Mapping Structural Need: Food & Healthcare Access Across 74 Texas Counties

(Prepared for the Center for Civic & Public Policy Improvement)

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Executive Summary

Persistent gaps in food access, healthcare availability, and community infrastructure continue to shape where people choose to live—and whether they can remain there over long periods of time. In many Texas counties, rising living costs and limited investment in these social determinants of health have contributed to population shifts from urban centers to surrounding suburban and rural areas. As residents enter new life stages, such as starting families or joining the workforce, they often seek safer neighborhoods, greater housing affordability, stronger educational opportunities, and improved quality of life—conditions not equally available across all regions. These migration patterns can place strain on public health systems: some counties face rapid population growth that outpaces their infrastructure's capacity, while others lose critical services as populations decline. In both cases, disconnection emerges between community needs and the availability of resources, particularly in food access and healthcare services.

In partnership with the Center for Civic & Public Policy Improvement (CCPPI) and Methodist Health Ministries (MHM), our study examines how migration patterns may impact the viability of public health resources, and where these movement shifts are creating or heightening disparities. Our goal is to inform targeted interventions and resource allocation strategies that address food and healthcare access disparities within the targeted area for CCPPI and MHM.

Drawing on a cross-sectional dataset of the defined 74 counties within the Area of Strategic Opportunity (AOS), we analyze variables related to healthcare access, food insecurity – defined as the lack of consistent access to enough food for an active, healthy life, and Limited English Proficiency (LEP) – which refers to individuals who speak English "less than very well" as classified by the U.S. Census Bureau. From 2020 to 2024, our findings show that counties with high LEP populations were disproportionately affected by worsening food insecurity, even after controlling for income, migration, and Medicaid enrollment.

Our analysis reveals that food insecurity rose by up to 13% in high-LEP border counties, with LEP emerging as the strongest correlation of rising need. Notably, Supplemental Nutrition Assistance Program (SNAP) participation was associated with reduced food insecurity, and net migration slightly alleviated food insecurity in the poorest counties. These results highlight structural and linguistic barriers not fully captured by economic indicators alone and underscore the importance of targeting linguistically isolated, low-income areas for health and food assistance interventions.

Defining the Problem

By focusing on increased demand and potential strain of resources as a result of the change in migration patterns, we seek to observe which regions are experiencing an influx of people moving in from this urban landscape, and what their needs generally entail in regards to their nutrition and healthcare. We pose the question, *"Based on structural indicators, which regions within the AOS are most likely to benefit from expanded nonprofit services related to food access and healthcare support?"* This question reflects the core objective of our analysis: to identify what to invest in and where to target these investments in order to most effectively address the needs of underserved communities and promote equitable living conditions across the 74 counties within the AOS.

Previous studies have looked into the association between spatial access – the ability to easily reach desired locations – to food and healthcare sources, the quality of services, and the effects of migration influxes on local economies. A study done by Sharkey, et. al. (2009) sought to investigate food security within Texas *colonias*, which are substandard housing developments that typically lack basic services, such as water and sewage. These communities are mostly spread out along the Texas-Mexico border, which includes many counties that we are observing for the enhancement of this research. The study found that essential food suppliers were more likely to be located closer to densely populated urban areas, while residents who live further out benefit more from fast food chains, emphasizing the importance of being attentive to proximity rather than just the density of outlets if a community is seeking to increase access to nutritional means.

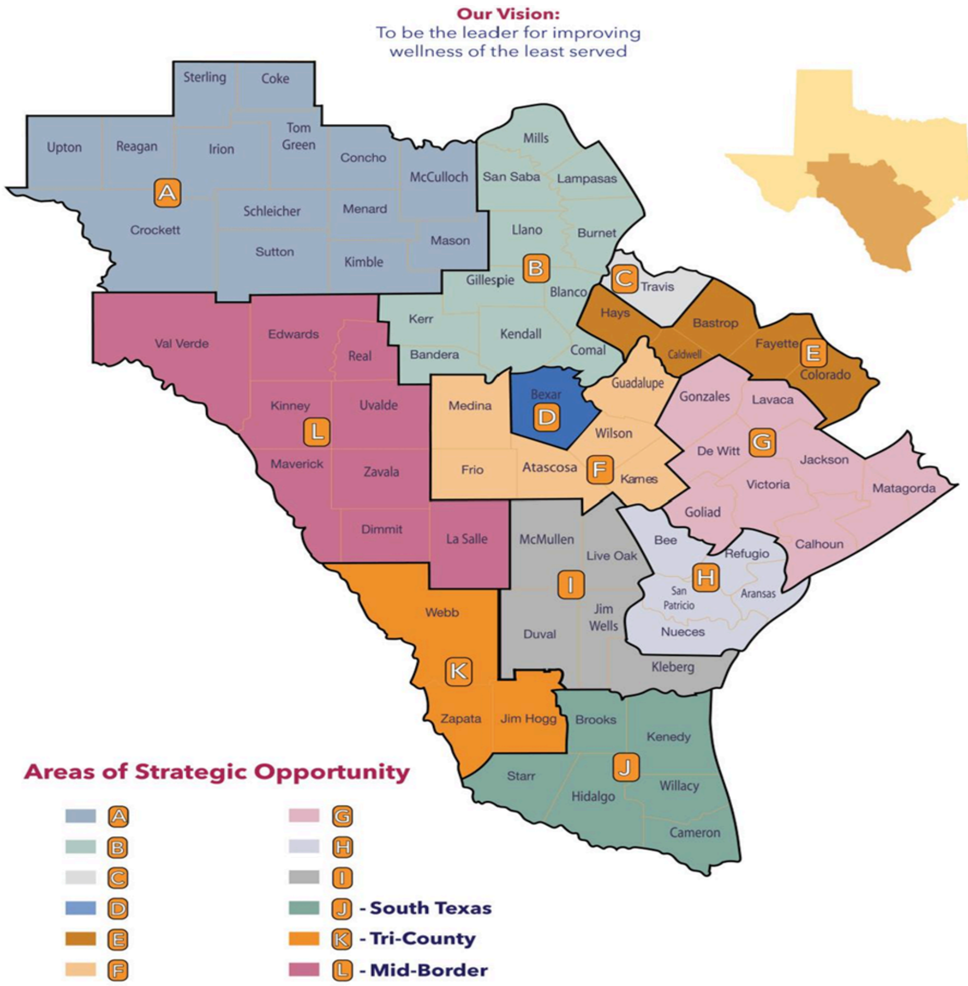
Further studies focusing on SNAP benefits in more rural areas have shown that increased migration can place a strain on local economies, as rural households have increased demands and more buying power due to being larger on average compared to their urban counterparts (Weerasooriya & Reimer, 2019). Regarding attentiveness to health, there are implications that migrants – even domestic ones – are placed at a disadvantage, as lack of comprehensive and accessible health resources can increase public health risks.

A 2023 study conducted by the BMC Public Health Review stated that migrants “often have to confront language barriers, unfamiliar systems, and limited social support, leading to poor management of chronic conditions and reduced access to preventive or cultural-competent care”(Goldenberg & Fischer, 2023). There exists an apparent lack of representation within the healthcare system with limited advocacy due to these barriers, which warrants intervention to promote equity in care.

Building upon this body of evidence, our analysis extends these concerns to a regional framework grounded in local Texas dynamics. Our target population is residents of the 74-county focus area that is divided into 12 different regions, A through L. The regional labels (A through L) used in this analysis were developed through internal CCPPI groupings rather than official government designations. These groupings were specifically designed to organize the 74 counties within the Area of Strategic Opportunity (AOS) into manageable clusters based on their geographic proximity to San Antonio and shared socioeconomic characteristics. This framework enables CCPPI and its partners to assess patterns of migration, resource gaps, and health-related needs at a broader regional level while maintaining a focus on local dynamics. By employing this customized regional structure, the analysis aligns closely with CCPPI’s operational priorities and strategic planning efforts. With our analysis, we aim to target areas that may have exhibited signs of disproportionate need compared to their neighboring regions.

Figure 1. Regional Map of 74 Counties - Areas of Strategic Opportunity

Source: CCPPI & MHM. Map showing the 74 AOS counties grouped into twelve CCPPI-defined regions (A-L) for targeted analysis and planning.



Analytical Approach

This analysis draws on a custom-built panel dataset integrating demographic, socioeconomic, and public service access indicators for 74 counties designated as Areas of Strategic Opportunity (AOS). The dataset spans from 2019 to 2025 and incorporates both publicly available administrative data and internal records developed through prior research initiatives conducted by the Center for Civic and Public Policy Improvement (CCPPI).

