SNAP Participation and Structural Cost Burdens Across U.S. Counties

Mutsa Mungoshi

July 31, 2025

Abstract

This study explores whether participation in the Supplemental Nutrition Assistance Program (SNAP) signals deeper structural affordability burdens at the county level across the United States. Rather than treating SNAP solely as a response to household poverty, we investigate its potential as a spatial indicator of regional cost pressures in housing, childcare, and other essential services. We combine detailed cost-of-living data with SNAP participation rates, median incomes, and metro classifications for over 3,000 U.S. counties. Using multivariate regression, principal component analysis, and unsupervised clustering, we find that SNAP rates are systematically higher in counties with disproportionately high housing and caregiving costs, even after controlling for income and geography. These findings suggest that SNAP may offer more than household support; it may also reveal geographic patterns of economic stress. By positioning SNAP as a diagnostic signal of structural burden, this study provides a novel lens for evaluating spatial inequality and tailoring policy interventions to regional affordability regimes.

Contents

1 Introduction

The Supplemental Nutrition Assistance Program (SNAP) is the largest federal food assistance initiative in the United States, serving over 40 million individuals annually [1]. Prior studies have established SNAP's role in reducing food insecurity [2], improving nutritional outcomes [3], and supporting low-income families. However, most analyses emphasize household-level poverty and understate the role of regional structural pressures in shaping SNAP participation.

Counties in the U.S. vary not only by income but also in the cost of basic necessities. Structural expenses such as housing [4], transportation, childcare, and taxation contribute to geographically uneven affordability burdens [5], [6]. These costs can strain budgets even for households above official poverty thresholds, making SNAP enrollment partly a function of location-based hardship.

This paper investigates whether SNAP participation rates reflect broader structural affordability pressures beyond household income. We combine county-level SNAP data with cost-of-living estimates from the Economic Policy Institute [7] and demographic indicators from the U.S. Census to assess whether SNAP can serve as a spatial indicator of economic stress.

We apply principal component analysis (PCA) to uncover latent dimensions of structural cost burden, followed by clustering to group counties into affordability regimes. Regression and statistical testing are then used to examine the relationship between these profiles and SNAP participation. Our findings underscore the importance of cost geography in shaping public assistance needs and point toward opportunities for more regionally responsive policy.

2 Literature Review

The Supplemental Nutrition Assistance Program (SNAP) has been extensively studied for its role in mitigating food insecurity and supporting household well-being. Ratcliffe et al. [2] found that SNAP participation significantly reduces food insecurity among low-income households. Hoynes and Schanzenbach [3] demonstrated long-term benefits of the program for child health, education, and employment outcomes. Research by Gundersen and Kreider [8], and Gundersen et al. [9], further supports the program's effectiveness in improving dietary quality and food access, even after adjusting for selection bias.

Evidence from the 2009 American Recovery and Reinvestment Act (ARRA) indicates that temporary increases in SNAP generosity contributed to reduced food insecurity during economic downturns [10]. However, Leung et al. [11] reported that SNAP recipients often exhibit poorer diet quality than income-matched non-recipients, suggesting that structural factors—such as access to affordable healthy food—may constrain outcomes.

Beyond income, SNAP participation is shaped by institutional and administrative contexts. Currie [12] and Moffitt [13] emphasize the influence of program design, stigma, and enrollment barriers. Geographic disparities in take-up rates have been documented by Bitler et al. [14], who highlight variation tied to policy and implementation environments.

Several studies have also explored SNAP's responsiveness to local labor market conditions. Ziliak [1] and Mabli et al. [15] found that unemployment and wage trends are key predictors of SNAP participation. Ganong and Liebman [16] investigated "benefit cliffs," showing how marginal income gains can reduce eligibility and disincentivize work. However, few of these studies account for structural cost burdens that vary by geography.

A parallel literature on spatial inequality has emphasized the role of regional affordability. Glaeser and Gyourko [4] and Quigley and Raphael [5] show that housing markets significantly shape opportunity structures and stratification. Fisher and Baum [17] demonstrate that high housing costs correlate with food insecurity among renters, while Fisher et al. [6] link housing costs and minimum wages to broader material hardship. The Economic Policy Institute's Family Budget Calculator shows that federal poverty thresholds often understate household needs in high-cost regions [7].

Despite this recognition, few studies explicitly link SNAP participation to regional cost burdens beyond income metrics. Pilkauskas et al. [18] observed that SNAP enrollment can rise during non-income shocks such as caregiving or health crises, hinting at structural determinants. Nevertheless, quantitative studies exploring spatial associations between cost profiles and SNAP enrollment remain limited.

This study addresses this gap by integrating county-level SNAP participation data with structural cost estimates and demographic controls. It builds on prior work by evaluating whether SNAP participation aligns with distinct affordability regimes identified through principal component and clustering analysis. The objective is to assess whether SNAP functions not only as a response to poverty, but also as an indicator of underlying structural cost stress.

Finally, it is important to note the methodological limitations in establishing causality. As Bitler and Hoynes [19] note, unobserved factors such as informal employment, stigma, or local administration can affect both affordability and enrollment. Furthermore, rising program use may be both a response to and a driver of regional costs, introducing endogeneity. This study, therefore, interprets associations as indicative of spatial co-location rather than causal pathways.

3 Research Questions and Contributions

3.1 Research Questions

This study addresses the following research questions:

- To what extent is SNAP participation statistically associated with structural cost burdens across U.S. counties, after controlling for income, metro status, and state-level variation?
- Which categories of household expenditure—such as housing, transportation, childcare, and taxation—are most strongly linked to variation in SNAP participation rates?
- Can U.S. counties be effectively grouped into distinct cost-of-living profiles, and does SNAP participation differ systematically across these affordability regimes?
- Does SNAP participation signal broader affordability stress that is not fully captured by conventional income or poverty thresholds [6], [7]?

3.2 Contributions

This study contributes to the literature on spatial inequality, affordability, and public assistance by:

- Reframing SNAP as both an income-based safety net and a geographic indicator of structural cost pressure, integrating individual-level and regional analyses [1], [14].
- Introducing a multidimensional framework for assessing cost of living, incorporating controls for income, metro status, family composition, and state effects to isolate structural burdens [4], [6].
- Applying principal component analysis (PCA) to uncover latent affordability dimensions, followed by clustering to classify counties into distinct cost regimes [5].
- Proposing a diagnostic tool for geographically responsive policy design, including regionally adjusted SNAP formulas and targeted supports for high-cost counties [18], [19].

