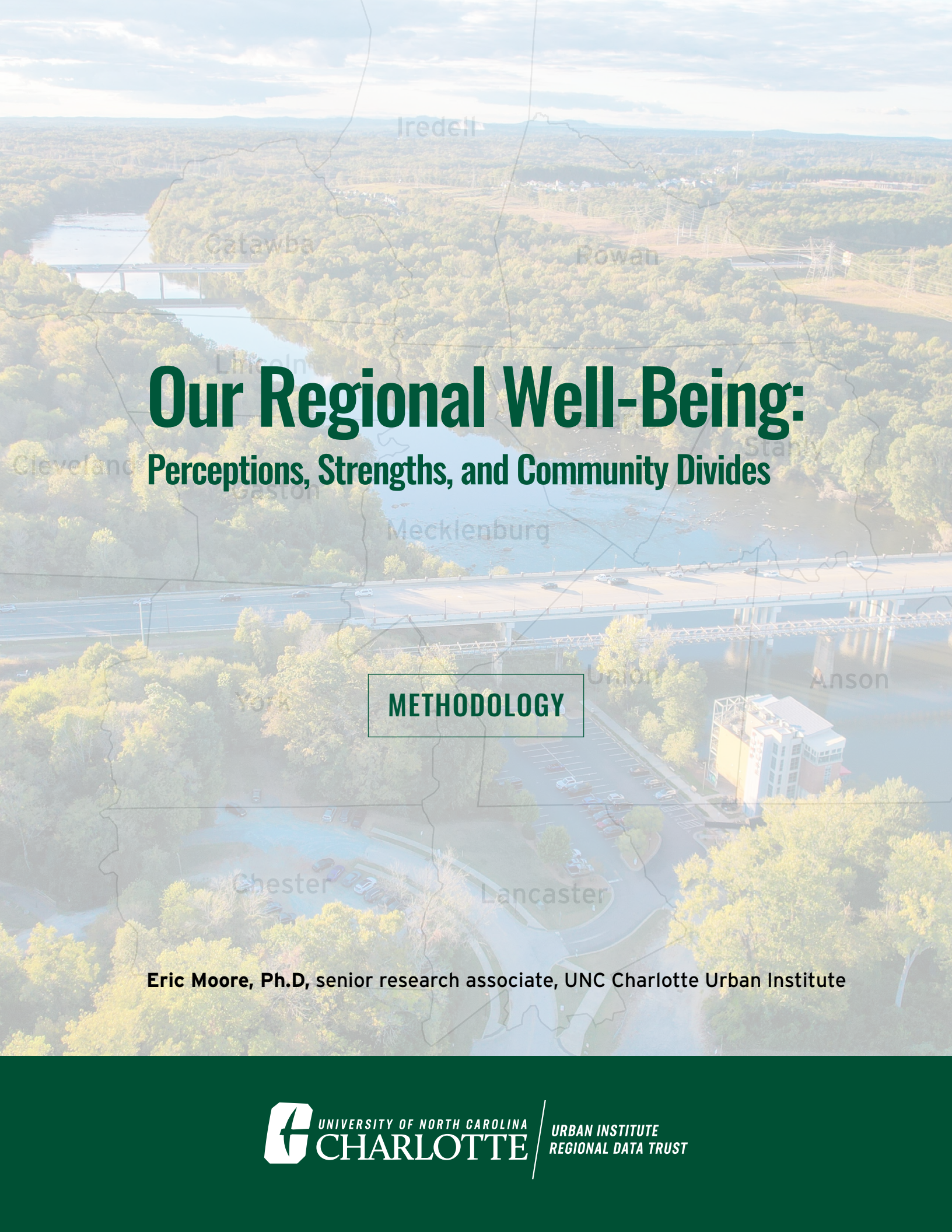




Our Regional Well-Being:

Perceptions, Strengths, and Community Divides

METHODOLOGY

Eric Moore, Ph.D, senior research associate, UNC Charlotte Urban Institute



UNIVERSITY OF NORTH CAROLINA
CHARLOTTE

URBAN INSTITUTE
REGIONAL DATA TRUST

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.

Your Voices Carolina Regional Well-being Survey Questions

Q1. When you think about your "community" in the context of this survey, which of the following best describes the area you are primarily referring to?

1. My immediate neighborhood
2. My town or city
3. My county
4. My state
5. A community of interest (e.g., faith group, social circle)
6. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q2. Thinking about the positive aspects of our area, what do you see as the greatest strengths of the Charlotte-Mecklenburg region today? Please select up to three options:

1. Job Opportunities
2. Cost of Living
3. Climate & Weather
4. Community/Culture
5. Diversity
6. Education
7. Food & Restaurants
8. Public Safety
9. Travel/Location
10. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q3. How do you prefer to get local news and information?