Primary data sources include the U.S. Census Bureau, Texas Health and Human Services, Feeding America's Map the Meal Gap project, County Health Rankings, and CCPPI's proprietary datasets. Together, these sources provide a comprehensive foundation for assessing structural disparities across counties. Key demographic, economic, and healthcare variables were selected to inform a multidimensional analysis of food insecurity and public service accessibility.

For a complete inventory of each variable, its data source, and any proxies or notes on usage, refer to *Appendix 1-A: Data Mapping Table.*

Descriptive Statistics

To analyze the socioeconomic and public health dynamics across the AOS counties, we employed a mixed-method quantitative approach. We created descriptive statistics regarding each county and region, which allowed us to create a scoring system to guide strategic decision making.

Descriptive statistics help uncover baseline conditions in each county and region, such as average food insecurity rates, SNAP access, and healthcare availability and find early disparities across regions A-L. Summarizing data by region reveals which areas had clusters of high or low performance across different metrics. These insights led to the creation of our composite Total Score, which systematically ranks counties based on their relative needs. The scoring system provides a data-driven framework for CCPPI & MHM to better understand where would be best for them to allocate their resources effectively.

Data Normalization & Scoring System

Having established the baseline disparities through descriptive analysis, we constructed a composite prioritization framework to guide actionable interventions. The variables that were included in our scoring system were:

- **Food Insecurity Rates** = The percentage of individuals in a county lacking consistent access to enough food for an active, healthy life, often due to limited financial resources or other barriers.
- **Food Environment Index** = A measure of access to healthy foods, incorporating proximity to grocery stores, availability of nutritious food options, and barriers such as transportation and cost.
- **Medicaid Caseloads per capita** = The number of individuals enrolled in Medicaid benefits per 1,000 residents in a county, providing a normalized measure of healthcare assistance demand relative to the county's population size.
- **SNAP Access** = The percentage of eligible individuals actively participating in the Supplemental Nutrition Assistance Program (SNAP), which supports low-income households in purchasing nutritious food.
- **Limited English Proficiency Rates** = The percentage of residents who speak English "less than very well," indicating potential challenges in accessing public services, healthcare, and community resources.
- **Income** = The median household income for each county, serving as an indicator of economic stability and the capacity to meet basic living needs.
- **Rate of Primary Care** = The number of primary care physicians per 100,000 population in a county, representing access to essential medical services for residents.

Key Steps in Constructing the scoring system included:

- **Normalization of Indicators:** Each variable mentioned above was ranked into a percentile ranking, allowing for equitable comparison across diverse metrics.
- **Composite Score Calculation:** Percentile scores were summed to create a Total Score for each county, reflecting its relative level of need across all dimensions. Higher scores indicate greater challenges in food security and healthcare access.
- **Priority Classification:** Total scores were grouped into three tiers –

    - ❖ <u>Least Prioritization</u>: Counties with relatively low composite scores, suggesting fewer immediate challenges and less need for targeted interventions compared to other areas

    - ❖ <u>Medium Prioritization</u>: Counties falling in the mid-range of scores, indicating moderate levels of need that may warrant selective support based on resource availability

    - ❖ <u>Highest Prioritization:</u> Counties with the highest composite scores, reflecting significant challenges in food security and healthcare access relative to the data set

- **Regional Summarization:** To better understand geographic patterns of need, county-level scores were aggregated at the regional level (Regions A–L). This aggregation identified regions with concentrated clusters of high-priority counties. Notably, Regions J, L, I, and K emerged as areas with the greatest proportion of "Highest Prioritization" counties, indicating systemic vulnerabilities requiring targeted support. Conversely, Regions B, C, and D exhibited stability, with most of their counties classified as "Least Prioritization."

To support the development of the Total Score and ensure methodological transparency, we selected variables that reflect critical dimensions of public health and social vulnerability. Each variable was chosen based on its relevance to food insecurity, healthcare access, and structural disadvantage across AOS counties. For additional context and rationale behind the selection of each variable—including interpretation notes—please refer to *Appendix 1-B. Total Scoring System Variable Justification*

Table 1. Regional Distribution of County Prioritization

Number and percentage of counties in each region categorized by prioritization level based on total composite scores (n = 74).

Region	Least Prioritization Counties	Medium Prioritization Counties	Highest Prioritization Counties	Total Counties in Each Region	Percent of Region in Highest Priority	Percent of Region in Least Priority
A	4	9	1	14	7.0%	28.6%
B	10	1	0	11	0.0%	91.0%
C	1	0	0	1	0.0%	100.0%
D	1	0	0	1	0.0%	100.0%
E	3	2	0	5	0.0%	60.0%
F	3	3	0	6	0.0%	50.0%
G	4	4	0	8	0.0%	50.0%
H	1	2	2	5	40.0%	20.0%
I	0	1	4	5	80.0%	0.0%
J	0	0	6	6	100.0%	0.0%
K	0	1	2	3	66.7%	0.0%
L	0	2	7	9	77.8%	0.0%
Totals	**27 Counties**	**25 Counties**	**22 Counties**	**74 Counties**		

The analysis of the 74-county Strategic Operating Area (SOA) reveals substantial variation in prioritization needs across regions. Regions J, L, I, and K emerge as the areas with the highest concentration of high-priority counties. Region J stands out with 100% of its counties (6 of 6) classified as "Highest Prioritization," followed closely by Region L (77.7%) and Region I (80%). Conversely, Regions B, C, and D exhibit the strongest stability, with no counties in the high-priority category and over 90% of their counties classified as "Least Prioritization." These findings suggest that while some regions may require only minimal intervention, others present systemic vulnerabilities in food security, healthcare access, and socioeconomic resilience that necessitate targeted support.

<u>Regional Priority Distribution Insights</u>

Figure 2. Bar Graph: Region Priority Distribution

Displays the raw count of counties within each region falling into Least, Medium, or Highest Prioritization tiers.