4 Methodology

4.1 Data Sources

This study integrates multiple publicly available datasets to construct a comprehensive, county-level analytical file for the year 2024:

- **SNAP Participation:** County-level SNAP enrollment figures were obtained from the U.S. Department of Agriculture's Food and Nutrition Service (FNS) for July 2024 [20]. SNAP participation rates were calculated as the ratio of enrolled recipients to total county population, using 2024 estimates from the U.S. Census Bureau [21].
- **Cost of Living Estimates:** County-specific expenditure estimates were drawn from the Economic Policy Institute's Family Budget Calculator [7], which reports costs for food, housing, transportation, healthcare, childcare, taxes, and miscellaneous necessities. Because these estimates are provided for distinct household configurations, we aggregated values across all available family types within each county. This aggregation aligned cost estimates with other county-level variables, such as SNAP participation and income, enabling a consistent unit of analysis and a composite affordability profile applicable across diverse household structures.
- **Demographic and Geographic Controls:** Median family income was obtained from the American Community Survey (ACS) [22], while metro status (binary metro vs. non-metro classification) was sourced from the USDA Rural-Urban Continuum Codes [23].

To ensure data integrity, extensive cleaning and validation procedures were applied. These included correcting inflated or misattributed population figures (e.g., resolving SNAP-population mismatches in counties such as Oneida, NY vs. ID), verifying FIPS codes, and filtering incomplete records. The final dataset includes 3,142 counties with complete observations across all variables.

4.2 Variable Construction

We derived several variables for analytical consistency:

- **SNAP Rate:** Share of county residents enrolled in SNAP.
- **Cost Shares:** For each spending category, we computed the proportion of total household expenditure to yield standardized cost burden metrics.
- **Controls:** Median income (continuous), metro status (binary), and state fixed effects (categorical) were included to control for local economic and policy context.

To address skewness in some variables, we log-transformed food, transportation, and healthcare cost shares prior to regression analysis. These transformations improved distributional symmetry, as confirmed by Q-Q plots and histograms. For PCA, however, we used z-scored *untransformed* shares to preserve loading interpretability.

4.3 Principal Component Analysis (PCA)

We applied Principal Component Analysis (via the `prcomp()` function in R) to the standardized (z-scored) cost shares to reduce dimensionality and capture latent structures in affordability burdens. The first three components explained over 80% of total variance and were interpreted as:

- **PC1 – General Burden:** Loaded positively across all categories, capturing overall affordability pressure.
- **PC2 – Housing vs. Caregiving:** Reflected a tradeoff between housing/transportation and food/childcare costs.
- **PC3 – Tax Load:** Emphasized variation in tax burdens and residual caregiving expenses.

These components served both as dependent variables in regression analysis and as inputs for clustering, allowing us to characterize structural cost regimes.

4.4 Regression Analysis

To test associations between SNAP participation and structural cost burdens, we estimated Ordinary Least Squares (OLS) models of the form:

$$\mathrm{PC}_i = \beta_0 + \beta_1 \cdot \mathrm{SNAPRate}_i + \beta_2 \cdot \mathrm{Income}_i + \beta_3 \cdot \mathrm{Metro}_i + \beta_4 \cdot \mathrm{State}_i + \epsilon_i$$

Separate models were estimated for each principal component using the `lm()` function in R. Robust standard errors were computed using the `sandwich` package to correct for potential heteroskedasticity. Model diagnostics included residual plots, Cook's distance, and Q-Q plots. We confirmed the absence of influential outliers ($D < 0.1$) and verified that residuals met normality and homoscedasticity assumptions. Multicollinearity was assessed using Generalized Variance Inflation Factors (GVIFs), which remained below the recommended threshold (GVIF < 2.5 for all predictors).

4.5 Clustering Analysis

We applied unsupervised learning to explore whether counties could be grouped into distinct cost-of-living regimes:

- **K-Means Clustering:** Clustering was performed on the first three principal components using the `kmeans()` function in R. Optimal k was selected using the elbow method, average silhouette width, and the gap statistic **tibshirani2001gap**.
- **Hierarchical Clustering:** As a robustness check, we applied hierarchical clustering using Ward's method with Euclidean distance (`hclust()` function). Dendrograms were examined for interpretability and cluster stability.
- **Cluster Profiling:** For each cluster, we examined average SNAP participation, cost burdens, and metro composition to identify meaningful spatial patterns and structural distinctions.

4.6 Statistical Validation and Visualization

To assess the robustness and interpretability of our cluster solution and cost structure analysis, we conducted the following diagnostics:

- **Chi-square Test:** A Pearson chi-square test (`chisq.test()`) was used to assess whether SNAP terciles or metro status were disproportionately distributed across clusters.
- **ANOVA on Cost Shares:** One-way ANOVA (`aov()`) was conducted to test whether average cost shares differed significantly across clusters. All six standardized cost shares showed significant between-cluster variation, validating the distinctiveness of the affordability profiles.
- **Visual Diagnostics:** Several visual tools were used to support interpretation and validate assumptions:
  - *Scree plots* (via `fviz`$_e ig())toselectthenumberofprincipalcomponents;$ $Biplotstointerpret PCAaxesandcategoryloadin$
  - *Residual plots* and *Cook's distances* to confirm regression assumptions;
  - *Cluster plots* and *choropleths* to spatially visualize affordability regimes.

4.7 Analytical Workflow Diagram

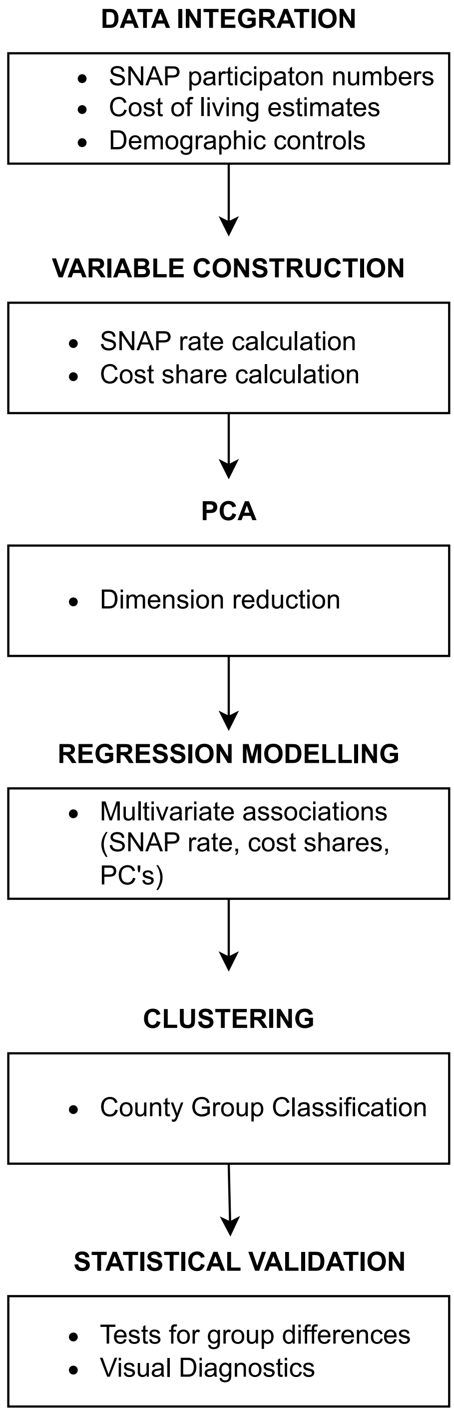

Figure 1: Cropped analytical workflow diagram summarizing main steps.