1. Television
2. Newspapers (online or print)
3. Radio/podcasts
4. Social media
5. I'm not interested in local issues
6. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q3b. Which social media platform do you primarily use? [ACCEPT ONE RESPONSE]
[ASK ONLY IF Q3 = 4 'Social media']

1. Reddit
2. Facebook
3. Instagram
4. TikTok
5. YouTube
6. X (formerly Twitter)
7. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q4. On a scale of 0 to 10, where 0 is "not at all" and 10 is "completely", overall, how satisfied are you with your life nowadays?

Q5. 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?

Q6. [MATRIX] Thinking about the past week, please indicate how much of the time you felt the following ways.

Response Scale:

1. Not at all
2. A little
3. Moderately
4. Quite a bit
5. Very much
99. Don't Know/Refused

Items to rate:

- a. Happy
- b. Sad
- c. Anxious
- d. Peaceful
- e. Angry
- f. Bored

Q7. [SOCIAL CONTACT] How often do you come into contact with the following groups of people? By contact, we mean talking or doing something together. It can be in-person, over the phone, over a video call, over social media / text messaging, etc.

Response Scale:

1. Never
2. Less than once a month
3. 1-3 times a month
4. Weekly
5. Daily
6. Not relevant
99. Don't Know/Refused

Groups to rate:

- a. Friends
- b. Family
- c. Neighbors
- d. Colleagues

Q8. How would you describe your sense of belonging to your local community?

1. Very Weak
2. Somewhat Weak
3. Somewhat Strong
4. Very Strong
5. No Opinion
99. Don't Know/Refused

Q9. Using 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?

Q10. Generally speaking, on a scale from 0 to 10, where 0 means you 'can't be too careful' and 10 means 'most people can be trusted,' where would you place yourself?

Q11. Compared to a year ago, would you say your financial situation is better, worse, or about the same?

1. I am better off now than I was a year ago
2. I am worse off now than I was a year ago
3. My financial situation is about the same
4. Don't Know
99. Refused

Q12. How confident are you that you could handle an unexpected expense (such as a car repair or urgent bill) without borrowing or asking for help?

1. Not at all confident
2. Slightly confident
3. Moderately confident
4. Very confident
5. Completely confident
99. Don't Know/Refused

Q13. In the past 7 days, not including today, on how many days did you eat each of the following meals?

- a. Breakfast [ENTER 0-7, 99= Don't Know/Refused]
- b. Lunch [ENTER 0-7, 99= Don't Know/Refused]
- c. Dinner [ENTER 0-7, 99= Don't Know/Refused]

Q14. In the past 7 days, not including today, on how many days did you eat each of the following meals with a friend, family member, or someone else you know?

- a. Breakfast [ENTER 0-7, 99= Don't Know/Refused]
- b. Lunch [ENTER 0-7, 99= Don't Know/Refused]
- c. Dinner [ENTER 0-7, 99= Don't Know/Refused]

Q15. In the past 12 months, how many different groups, organizations, or associations have you been actively involved in? This includes volunteering your time, attending regular meetings, or helping with organized events, either in-person or online.

1. 0 groups
2. 1 group
3. 2 - 3 groups
4. 4 - 5 groups
5. 6 or more groups
99. Don't Know/Refused

Q15b. [ASK ONLY IF Q15 = 2, 3, 4, OR 5] You mentioned being involved with [NUMBER FROM Q16] in the past 12 months. Which of the following types of organizations or associations were they? Please mention all that apply:

1. Community or Neighborhood
2. Religious or Spiritual
3. Civic or Service
4. Recreational, Sport, or Hobby
5. Educational or Youth-focused
6. Professional or Trade
7. Political or Advocacy
8. Cultural or Artistic
9. Health or Support
10. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q15c. [ASK ONLY IF Q15 = 1 '0 groups'] People have many different reasons for not being involved in community groups or organizations. Which of the following, if any, have made it difficult for you to participate in the past 12 months? You may select up to three choices.

1. I have other commitments (incl. work and family) or a busy schedule.
2. I have difficulty with transportation or the cost of participating.
3. I am not aware of opportunities or don't know how to get involved.
4. I don't feel welcome or like I would fit in.
5. I don't feel that my involvement would actually make a difference.
6. Illness or physical/mental health challenges make it difficult.
7. I am simply not interested in being part of a group at this time.
8. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q16. In the area where you live, how much of a problem are environmental issues such as air pollution, noise, or lack of green space?

1. None at all
2. A little
3. A moderate amount
4. A lot
5. A great deal
99. Don't Know/Refused

Q17. How safe do you feel when you walk alone in your local area?

a. During the day

1. Very unsafe
2. Unsafe
3. Neutral
4. Somewhat safe
5. Very safe
99. Don't Know/Refused

b. At night

1. Very unsafe
2. Unsafe

3. Neutral
4. Somewhat safe
5. Very safe
99. Don't Know/Refused

Q18. On a scale of 0 to 10, where 0 means you are 'not at all satisfied' and 10 means you are 'completely satisfied', how satisfied are you with your current housing situation (including the condition of your home, location, and space)?