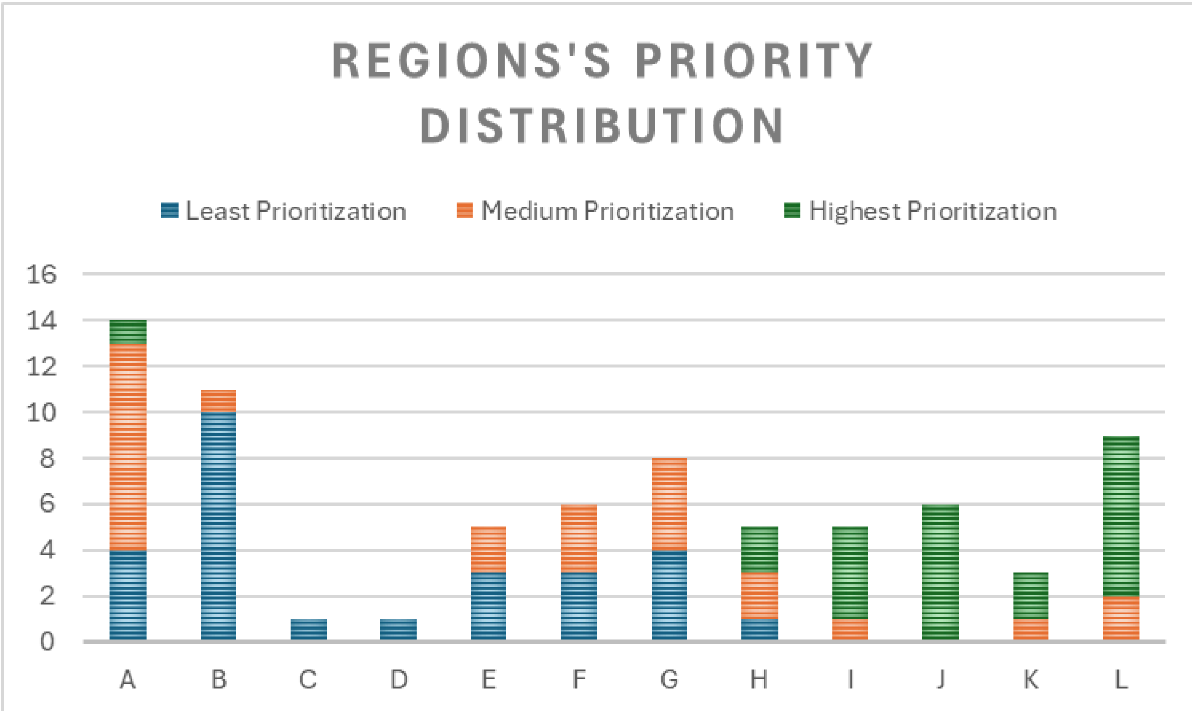
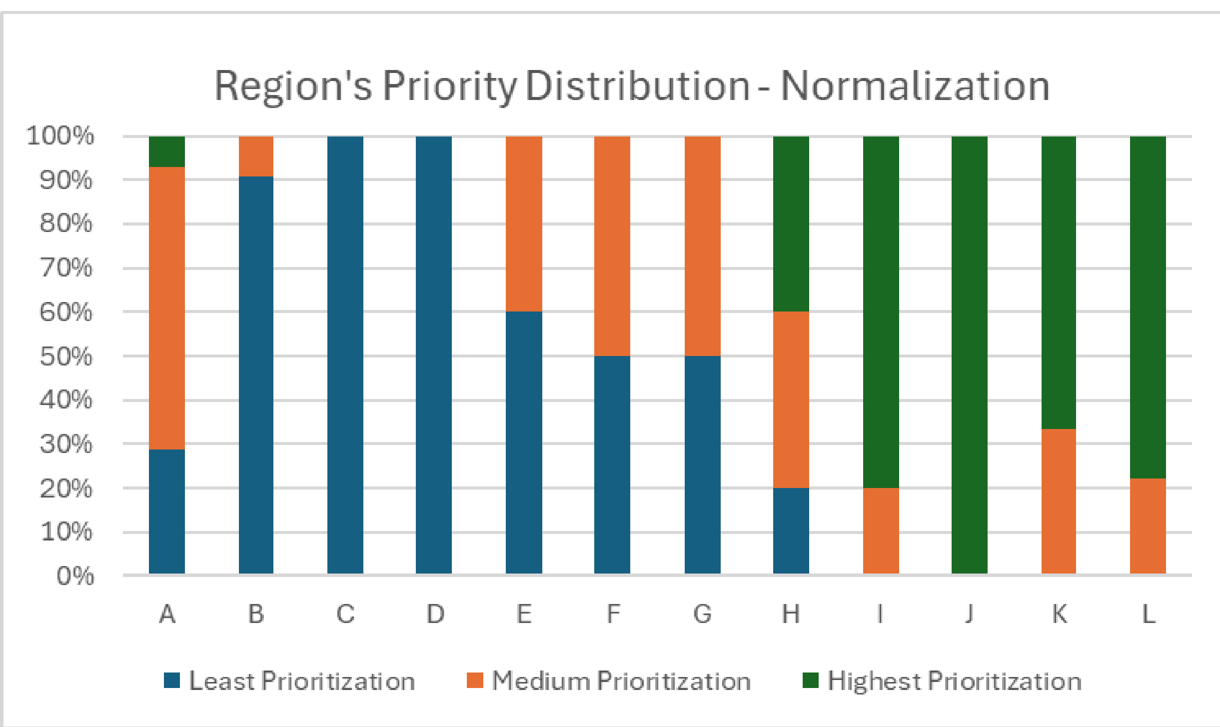


Figure 3. Bar Graph: Region Priority Distribution (Normalized)

Shows the proportion of counties in each region within each prioritization tier, allowing for cross-region comparison regardless of total county count.



The two visualizations presented in this section offer complementary perspectives on how prioritization scores are distributed across the twelve AOS regions. The graph in Figure 1, which shows the raw distribution of counties by prioritization tier (High, Medium, Low), highlights that certain regions—most notably Regions J, L, I, and K—contain the highest concentration of high-priority counties based on structural indicators of food insecurity and public service need. However, this raw count alone does not account for differences in the number of counties per region.

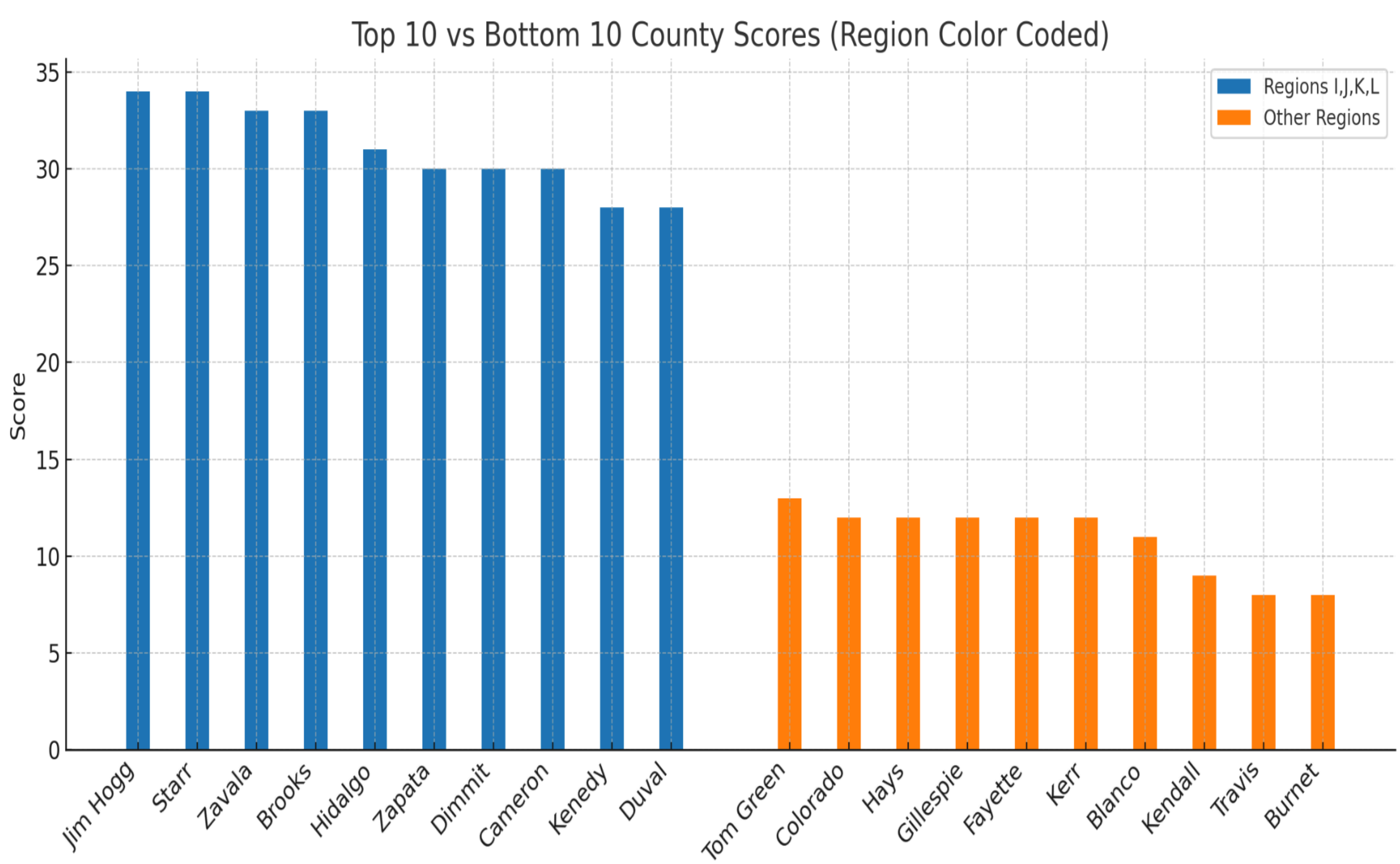
To address this, Figure 2 normalizes the distribution by showing the *proportion* of each region's counties that fall into the highest priority tier. This enables more accurate cross-regional comparisons. For example, while Region A and H may include high-priority counties, Regions J and L show 100% and 77.7% of their counties in the highest priority tier, respectively—indicating a region-wide need rather than isolated county-level challenges.

Together, these graphs help clarify not only where the greatest concentration of high-need counties exists, but also where the need is most pervasive relative to regional size. This dual perspective reinforces the rationale for focusing resources and intervention efforts in Regions I, J, K, and L, where indicators of structural disadvantage appear both concentrated and persistent.