4.8 Limitations

Several limitations should be acknowledged:

- **Cross-sectional Design:** The analysis is based on 2024 data only, limiting causal inference and precluding assessment of temporal dynamics or policy change effects.

- **Aggregated Cost Profiles:** Cost estimates were aggregated across multiple family types to align with county-level units of analysis. While enabling consistency, this may mask heterogeneity by household structure.
- **Omitted Variable Bias:** Factors such as administrative burden, stigma, or local economic shocks may influence SNAP uptake but are not captured in the dataset.
- **Clustering Sensitivity:** Cluster results depend on methodological choices including PCA retention, scaling, and initialization. Although we validated clusters using multiple techniques, interpretations remain exploratory.

5 Results

5.1 Descriptive Statistics

The cleaned dataset includes 3,144 U.S. counties with complete information on SNAP participation rates, structural cost burdens (as expenditure shares), income levels, and metro classification. Table 1 summarizes the key variables.

SNAP rates ranged from 0.8% to 47.3%, with a mean of 13.2%. Cost shares varied substantially across counties: housing costs averaged 29.4% of total household expenses, while childcare averaged 11.6% but with extreme right skew. Notably, childcare costs were recorded as zero in a large number of rural counties.[1]

Table 1: Summary Statistics for Key Variables

Variable	Mean	SD	Min	Max
SNAP Rate (%)	13.2	6.1	0.8	47.3
Housing Share (%)	29.4	5.8	18.3	45.7
Childcare Share (%)	11.6	7.3	0.0	31.2
Tax Share (%)	12.3	3.7	4.1	26.8
Median Income ($)	74,200	13,850	35,500	130,000
Metro Status (Binary)	0.46	0.50	0	1

Note: Zero childcare shares typically reflect rural counties where market-based care is limited or assumed unnecessary for modeled households.

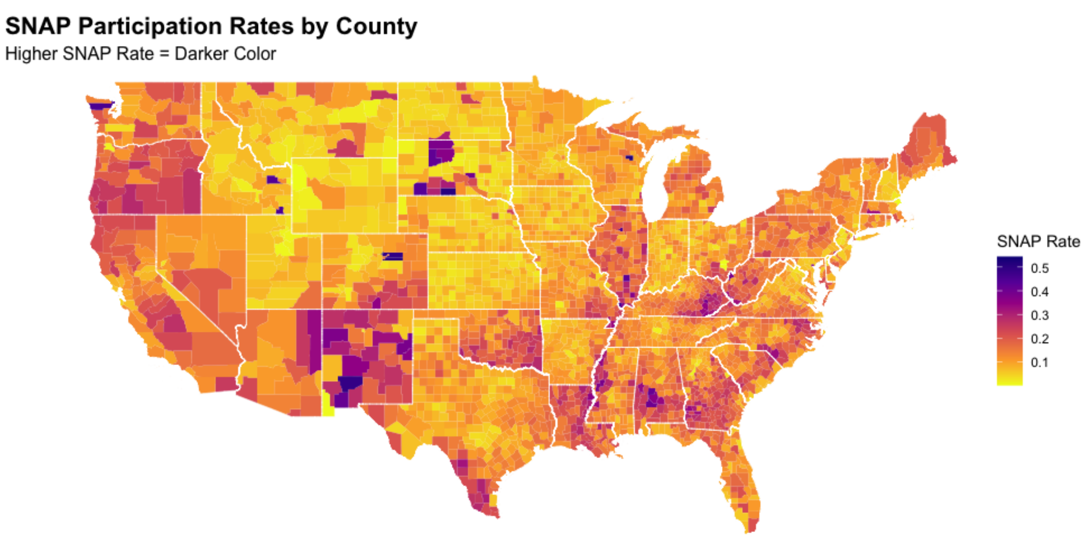

Figure 2: SNAP Participation Rates by County. Darker shades indicate higher participation.

[1]Zero childcare shares typically reflect rural counties where market-based care is limited or assumed unnecessary for modeled households.

5.2 Multicollinearity and Variable Diagnostics

A Pearson correlation matrix (Fig. 3) revealed strong associations between several structural cost components, particularly housing and taxes ($r = 0.71$) and childcare and food ($r = 0.63$). These associations support the need for dimensionality reduction using PCA.

Variance inflation factors (GVIF) confirmed low multicollinearity (< 2.5 for all predictors), supporting regression validity.

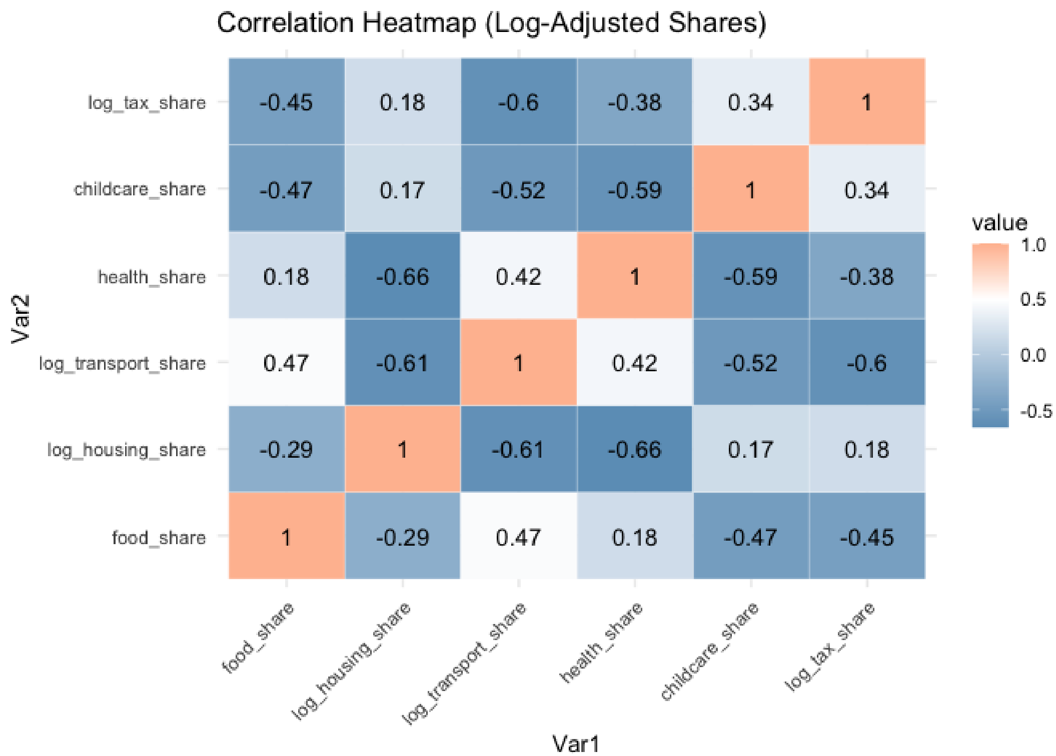

Figure 3: Correlation heatmap for cost share variables.