Q19. In your opinion, how easy or difficult is it for people in your community to find housing they can afford?

1. Extremely difficult
2. Somewhat difficult
3. Somewhat easy
4. Extremely easy
99. Don't Know/Refused

Q19b. [ASK IF Q19 = 1 OR 2] What do you think are the main reasons that housing is difficult to afford? You may select up to three choices.

1. Corporations/national investors buying properties
2. Landlords can raise rent without limit
3. Opposition to affordable housing in neighborhoods
4. People moving in from out of state
5. Developers only building expensive homes
6. Local government is not doing enough
7. Not enough housing being built
8. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q20. What do you think are the biggest problems facing the Charlotte-Mecklenburg region today? Please select up to three options:

1. Housing affordability
2. Crime/safety
3. Economic opportunity
4. Public education
5. Transportation
6. Racial Equity
7. Public health
8. Climate/environment
9. Taxes
10. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q21. Looking ahead 3–4 years, do you think living conditions in your community will be better, worse, or about the same as today?

1. Better in 3-4 years
2. Worse in 3-4 years
3. About the same as today

4. Don't know
99. Refused

Q22. What is your zip code?

Q23. Please select your age range.

1. 18 to 24
2. 25 to 39
3. 40 to 54
4. 55 to 65
5. Over 65
99. Don't Know/Refused

Q24. Which of the following best describes your current employment status? Are you...

1. Working full time
2. Working part time
3. Not employed, but looking for work
4. Not employed and not looking for work
5. Not employed, unable to work due to a disability or illness
6. Student
7. Retired
8. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q24b. [ASK ONLY IF Q24 = 1 'Working full time' OR 2 'Working part time'] What best describes your current work schedule?

1. I work completely remotely
2. I work remotely some of the time, and from a place of business at other times (hybrid)
3. I work at an office location or place of business
99. Don't Know/Refused

Q25. Which of the following income categories best describes your household's annual gross income?

1. Less than \$15,000
2. \$15,000 - \$24,999
3. \$25,000 - \$34,999
4. \$35,000 - \$49,999
5. \$50,000 - \$74,999
6. \$75,000 - \$99,999
7. \$100,000 - \$149,999
8. \$150,000 or more
99. Don't Know/Refused

Q26. Do you describe yourself as a man, a woman, or in some other way?

1. Man
2. Woman
3. Some other way ('non-binary' 'transgender' 'genderfluid' etc.)
99. Don't Know/Refused

Q27. Generally speaking, when it comes to politics, do you usually think of yourself as a...

1. Democrat
2. Republican
3. Independent
4. Other party (specify): [SPECIFY]
5. No preference
99. Don't Know/Refused

Q27b. [ASK ONLY IF Q27 = 1 'Democrat' OR 2 'Republican'] Would you call yourself a strong [PARTY FROM Q28] or a not very strong [PARTY FROM Q28]?

1. Strong
2. Not very strong
99. Don't Know/Refused

Q27c. [ASK ONLY IF Q27 = 3 'Independent' OR 4 'Other party' OR 5 'No preference'] Do you think of yourself as closer to the Republican Party or to the Democratic Party?

1. Closer to Republican
2. Neither
3. Closer to Democratic
99. Don't Know/Refused

Q28. Is your current house, apartment, or mobile home...

1. Owned by you or someone in this household with a mortgage or loan
2. Owned by you or someone in this household free and clear (without a mortgage or loan)
3. Rented (includes living with someone else who pays rent)
99. Don't Know/Refused

Q29. Do you speak a language other than English at home?

1. Yes
2. No
99. Don't Know/Refused

Q29b. [ASK ONLY IF Q29 = 1 'Yes'] What is this language?

1. Arabic
2. Chinese (incl. Mandarin, Cantonese)
3. French, Haitian, or Cajun
4. German or Other West Germanic Languages
5. Indian (incl. Hindi, Bengali)
6. Korean
7. Russian, Polish, or Other Slavic Languages
8. Spanish
9. Vietnamese
10. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q30. How would you describe your race? You may select up to three choices.

1. White
2. Black or African American
3. Asian
4. American Indian or Alaskan Native
5. Middle Eastern or North African
6. Native Hawaiian or other Pacific Islander
7. Other (specify): [SPECIFY]
99. Don't Know/Refused

Q31. Are you of Hispanic, Latino(a), or Spanish origin?

1. **No**, not of Hispanic, Latino(a), or Spanish origin
2. **Yes**, Hispanic, Latino(a), or Spanish origin
99. Don't Know/Refused



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