Total Score Insights

Figure 4. Bar Chart: Top 10 vs. Bottom 10 County Prioritization Scores

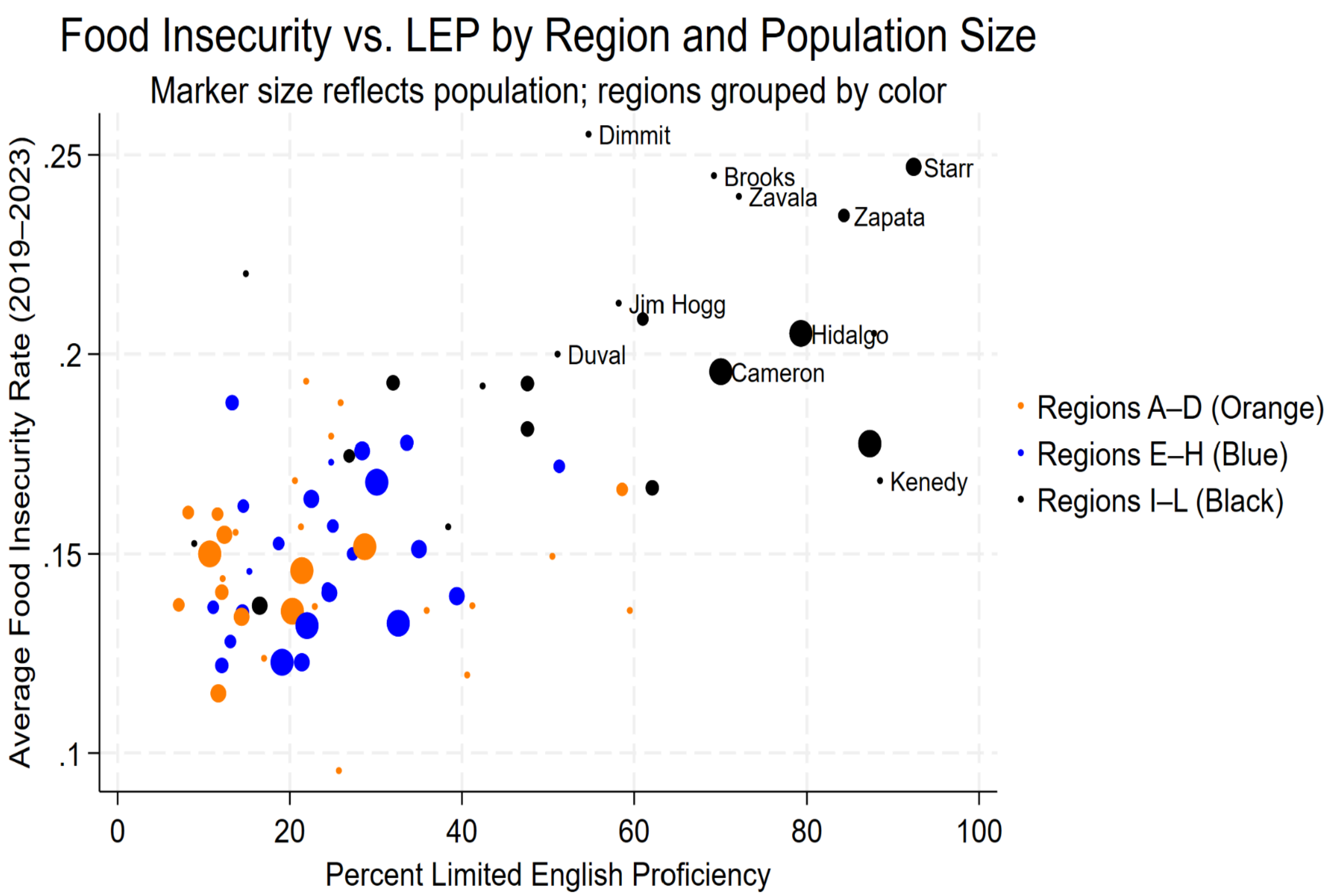
Compares the highest and lowest scoring counties by total prioritization score. Counties from Regions I,J,K, and L are color-coded to highlight their concentration among top scorers.



To add to the insights from our Regional Priority Distribution analysis, we have compiled a bar chart in Figure 4 showing the Top 10 and Lowest 10 counties in terms of their total score. It is important to remember that a higher score signals a higher need, and vice versa. We see again the reiteration that there is a clear dominant pattern within Regions I, J, K, and L. Not only do these regions show a clear trend of having the majority of "High Priority" needs relative to the population (74 counties), but they also own each and every county within the Top 10 of total scores. From our *Regional Priority Score Table*, we observe that there are 22 counties within the "Highest Priority". Out of those 22 counties, the Top 10 (Higher Score = Higher Need) are within the regions we've been discussing. We also see that all of the Lowest 10 (Lower Score = Lower Need) do not have a county from Regions I, J, K, and L either. These results emphasize the persistent disparity we have been seeing between these regions and their neighboring areas.

Figure 5. Scatterplot: Food Insecurity vs. Limited English Proficiency by Region and Population Size (Top 10 Score Counties Labeled)

Displays the relationship between average food insecurity rates and limited English proficiency rates. Marker size represents relative population size, allowing for quick visual comparison of county populations. Top 10 highest-priority counties are labeled. Regions A-D, E-H, and I-L are color-coded to show regional groupings.



The scatter plot in Figure 5 illustrates the relationship between average food insecurity rates and the percentage of Limited English Proficiency (LEP) across all 74 counties in the Area of Strategic Opportunity (AOS). The plot distinctly highlights the Top 10 counties with the highest composite prioritization scores – those identified as the "Highest Priority" for intervention based on compounded socioeconomic and health indicators. Consistent with previous studies, all of these Top 10 counties are situated within regions I, J, K and L, which are geographically clustered along the Texas-Mexico border.

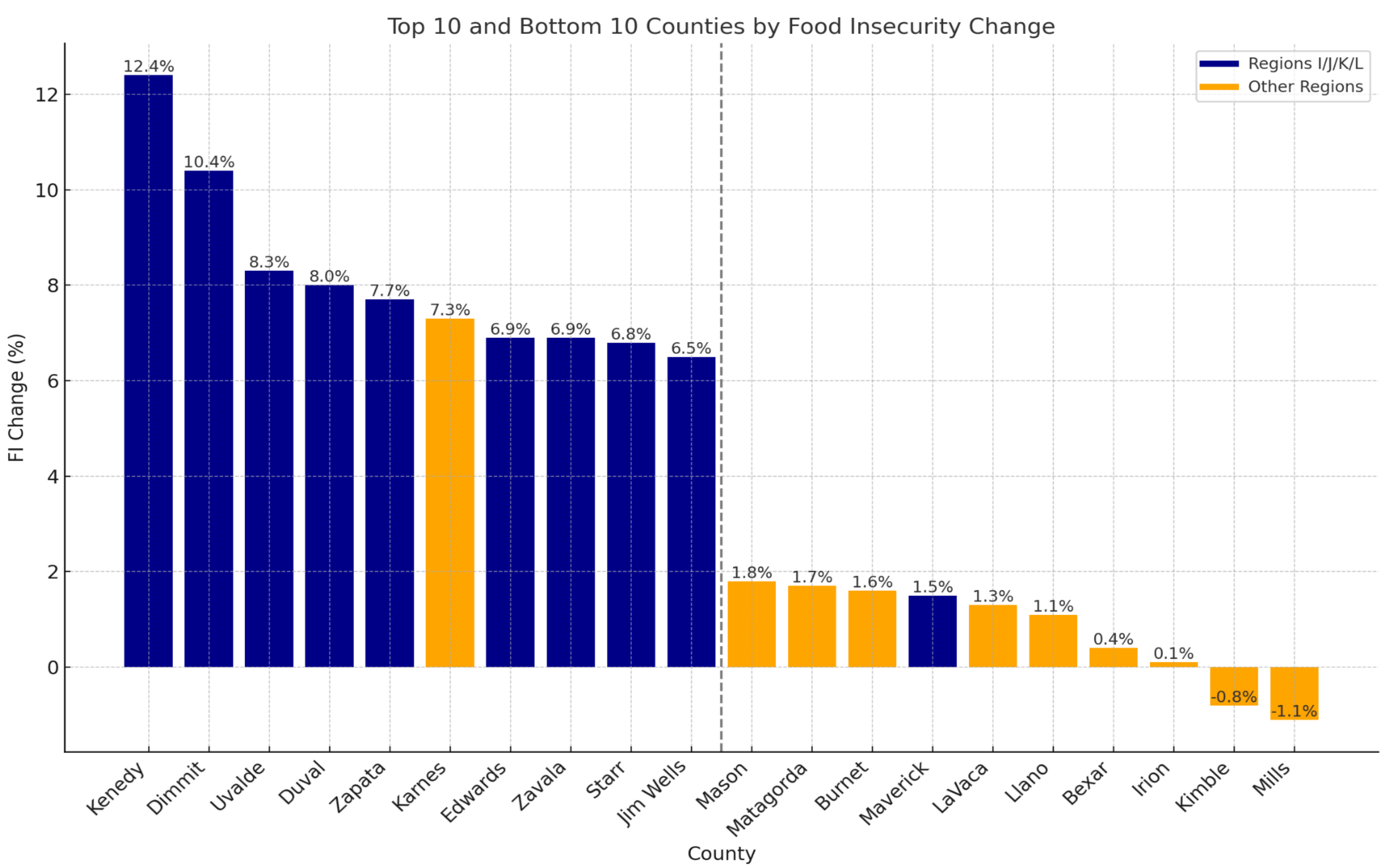
Figure 5 further reveals a moderately strong positive association between the percentage of Limited English Proficiency (LEP) residents and average food insecurity rates ($r = 0.619$, $p < 0.001$). This indicates that counties with higher proportions of LEP populations tend to experience elevated levels of food insecurity. Counties such as Starr, Zapata, Hidalgo, and Brooks exhibit some of the highest combined LEP and food insecurity rates in the dataset.