5.3 Transformation and Normality Checks

Food, transportation, and healthcare shares were log-transformed prior to regression modeling. PCA, however, was performed on standardized but untransformed cost shares. Histograms and Q-Q plots confirmed improved distributional properties.

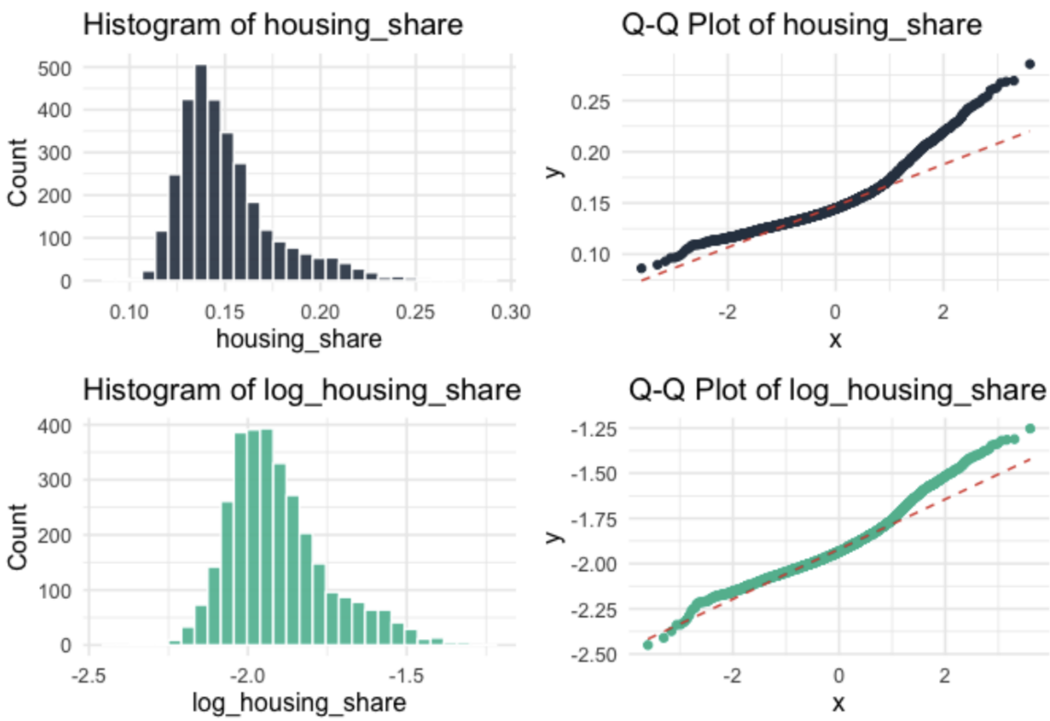

Figure 4: Histograms and Q-Q plots for housing share before and after transformation.

5.4 Principal Component Analysis (PCA)

PCA extracted three principal components explaining 84.6% of total variance. Scree plot and eigenvalues confirmed component selection.

- **PC1 (General Cost Burden – 56.7%)**: High housing, childcare, and tax loadings.
- **PC2 (Care vs. Housing Tradeoff – 17.1%)**: Positive childcare and food; negative housing and transport.
- **PC3 (Tax-Centric Residual – 10.8%)**: High tax loading, moderate childcare.

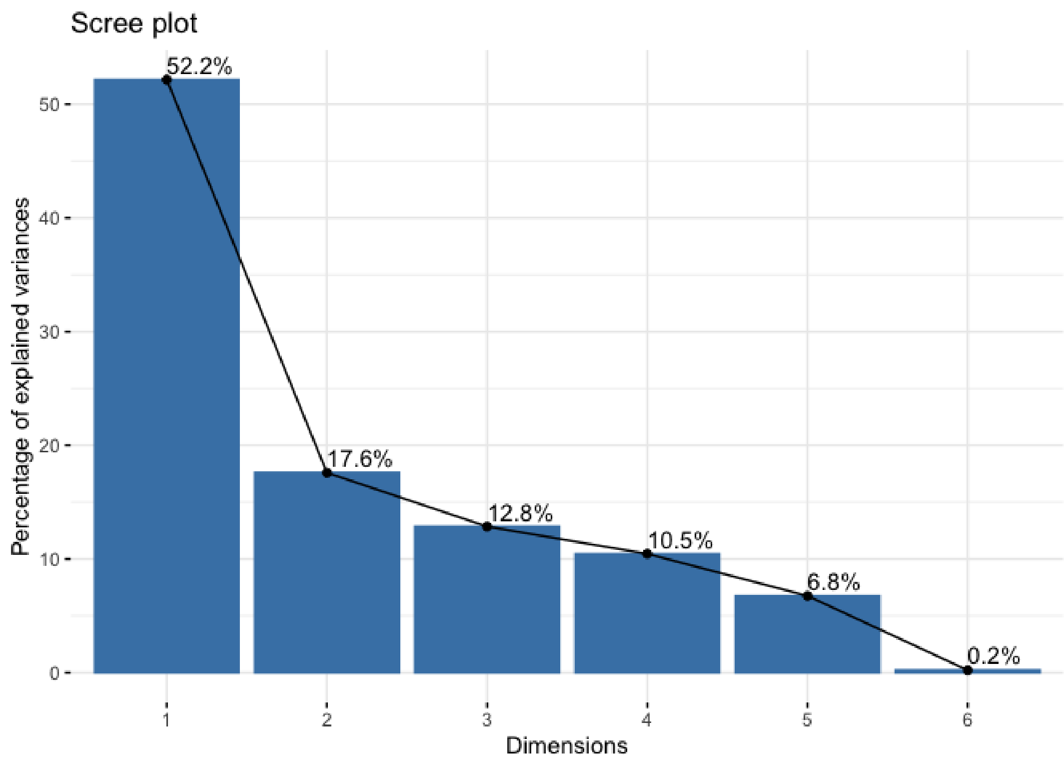

Figure 5: Scree plot showing variance explained by principal components.