The analysis of the Area Of Strategic Opportunity (AOS) demonstrates a clear trend concentrated along Texas's southern border. Regions I, J, K, and L, which border Mexico, stand out for their consistently elevated Limited English Proficiency (LEP) rates and higher average food insecurity rates compared to other regions.

Top 10 and Bottom 10 - Changes in Food Insecurity (2019-2023)

Figure 6. Bar Chart: Top and Bottom 10 Counties by Change in Food Insecurity Rate

Highlights the counties with the largest increases and lowest increases(even decreases) in food insecurity rates from 2019 to 2023. Regions I-L are color-coded distinctly to emphasize their elevated need; Regions A-H are grouped under a separate color(Orange).



The bar chart above illustrates which counties have seen the largest and lowest absolute increases in food insecurity rates over the past four years. Kenedy County has the highest increase, at 12.4%. Trailing behind are counties such as Dimmit, Uvalde, and Duval, which each experienced rises in food insecurity ranging from 8 to10%.

With combined analysis, we see again that the majority of large increases in food insecurity occur in regions near the border with high Limited English Proficiency rates. This may be reflective that many of these counties share similar barriers to health and wellness, such as inadequate knowledge and understanding of public programs that assist with increasing community health and well-being. Given these conditions, these counties could benefit from expanded SNAP outreach, mobile grocery or retail support, bilingual health campaigns, and targeted assistance from organizations such as Methodist Health Ministries. Furthermore, the right side of the bar chart highlights the bottom 10 counties that experienced the smallest increases–or even decreases–in food insecurity rates over the past four years. Mills, Kimble, and Irion Counties showed zero or slightly negative growth in food insecurity, which may suggest that they receive targeted food assistance, retain stable populations, or benefit from strong local food networks or nonprofit support.

Other counties like Llano, LaVaca Maverick, Burnet, Matagorda, Mason, and Schleiche, saw modest increases of just 1% to 2%, which is significantly lower than the statewide average of 4% in the model. These areas could serve as examples of community resilience, limited demographic shifts, or effective social infrastructure. Despite its border location, Maverick County stands out in particular. It has maintained relatively low growth in food insecurity—possibly a result of local initiatives, cross-border economic activity, or efficient implementation of federal aid programs.

Regression Modeling

This section presents model outputs used to examine the relationship between migration flows, demographic characteristics, and the observed increase in food insecurity across Texas counties in the AOS from 2019 to 2023. We conducted multiple linear regression analyses to examine how county-level factors are associated with changes in food insecurity rates. The dependent variable in our regression models is the *Change in Food Insecurity Rate (2019-2023),* which takes the difference between the Food Insecurity Rates from 2019 to 2023 in all 74 counties.

These regressions identify statistically significant correlations between Limited English Proficiency and Changes in Food Insecurity Rate, holding income levels and public assistance variables constant. We used these regressions not to predict food insecurity precisely, but to help pinpoint priority counties and understand patterns of association that may guide CCPPI on what we need to have a stronger focus on when deciding where resources should be allocated. Before conducting regressions, we reviewed bivariate scatterplots of key variables which can be found in *Appendix 1-C* to visually assess patterns, which helped motivate variable selection and inform expected relationships prior to regression analysis.

Table 2. OLS Regression Predicting Change in Food Insecurity Rate

	(1) Δ Food Insecurity Rate
Net Flow Migration	0.000
	(0.001)
Income per 1k	-0.020
	(0.014)
Limited English Proficiency	0.055***
	(0.011)
Caseloads per 1k	-0.001
	(0.006)
Constant	3.380***
	(1.130)
Observations	71
Adj. R-squared	0.3775

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We estimated a multi-variable linear regression model, analyzing the effects of variables like net migration, median household income, limited English Proficiency, and number of caseloads on the changes in Food Insecurity in Table 2:

$$\text{Change in FI Rate} = \beta_0 + \beta_1\text{NetFlow} + \beta_2\text{Income} + \beta_3\text{LEP} + \beta_4\text{MedicaidCaseloads} + \varepsilon$$

Our first regression analysis in Table 2 found that the Limited English Proficiency (LEP) rate is the only statistically significant predictor of changes in food insecurity rates at a 1% level, being interpreted as a 0.055 percentage point increase in change in food insecurity rate for every percentage point increase in LEP. This indicates that counties with higher LEP populations are most at risk for worsening food insecurity, likely due to language barriers in accessing public assistance, lower civic participation, and broader institutional exclusion.

A majority of LEP individuals speak Spanish as their primary language, and are mostly concentrated within adult populations, as children of LEP migrants are more likely to be bilingual. It suggests that individuals who might otherwise benefit from community resources or public programs may face barriers in areas that lack adequate language accessibility for non-English speakers. Other variables like net migration flow, median household income, and Medicaid caseloads, do not show statistically significant predictors of food insecurity changes.

This suggests that LEP may be capturing much of the explanatory power typically associated with poverty and social exclusion.

The results of the Variance Inflation Factor (VIF) test confirm that multicollinearity is not a concern since that the values are less than 10; the predictors are independent enough to interpret confidently, which is shown in *Appendix 2-E.* While there's significant correlation between LEP and changes in food insecurity, this correlation should be interpreted with caution. Further analysis is needed to rule out confounding factors that could also influence food insecurity.

Table 3. OLS Regression Predicting Change in Food Insecurity Rate with SNAP Variable Included

	(1) Δ Food Insecurity Rate
Net Flow Migration	0.000
	(0.001)
Income per 1k	0.006
	(0.019)
Limited English Proficiency	0.044***
	(0.012)
Caseloads per 1k	-0.002
	(0.006)
SNAP Rate 2023	-0.209**
	(0.102)
Constant	0.770
	(1.688)
Observations	71
Adj. R-squared	0.4061

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We then estimated another multiple linear regression model with SNAP participants included as an additional predictor to better understand the drivers of food insecurity rate changes in Table 3. The goal was to assess whether SNAP participation, as a proxy for need-based assistance uptake, and it could help explain variation not captured by the original model.

$$\text{Change in FI Rate} = \beta_0 + \beta_1\text{NetFlow} + \beta_2\text{Income} + \beta_3\text{LEP} + \beta_4\text{MedicaidCaseloads} + \beta_5\text{SNAP} + \varepsilon$$

The regression in Table 3 after adding in SNAP participation yields an R^2 of 0.4061, suggesting that approximately 40.6% of the variation of food insecurity changes are explained. The Limited English Proficiency variable is still statistically significant and is interpreted as a 1 percentage point increase in Limited English proficiency is associated with a 0.044 percentage point increase in food insecurity rate. Most notably, our newly added variable about SNAP participation rate is statistically significant at 5%, with a 1 percentage point increase in SNAP enrollment in 2023 being associated with a 0.209 percentage point decrease in food insecurity change. Other variables that we also have included in our previous regression remain statistically insignificant, suggesting they do not meaningfully explain the variation in food insecurity rate within this specification. Based on the model, it suggests that factors such as limitation in language access and participation in SNAP exhibit strong associations with recent changes in food insecurity, relative to structural economic indicators.

Targeting High-Residual Counties for Deeper Analysis

In addition to the overall regression results, certain counties display substantial unexplained increases in food insecurity that warrant closer policy attention. As shown in *Appendix 2-C*, counties such as Dimmit, Karnes, and Uvalde exhibit residuals exceeding 3 percentage points, indicating that actual food insecurity increases are significantly higher than predicted by the model. These outliers suggest the presence of localized structural barriers or service delivery gaps not fully captured by traditional indicators such as income, migration, or LEP rates. From a policy perspective, these counties represent strategic opportunities for targeted investigation, including field assessments or community-based participatory research, to uncover unmeasured drivers such as nonprofit fragmentation, disaster recovery delays, or barriers to federal assistance enrollment. Prioritizing high-residual counties for exploratory engagement could help Methodist Health Ministries and CCPPI refine intervention strategies and close data blind spots in future planning efforts.