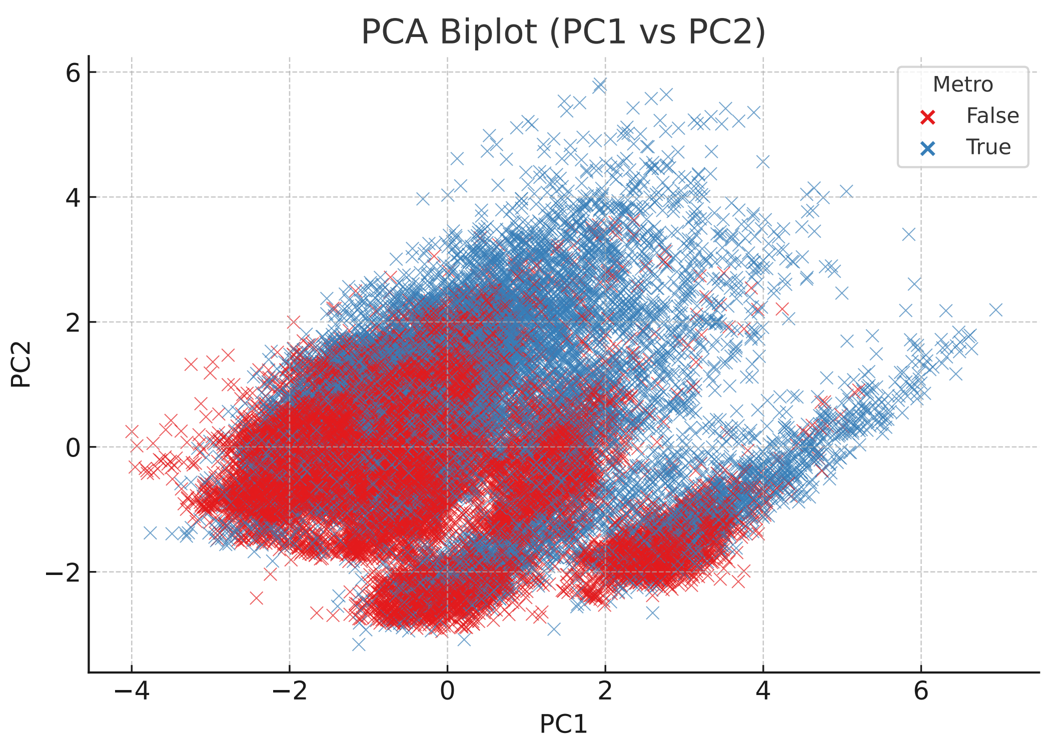

Figure 6: Biplot of counties in PC1–PC2 space with metro status overlay.

5.5 Regression Models and Residual Diagnostics

Each PCA component was regressed on SNAP rate, income, metro status, and state fixed effects. The strong PC1–SNAP association ($\beta = 2.89$) suggests that SNAP uptake intensifies where cumulative affordability burdens converge. In contrast, PC3's negative coefficient indicates that even with elevated tax and caregiving burdens, SNAP use may fall—potentially reflecting policy access gaps or administrative friction.

Table 2: Regression Results: SNAP Rate Predicting PCA Scores

Component	Estimate	Std. Error	t-Stat	p-Value	PC	R^2
SNAP Rate	2.89	0.30	9.66	8.85×10^{-22}	PC1	0.803
SNAP Rate	0.92	0.22	4.19	2.84×10^{-5}	PC2	0.688
SNAP Rate	-1.13	0.22	-5.22	1.93×10^{-7}	PC3	0.583

Note: Each model regresses the given principal component on SNAP rate, controlling for median income, metro status, and state fixed effects. Standard errors are robust to heteroskedasticity.

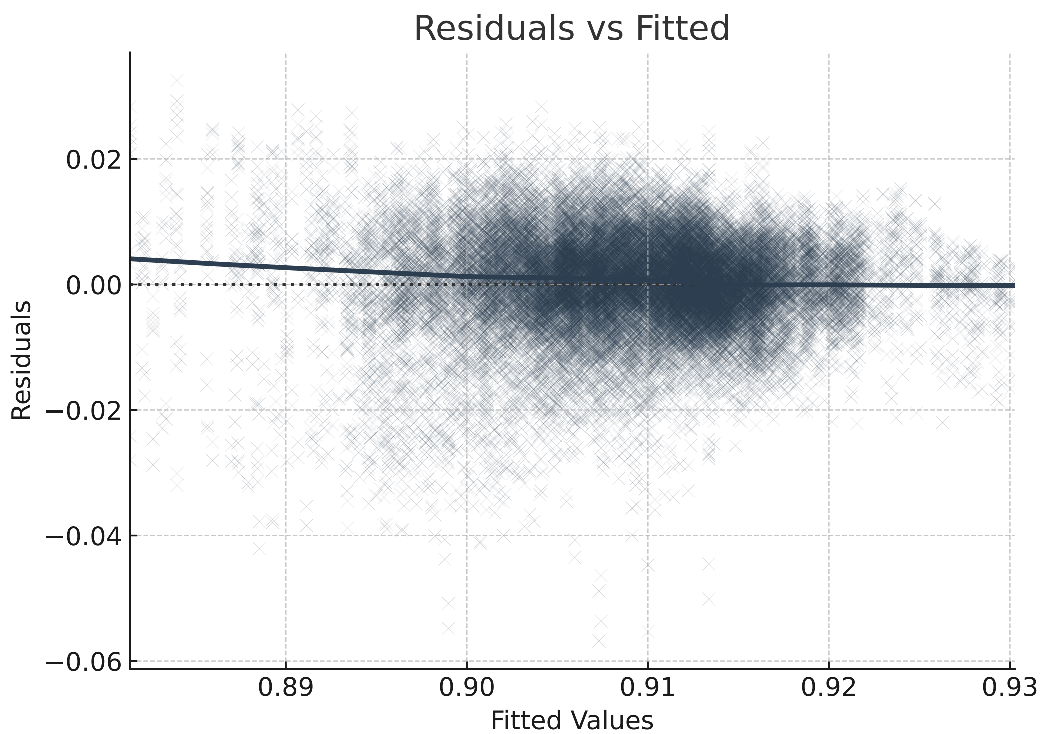

Figure 7: Residuals vs fitted values for PC1 model.

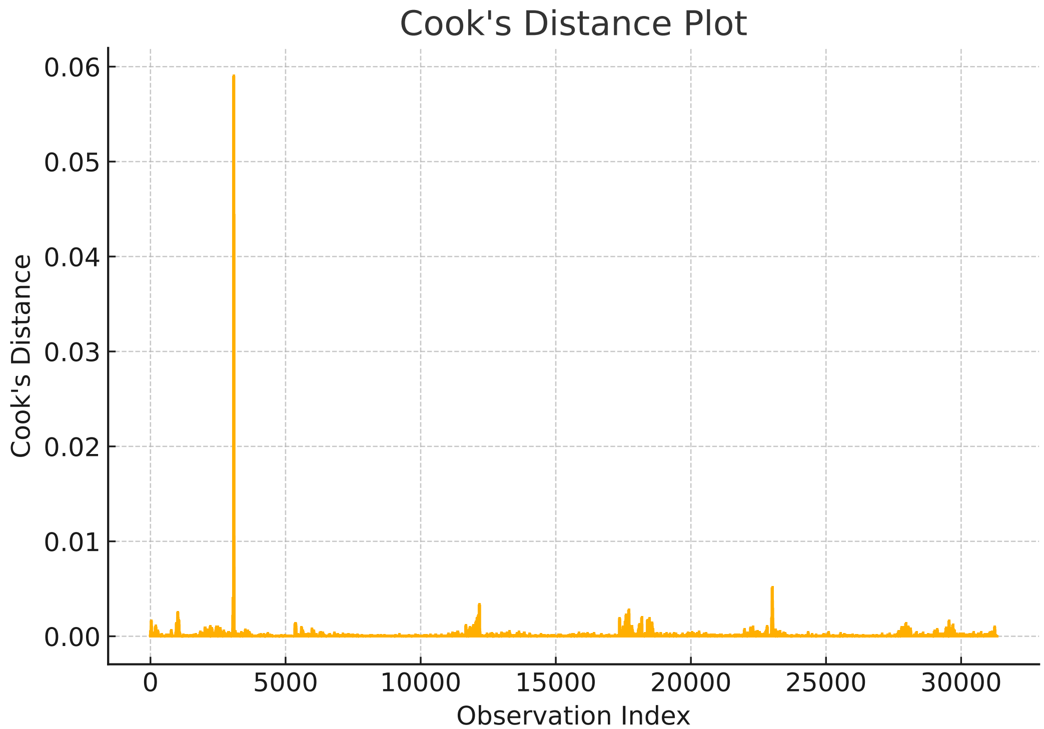

Figure 8: Cook's distance values across counties. No values exceeded the 0.1 threshold.

5.6 Clustering Analysis

K-means clustering on PCA scores revealed three affordability regimes. Silhouette analysis ($s = 0.47$) confirmed the robustness of $k = 3$.

- **Cluster 1 – Care-Heavy Counties:** High caregiving/food burden. Rural and semi-urban.
- **Cluster 2 – Housing-Stressed Counties:** High housing/transport costs, lower SNAP use.
- **Cluster 3 – SNAP-Tax Counties:** High SNAP rates, high tax shares. Often urban.

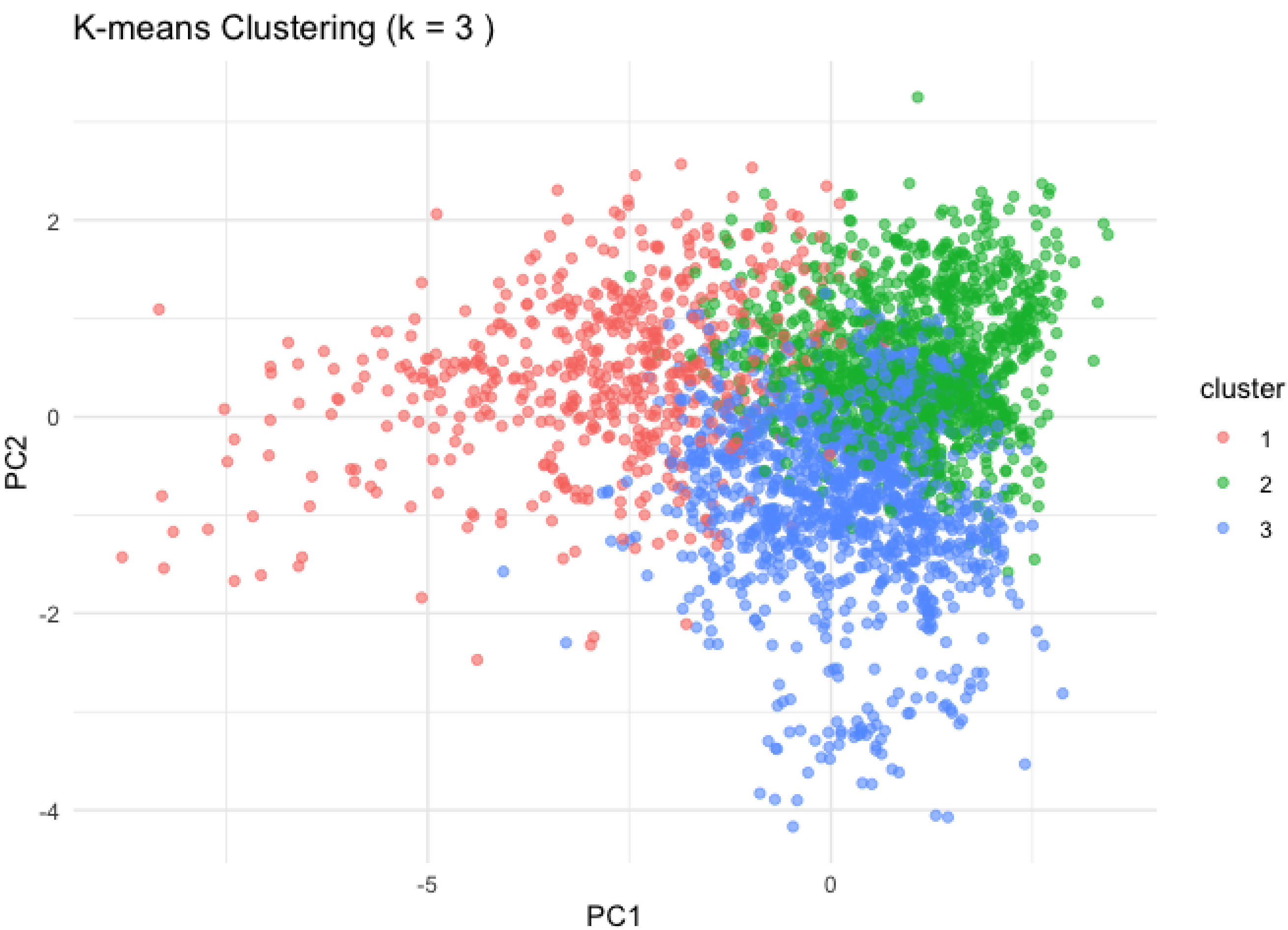

Figure 9: Cluster separation in PCA space.