Table 4. OLS Regression Predicting Change in Food Insecurity Rate with Interaction Term (Income Quintile x Migration Net Flow):

	(3) ΔFood Insecurity Rate
Net Flow Migration	-0.00968***
	(0.00333)
Income Quintile 2	-0.0368
	(0.787)
Income Quintile 3	-1.155
	(0.715)
Income Quintile 4	-0.456
	(0.730)
Income Quintile 5	-0.461
	(0.926)
Income Quintile 2 x Net Flow	0.0109***
	(0.00382)
Income Quintile 3 x Net Flow	0.0106***
	(0.00358)
Income Quintile 4 x Net Flow	0.00965***
	(0.00354)
Income Quintile 5 x Net Flow	0.00925**
	(0.00348)
Limited English Proficiency	0.0587***
	(0.0159)
Caseloads per 1k	-0.000703
	(0.00696)
SNAP Rate 2023	0.0705
	(0.124)
Constant	2.007*
	(1.037)
Observations	71
Adj. R-squared	0.549

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: *Although the migration coefficient for quintile 1 is statistically significant, the magnitude is very small (–0.00968), indicating limited practical significance. In real terms, a unit increase in net migration is associated with less than a 0.01 percentage point change in food insecurity rate — an effect unlikely to influence policy decisions.*

To evaluate whether the effect of net migration flow on food insecurity change varies by income levels, we created a third and final regression analysis to estimate marginal effects at different income thresholds. By interacting net migration with median household income and grouping counties into income quintiles based on a county's median household income, we conducted tests to observe whether the association between migration and food insecurity shifts depends on counties and the overall income distribution. We did this by creating a regression analysis in Table 4 and even visualized the regression through a plot, specifically for the interaction term between net migration and income quintile.

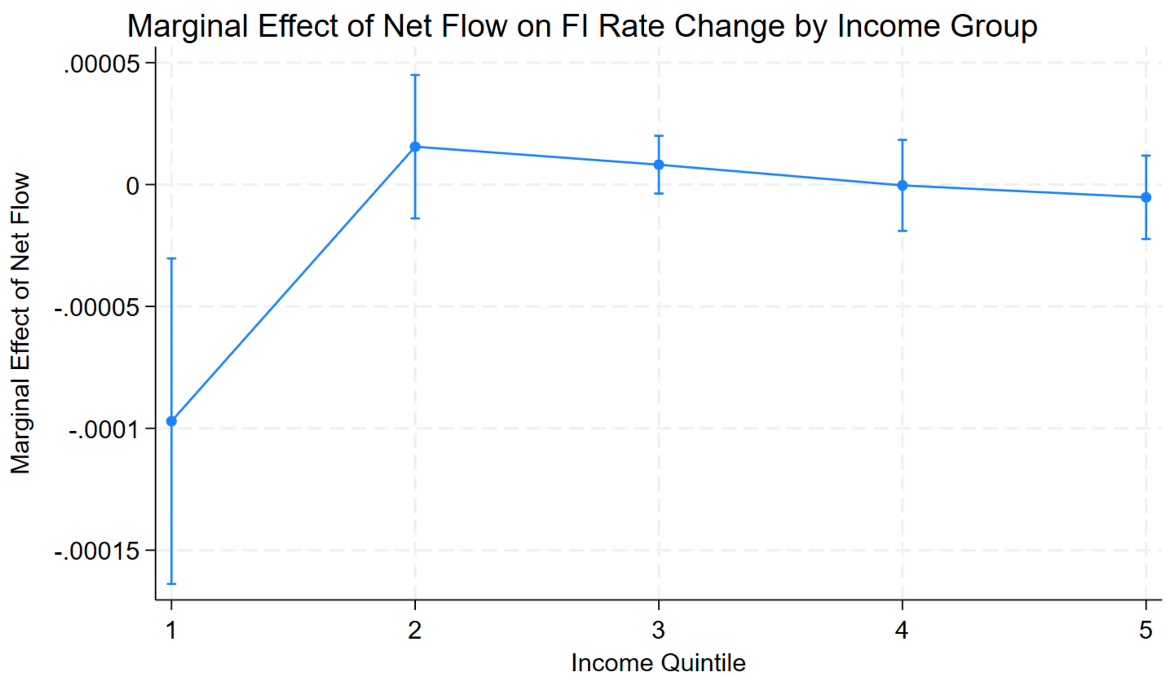
$$
\begin{aligned}
\text{Change in FI Rate}_i = \beta_0 &+ \beta_1 \text{NetFlow}_i + \beta_2 Q2_i + \beta_3 Q3_i + \beta_4 Q4_i + \beta_5 Q5_i \\
&+ \beta_6(\text{NetFlow}_i \times Q2_i) + \beta_7(\text{NetFlow}_i \times Q3_i) \\
&+ \beta_8(\text{NetFlow}_i \times Q4_i) + \beta_9(\text{NetFlow}_i \times Q5_i) \\
&+ \beta_{10}\text{LEP}_i + \beta_{11}\text{MedicaidCaseloads}_i + \beta_{12}\text{SNAP} + \varepsilon_i
\end{aligned}
$$

Results in Table 4 reveal that net migration has a small but statistically significant effect on food insecurity in the *lowest-income counties (quintile 1).* Specifically, the coefficient for net migration is -0.00968, indicating that a 1 unit increase in change in migration is associated with a 0.00968 percentage point decrease in the food insecurity rate in the lowest-income counties. Based on this association, it suggests that inflows of people might lead to improved food access, potentially due to how new residents increase local demand for services, which can lead local government or nonprofits to expand on food assistance programs. Additionally, the interaction terms between net migration and income quintiles 2 and 5 are statistically significant, with coefficients of 0.0109 and 0.00925, suggesting that the relationship between migration and food insecurity may differ by income level. However, these coefficient-level interpretations must be treated with caution, as they are based on comparisons relative to quintile 1.

The results in Table 4 signify that although migration may be statistically associated with small shifts in food insecurity in some models, the magnitude of the effect is extremely limited, with the coefficient consistently below –0.01 across all income quintiles. In practical terms, even a large change in net migration would translate to negligible changes in food insecurity rates. While lower-income counties may experience minor shifts due to population inflows, migration does not appear to be a meaningful or policy-relevant driver of food insecurity changes. This underscores the need to focus on more substantial structural predictors, such as Limited English Proficiency and SNAP access. It’s also worth mentioning another consideration that while our model tests whether the net migration variable may affect food insecurity, it is also plausible that changes in food insecurity themselves influence migration patterns. For instance, counties with worsening food insecurity could see an outflow of residents seeking better living conditions, while counties with improving food access may attract new arrivals. This means that part of the association we observe could reflect people moving in response to food insecurity trends, rather than migration causing those trends, resulting in a possibility of reverse casualty. Without longitudinal or instrumental variable methods to isolate directionality, the relationship between migration and food insecurity should be interpreted very cautiously and should not be interpreted as strictly one-way.

When viewed alongside the broader set of regression findings, these results reinforce the central role of Limited English Proficiency (LEP) as the most robust and consistent predictor of changes in food insecurity. While migration and its interaction with income provide some explanatory power, its magnitude is not meaningful, while our Limited English Proficiency variable reflects deeper structural barriers, such as language inaccessibility from public programs that are more associated with food access.

Figure 7. Average Marginal Effect of Net Migration on Change in Food Insecurity Rate by County Income



The plot in Figure 7 shows the average marginal effect of food security rates on net migration, segmented by income quintiles to clearly interpret the conditional effect of net migration. On the X-axis, counties are grouped into five income quintiles, from lowest (1) to highest (5). The Y-axis represents the marginal change in food insecurity rate associated with a unit increase in net migration within each quintile. The vertical bars denote 95% confidence intervals.

From Figure 7*,* we observe that the marginal effect of net migration is consistently close to zero across all income groups except quintile 1, meaning that migration primarily impacts food insecurity in low-income counties. In the lowest income quintile, the effect is slightly negative (approximately –0.0002), with a wide confidence interval that does not cross zero—indicating that the effect is statistically significant but small for counties within that lowest income quintile. This suggests that in low-income counties, there is a statistically significant but very small association between higher net migration and lower food insecurity, though the direction and cause of this relationship remain unclear.

As we move toward higher income quintiles, the marginal effect of migration on food insecurity is negligible and not statistically significant. These counties likely have stronger infrastructure and social services that buffer against demographic shifts. Although there is evidence of an effect in the lowest income quintile, the broader pattern indicates that net migration is not a robust or reliable predictor of changes in food insecurity across most income levels.