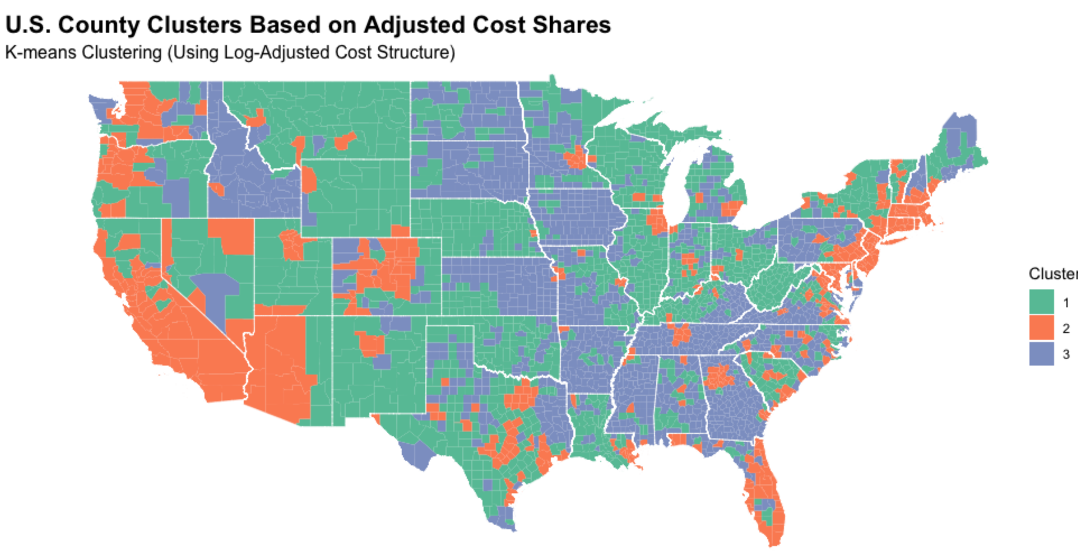

Figure 10: Geographic distribution of affordability clusters across U.S. counties.

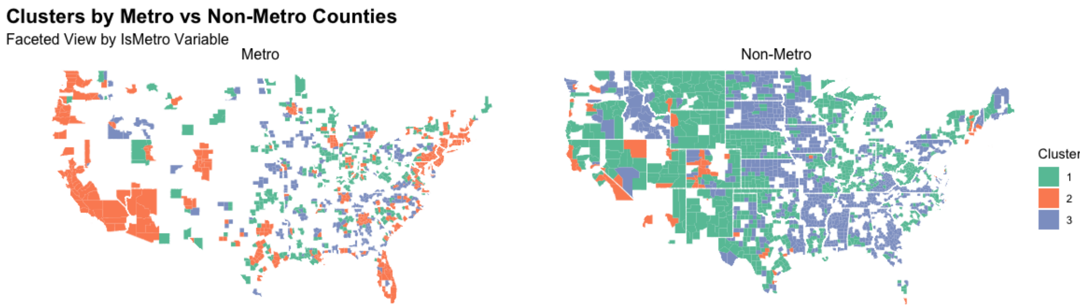

Figure 11: Clustered counties by metro vs non-metro status.

5.7 Statistical Validation

We validated clustering and model fit using:

- **ANOVA:** Cost shares differed significantly across clusters ($p < 0.001$), confirming that the structural composition of household expenses varies meaningfully across identified regimes.

Table 3: ANOVA Results: Cost Shares Across Clusters

Cost Share	Df	F-Statistic	p-Value
Food Share	2	115.3	< 0.001
Housing Share	2	248.6	< 0.001
Transport Share	2	198.4	< 0.001
Health Share	2	16.9	< 0.001
Childcare Share	2	298.7	< 0.001
Tax Share	2	176.2	< 0.001

Note: One-way ANOVA tests comparing mean cost shares across the 3 identified clusters. High F-statistics indicate strong group separation.

- **Chi-Square:** SNAP terciles associated with cluster membership ($\chi^2(4) = 404.7$, $p < 0.001$), suggesting structural affordability burdens significantly align with SNAP usage patterns.

Table 4: Chi-Square Test: SNAP Tercile vs. Cluster Membership

Statistic	Value	p-Value
Chi-Squared (χ^2)	404.7	< 0.001
Degrees of Freedom	4	
Cramér's V	0.345	

Note: Chi-squared test for independence between SNAP terciles and affordability cluster membership. Cramér's V indicates moderate association.

- **Silhouette Scores:** Moderate cohesion ($s = 0.47$) validated the $k = 3$ solution.

5.8 Summary of Findings

Our results demonstrate that SNAP participation is not solely driven by income, but is instead closely aligned with multidimensional affordability burdens captured by principal components. Regression results highlight statistically robust associations between SNAP rates and latent cost structures (PC1–PC3), even after adjusting for income, urbanicity, and state effects. K-means clustering further uncovers three distinct regional cost regimes, corroborated by significant ANOVA and chi-squared tests. Together, these findings suggest that SNAP is both a response to and a marker of structural affordability constraints—and that regional disparities in participation may reflect more than eligibility differences, pointing instead to uneven exposure to financial stress.

6 Discussion and Conclusion

This study demonstrates that SNAP participation is shaped not only by income but by broader structural affordability regimes that differ across U.S. counties. By integrating county-level cost shares, principal component analysis, multivariate regression, and clustering, we uncover multidimensional patterns of vulnerability. SNAP uptake emerges not as a simple function of poverty, but as a spatially variable response to composite financial stress—particularly in counties where housing, caregiving, and tax burdens dominate household budgets.

6.1 Interpreting the Principal Components

The first principal component (PC1), which captures over half the variance in structural cost shares, represents a generalized affordability burden—high shares of housing, childcare, and taxes. Its strong positive association with SNAP participation (even after controlling for income and metro status) reinforces the interpretation of SNAP as a broad affordability buffer. In high-cost counties—especially urban ones—SNAP enrollment appears to reflect cumulative structural stress rather than mere poverty.

The second component (PC2) reflects a tradeoff between housing and transportation costs (negative loadings) versus food and childcare costs (positive loadings). Its inverse association with SNAP participation suggests that households in housing-burdened regions may be underrepresented in SNAP, despite caregiving needs. This may stem from policy misalignment: eligibility rules that fail to account for non-income stressors or regional inflation, and thus exclude families with high structural costs but moderate reported income [12], [14].

The third component (PC3) highlights tax-centric and caregiving burdens not captured by income alone. Its positive association with SNAP participation suggests that regressive tax structures or limited public caregiving supports increase reliance on food assistance—even in counties with ostensibly higher earnings. This component underscores the importance of policy context in shaping need.

6.2 Insights from Clustering

K-means clustering of PCA scores revealed three interpretable cost structure regimes:

- **Cluster 1 – Caregiving Burdened Counties:** Predominantly rural and semi-urban, these counties have elevated childcare and food shares but relatively low SNAP participation. Barriers may include lack of administrative capacity, access constraints, or social stigma.
- **Cluster 2 – Housing-Stressed Counties:** Often suburban, with disproportionately high housing and transport shares. SNAP uptake remains low to moderate, possibly due to eligibility thresholds that do not adjust for regional affordability pressures.
- **Cluster 3 – SNAP-Tax Counties:** Largely urban counties with high SNAP enrollment and elevated tax burdens. These areas may benefit from infrastructure (e.g., transit, services) that enables participation, even under structural strain.

The emergence of these distinct regimes supports a structural, place-based theory of food assistance: SNAP usage reflects not just poverty, but how local cost burdens compound or mitigate economic vulnerability.

6.3 Policy Implications

Our findings yield several concrete recommendations for improving SNAP and broader affordability policy:

- **Regionally Sensitive Eligibility Formulas:** SNAP benefit and eligibility calculations should incorporate local cost indices—particularly for housing and caregiving. Current thresholds based on national poverty lines misrepresent need in high-cost areas.

- **Structural Adjustments to Income Thresholds:** Eligibility rules should reflect disposable income, not just gross income. Households paying 40% of income toward housing are not equivalently resourced as those with lower structural burdens [4], [6].
- **Complementary Investments:** Expanding access to affordable housing, subsidized childcare, and state-level tax relief could reduce structural dependence on SNAP by addressing root affordability gaps.
- **Affordability Monitoring and Targeting:** PCA-based cost profiling offers a scalable method for identifying structural vulnerability. Policymakers could use such models to prioritize outreach, allocate resources, or design cost-adjusted interventions.

6.4 Limitations and Directions for Future Research

This analysis is limited by its cross-sectional design and county-level aggregation. While we demonstrate statistical alignment between cost structures and SNAP participation, we cannot infer causality. It is also plausible that SNAP uptake itself feeds back into local price dynamics (e.g., food or housing inflation in high-participation areas) [24].

Moreover, averages at the county level mask within-county disparities. Future work should pair this structural lens with household-level microdata stratified by race, family composition, and immigration status to assess how costs and program use vary within regions. Qualitative studies could also deepen understanding of administrative, geographic, and social barriers to access—especially in caregiving-burdened rural regions with low enrollment.

6.5 Conclusion

SNAP participation is a spatial indicator of structural stress—not just a proxy for poverty, but a reflection of systemic mismatches between household needs and local cost regimes. Our findings suggest that policy should evolve beyond income-based targeting to recognize how place shapes affordability.

By situating SNAP within a broader framework of cost-burden geography, this study offers a more nuanced understanding of economic vulnerability and the role of public assistance. In an era of widening regional inequality, such insights are critical—not only for equitable SNAP design, but for building resilient local support systems that adapt to where and how people experience need.

References

[1] J. P. Ziliak, "Economic conditions and snap program participation," *Social Service Review*, vol. 89, no. 4, pp. 729–757, 2015.

[2] C. Ratcliffe, S.-M. McKernan, and K. Finegold, "The effects of snap on food insecurity," *Family Economic Well-Being*, 2011.

[3] H. Hoynes, D. W. Schanzenbach, and D. Almond, "The long-run impact of the earned income tax credit on children's education and employment outcomes," *American Economic Review*, vol. 106, no. 4, pp. 903–934, 2016.

[4] E. L. Glaeser and J. Gyourko, "Urban decline and durable housing," *Journal of Political Economy*, vol. 113, no. 2, pp. 345–375, 2003.

[5] J. M. Quigley and S. Raphael, "Housing affordability and urban growth," *Brookings-Wharton Papers on Urban Affairs*, pp. 83–140, 2004.

[6] M. Fisher, B. Kreider, and J. V. Pepper, "Minimum wages, housing costs, and material hardship," *Labour Economics*, vol. 47, pp. 138–151, 2017.

[7] Economic Policy Institute, *Family budget calculator*, https://www.epi.org/resources/budget/, 2024.

[8] C. Gundersen and B. Kreider, "Food insecurity and food assistance programs," in *Handbook of Agricultural Economics*, vol. 1, Elsevier, 2008, pp. 199–200.

[9] C. Gundersen, B. Kreider, and J. V. Pepper, "Snap and food insecurity," *American Journal of Agricultural Economics*, vol. 99, no. 4, pp. 875–893, 2017.

[10] H. L. Shaefer, I. Gutierrez, and K. J. Edin, "The impact of the 2009 stimulus package on snap and food insecurity," *Social Service Review*, 2010.

[11] C. W. Leung, J. M. Tester, E. B. Rimm, and W. C. Willett, "Diet quality by snap participation status among us adults," *JAMA Internal Medicine*, vol. 178, no. 4, pp. 546–554, 2018.

[12] J. Currie, "Us food and nutrition programs," in *Means-Tested Transfer Programs in the United States*, University of Chicago Press, 2003, pp. 199–290.

[13] R. Moffitt, "The evaluation of social programs and policies," in *Handbook of Income Distribution*, vol. 2, Elsevier, 2015, pp. 1571–1614.

[14] M. Bitler, J. Currie, and J. K. Scholz, *Can administrative records improve survey-based measurement of poverty?* NBER Working Paper No. 10128, 2003.

[15] J. Mabli, J. Ohls, L. Dragoset, L. Castner, and B. Santos, *Measuring the effects of snap participation on food security*, 2013.

[16] P. Ganong and J. B. Liebman, "Making the most of the earned income tax credit," *American Economic Journal: Economic Policy*, vol. 10, no. 2, pp. 183–219, 2018.

[17] M. Fisher and C. Baum, "Linking housing insecurity to food insecurity and health outcomes," *Social Science & Medicine*, vol. 175, pp. 58–65, 2017.

[18] N. V. Pilkauskas, J. Currie, and I. Garfinkel, "Snap participation and family wellbeing," *Social Service Review*, vol. 86, no. 3, pp. 403–437, 2012.

[19] M. Bitler and H. W. Hoynes, "The safety net and the great recession," *Journal of Economic Perspectives*, vol. 30, no. 2, pp. 53–78, 2016.

[20] U.S. Department of Agriculture, *Supplemental nutrition assistance program (snap) data*, Accessed July 2024, 2024. [Online]. Available: https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap.

[21] U.S. Census Bureau, *County population totals: 2024*, Accessed July 2024, 2024. [Online]. Available: https://www.census.gov/data/datasets/time-series/demo/popest/2020s-counties-total.html.

[22] U.S. Census Bureau, *American community survey (acs) 5-year data*, Accessed July 2024, 2024. [Online]. Available: https://www.census.gov/data/developers/data-sets/acs-5year.html.

[23] U.S. Department of Agriculture, Economic Research Service, *Rural-urban continuum codes*, Accessed July 2024, 2024. [Online]. Available: https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/.

[24] M. P. Bitler and H. W. Hoynes, "Strengthening snap for a more food-secure, healthy america," *The Hamilton Project*, 2016. [Online]. Available: https://www.hamiltonproject.org/assets/files/strengthening_snap_food_secure_healthy_america.pdf.