While the effect in the lowest income quintile is statistically significant, the coefficient is extremely small (approximately –0.0002), meaning even large shifts in migration would result in marginal changes in food insecurity. From a policy perspective, such a small effect size limits the practical usefulness of migration as a predictive or intervention variable. Therefore, although net migration contributes to explanatory models, it should not be emphasized in strategic resource allocation compared to stronger predictors like LEP and SNAP participation.

Overall, Limited English Proficiency and SNAP participation rates consistently emerge as the most robust predictors, even when accounting for income and other public support measures. The observed patterns provide useful signals for identifying priority counties that may warrant closer attention or targeted resources. However, these associations should be interpreted with caution due to potential issues such as endogeneity, omitted variable bias, reverse casualty, and the cross-sectional nature of the data, and that these regression findings do not show casual effects. To more rigorously evaluate the structural drivers of food insecurity, future research should pursue longitudinal designs or quasi-experimental methods. This could include evaluating program access over time, isolating treatment effects, or conducting focused case studies on LEP households and benefit uptake. For now, our analysis contributes to a better understanding of where food insecurity is changing most and which populations may face the greatest barriers to food access.

Recommendations

Our research identifies clear structural barriers disproportionately affecting counties with high Limited English Proficiency (LEP) populations—particularly in Regions I, J, K, and L. These areas have experienced significant increases in food insecurity but remain underserved due to linguistic isolation and limited access to public assistance infrastructure. Notably, these counties also ranked among the highest in our prioritization scoring system, signaling significant need relative to the rest of the AOS. These findings directly support Methodist Healthcare Ministries' (MHM) mission to improve the wellness of the least served and its long-term goal of addressing the social determinants of health. To help advance MHM's 10-year strategic vision of strengthening communities and driving systems change, we propose the following data-driven, regionally targeted strategies:

1. Prioritize High-Need Counties for Service Expansion

Our composite scoring framework highlights counties such as Dimmit, Cameron, Starr, Zavala, and Zapata as facing the highest levels of structural vulnerability. These counties should be prioritized for expanded programming—including health, food, and outreach services—given their compounded challenges with public assistance access, healthcare infrastructure, and high LEP rates.

2. Expand Bilingual Outreach and Culturally Responsive Engagement

To improve service accessibility and promote trust, we recommend deploying bilingual (Spanish-English) outreach teams across high-priority counties. These teams can facilitate SNAP and Medicaid enrollment, organize culturally tailored community events, and serve as trusted messengers within LEP communities. This directly supports MHM's organizational commitment to cultural responsiveness and equity-centered internal processes.

3. Deploy Mobile Health and Nutrition Services in Underserved Areas

Southern border counties demonstrate both limited healthcare infrastructure and high LEP rates. We recommend expanding mobile health units—especially those equipped with telehealth capabilities—to deliver preventive care, manage chronic conditions, and offer specialist consultations in remote areas. In parallel, mobile food distribution units and nutrition education efforts can address rising food insecurity. These strategies advance health equity, support digital inclusion, and build civic trust in regions that have long been structurally marginalized.

4. Develop an Interactive Data Dashboard

To strengthen transparency and guide resource allocation, we recommend that MHM develop an interactive, county-level data dashboard. This tool should integrate MHM's core indices—such as the Civic Engagement Index, Social Responsibility Index, Social Vulnerability Index, and Equity Index—along with a cumulative prioritization score. Features should include:

- Filters by region, migration trends, and access indicators.
- Geographic visualizations of structural need.
- Time-trend monitoring for key service gaps and public health indicators.

This dashboard can serve both internal planning and public engagement purposes, modeled after best practices from the **Texas Demographic Cente**r[1].

[1] https://idser.maps.arcgis.com/apps/MapSeries/index.html?appid=99dbf561151b4a2993248557e8f7aa56

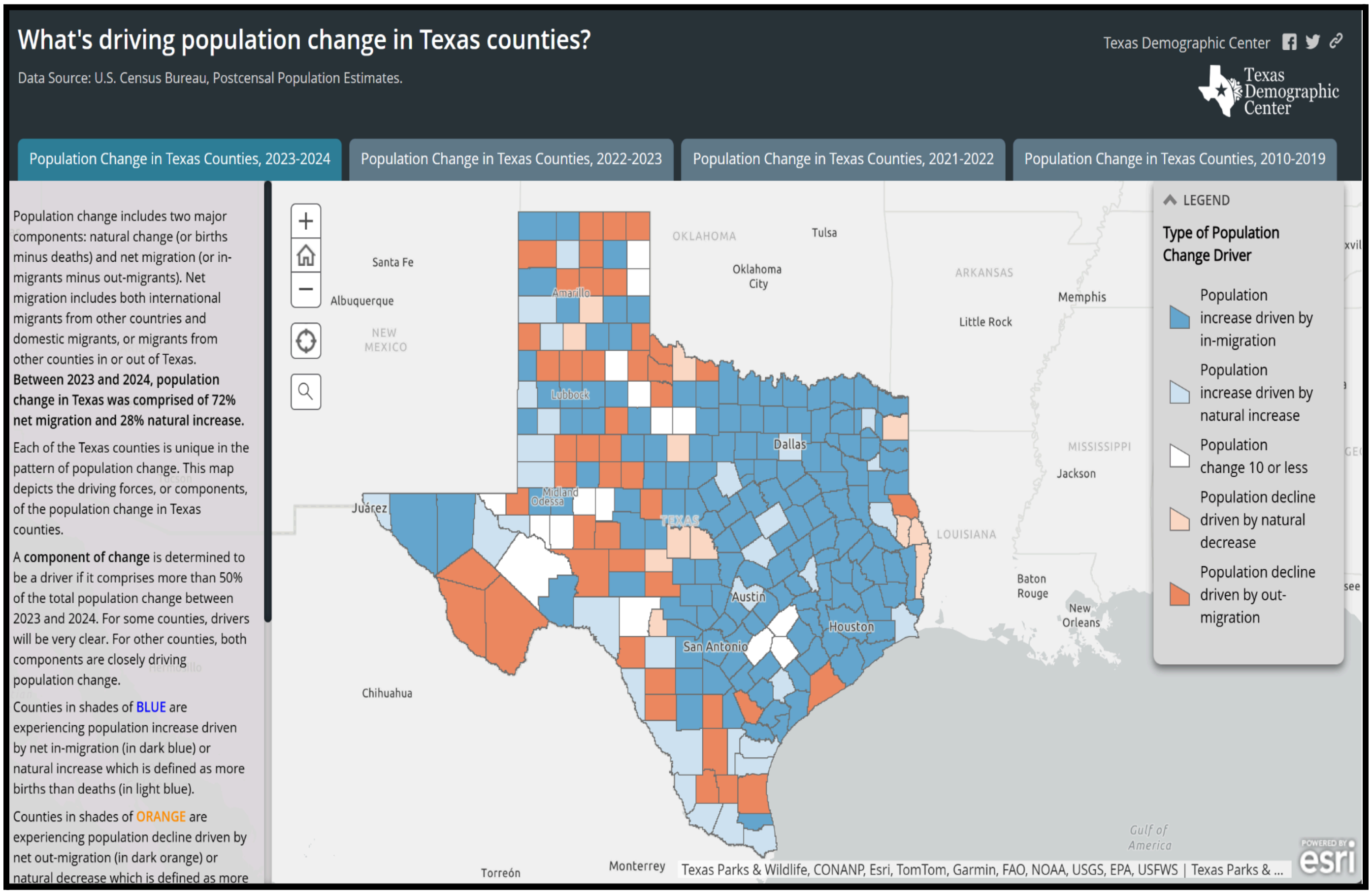


Figure 8. Example of an Interactive Data Dashboard - Texas Demographic Center
Image of the Texas Demographic Center Interactive dashboard, which provides interactive, county-level migration maps and trend data. This visual serves as a model for the proposed MHM interactive dashboard, which would integrate MHM's core indices and prioritization scores with similar mapping, filtering, and trend-monitoring capabilities to guide strategic resource allocation.

5. Institutionalize Language Access Policies

To promote equity and system-wide accountability, MHM should implement comprehensive language access policies across all service touchpoints. This includes translation services, bilingual program materials, and culturally informed service delivery protocols. Institutionalizing these measures ensures LEP populations are not only reached but fully supported in navigating healthcare and nutrition systems.

By incorporating bilingual support, culturally responsive communication, and inclusive program design, we aim to reduce barriers to service access and foster greater civic engagement in underserved areas." By investing in these strategies, MHM and CCPPI can significantly advance their mission to serve humanity and promote systemic change. These recommendations not only respond to the needs highlighted in our analysis but also reinforce MHM's strategic goals of fostering Thriving People and Thriving Places across South and Central Texas.

Conclusion

This study identified the most underserved regions within the AOS (Regions A–L) and revealed notable patterns that can inform targeted strategies to advance health equity. Through multivariate regression models, Limited English Proficiency (LEP) emerged as a consistent and statistically significant predictor of increased food insecurity. Specifically, LEP rates were observed to be strongly and positively associated with rising food insecurity, even after controlling for other variables. Conversely, greater SNAP participation was linked to reductions in food insecurity, underscoring the role of public assistance access as a mitigating factor. On the other hand, our interaction model revealed that net in-migration is modestly associated with improved food insecurity outcomes in low-income counties, a trend not observed in higher-income areas, however its magnitude of the effect across all income groups is very small.

Although net in-migration was statistically significant in a few specifications, its effect size was negligible and not practically meaningful. This reinforces our conclusion that structural and linguistic barriers, rather than population flows, are the primary predictors of food insecurity in this region.

To guide responsive planning, we constructed a county-level prioritization framework based on key structural indicators. This scoring system helped classify counties into high, medium, and low priority tiers for potential intervention. Notably, *Regions I, J, K, and L,* located near the Texas-Mexico border, emerged as areas of highest need, with over 70% of their counties ranking in the "Highest Priority" tier. These regions not only experience heightened linguistic and economic vulnerabilities, but also consistent gaps in public service infrastructure, making them critical focal points for future programming.

Our findings reinforce a geographic and structural pattern: *linguistically diverse, low-income counties along the southern border face disproportionate barriers to food and health services.* While this study does not claim causal inference, the evidence strongly supports the need for policy and programmatic innovations centered on language accessibility, culturally competent service delivery, and responsive infrastructure. These insights are well-aligned with MHM's long-term goals to advance health equity, improve wellness for the least served, and support data-driven systems change across South Texas. Ultimately, this research serves as both a diagnostic and strategic tool—highlighting urgent regional disparities while proposing tangible pathways for MHM and its partners to prioritize high-need communities, mobilize targeted resources, and strengthen long-term community resilience.

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Appendix

1- A. Data Mapping Table

This table provides a detailed overview of each variable used in the research, including the corresponding criterion it supports, the original data source, any proxy measures employed, and important notes to clarify assumptions or data nuances. It serves as a documentation tool to ensure transparency in how inputs were selected and interpreted for analysis and dashboard development.

Criterion	Variable Name	Data Source	Proxy Used?	Notes
Demographic	Population Estimates (2020–2024)	U.S. Census Bureau	No	Used for Net Migration calculation
Food Security	Food Insecurity Rates (2019–2023)	Feeding America, Map the Meal Gap	No	County-level model-based estimates
Food Security	Change in Food Insecurity Rate	Derived from Feeding America data	Yes	2023 Food Insecurity Rate - 2019 Food Insecurity Rate
Food Security	Average Food Insecurity Rates	Derived from Feeding America data	Yes	Mean Food Insecurity Rate across years 2019-2023
Migration	Net Migration	U.S. Census Bureau Population Estimates	Yes	2024 Population Estimate - 2020 Population Estimate
Economic	Median Household Income	U.S. Census Bureau ACS	No	Inflation-adjusted
Economic	Median Household Income per 1,000	Derived from Median Household Income	Yes	For scaling across counties
Demographic	Limited English Proficiency Rates	U.S. Census Bureau ACS	No	% of residents with limited English ability
Healthcare Access	Medicaid Caseloads	Texas Health and Human Services (HHS)	No	Total individuals enrolled
Healthcare Access	Medicaid Caseloads per capita	Derived from HHS & Population Estimates	Yes	Caseloads divided by population
Public Assistance	Active SNAP Participants	Texas Health and Human Services (HHS)	No	Residents actively enrolled in SNAP
Public Assistance	Eligible SNAP Participants	Texas Health and Human Services (HHS)	No	Total residents eligible for SNAP
Public Assistance	SNAP Access Rate	Derived from Active/Eligible SNAP Participants	Yes	% of eligible residents participating
Food Environment	Food Environment Index	County Health Rankings	No	Score (0–10) based on access/proximity to healthy foods
Healthcare Access	Rate of Primary Care	County Health Rankings, CCPPI archives	No	Providers per 100,000 residents

1- B: Total Scoring System Variable Justification

This appendix provides detailed documentation of the variables included in the composite scoring system used to assess county-level prioritization. It outlines each variable's purpose, and key notes explaining its relevance to food insecurity and healthcare access within AOS counties.This table ensures transparency in how prioritization scores were constructed and supports replicability for future research or program design.

<u>Food Insecurity Rate</u>

This measure captures the percentage of individuals in a county who lack consistent access to enough food for an active, healthy life. It reflects households experiencing uncertainty or inability to acquire adequate food due to financial hardship or limited local resources.

How It's Measured:

Food insecurity rates are derived from model-based estimates produced by Feeding America's Map the Meal Gap project. These estimates integrate data on poverty, unemployment, median household income, and housing costs from the American Community Survey (ACS), combined with food cost variations across counties.

Why It Matters:

High food insecurity rates indicate significant nutritional vulnerability and are linked to negative health outcomes such as obesity, diabetes, and increased healthcare costs. This measure is crucial for identifying populations at risk of food deserts and hunger.

Context in Literature:

Research consistently ties food insecurity to adverse health effects, academic underachievement, and cyclical poverty. Addressing food insecurity requires interventions that combine food access with economic stability initiatives.

<u>Food Environment Index</u>

This composite index measures factors contributing to a healthy food environment, scaled from 0 (worst) to 10 (best). It reflects both physical and economic access to nutritious food within a community.

How It's Measured:

The index accounts for two dimensions:

Proximity to grocery stores and supermarkets (measured as the share of the population with limited geographic access).

Household income levels relative to food affordability.

Data sources include County Health Rankings (which integrates USDA Food Access Research Atlas data) and ACS income data.

Why It Matters:

Communities with low Food Environment Index scores face greater barriers to accessing healthy food options, contributing to higher rates of diet-related diseases.

Context in Literature:
Low scores often correlate with food deserts, where residents rely on convenience stores or fast food for nutrition. Improving food environments is a key strategy to mitigate obesity and chronic disease prevalence.

Medicaid Caseloads per Capita
This metric represents the proportion of residents enrolled in Medicaid, providing insight into healthcare reliance among low-income populations.

How It's Measured:
Calculated by dividing the total number of Medicaid enrollees (sourced from Texas Health and Human Services) by the county population (from ACS), scaled per 1,000 residents for comparability.

Why It Matters:
High caseloads suggest communities with heightened demand for public health services and greater vulnerability to healthcare system disruptions.

Context in Literature:
Areas with high Medicaid enrollment often struggle with provider shortages, leading to unmet health needs and preventable hospitalizations.

SNAP Access Rate
This measure captures the percentage of eligible residents actively participating in the Supplemental Nutrition Assistance Program (SNAP), previously known as food stamps.

How It's Measured:
SNAP participation data from Texas Health and Human Services is compared to ACS population and income data to estimate county-level access rates.

Why It Matters:
SNAP access reflects a community's ability to utilize nutritional support programs. Low participation rates may indicate barriers such as lack of awareness, administrative challenges, or stigma.

Context in Literature:
Studies have shown that SNAP participation significantly reduces food insecurity and improves health outcomes, particularly in low-income and high-need populations.

Limited English Proficiency (LEP) Rate

This metric represents the percentage of residents who report speaking English "less than very well," reflecting linguistic isolation and potential barriers to healthcare and public services.

How It's Measured:

LEP rates are derived from ACS 5-Year Estimates, calculated as the share of individuals over age 5 with limited English proficiency.

Why It Matters:

High LEP rates often correlate with reduced access to health resources, public assistance, and civic engagement due to language barriers.

Context in Literature:

Language isolation contributes to disparities in healthcare utilization, preventive care, and health literacy, particularly in immigrant and minority communities.

Median Household Income

Median household income measures the midpoint of household earnings in a county, serving as a core indicator of socioeconomic status.

How It's Measured:

Reported annually by the ACS 5-Year Estimates, adjusted for inflation to ensure comparability across years.

Why It Matters:

Lower income levels are closely tied to food insecurity, poor health outcomes, and reduced access to healthcare and housing stability.

Context in Literature:

Income disparities drive unequal health outcomes, with lower-income households experiencing higher rates of chronic disease and food insecurity.

Rate of Primary Care

This measure reflects the availability of primary care physicians relative to the population, expressed as providers per 100,000 residents.

How It's Measured:
Data from the County Health Rankings and Health Resources and Services Administration (HRSA), dividing total primary care providers by population estimates from ACS.

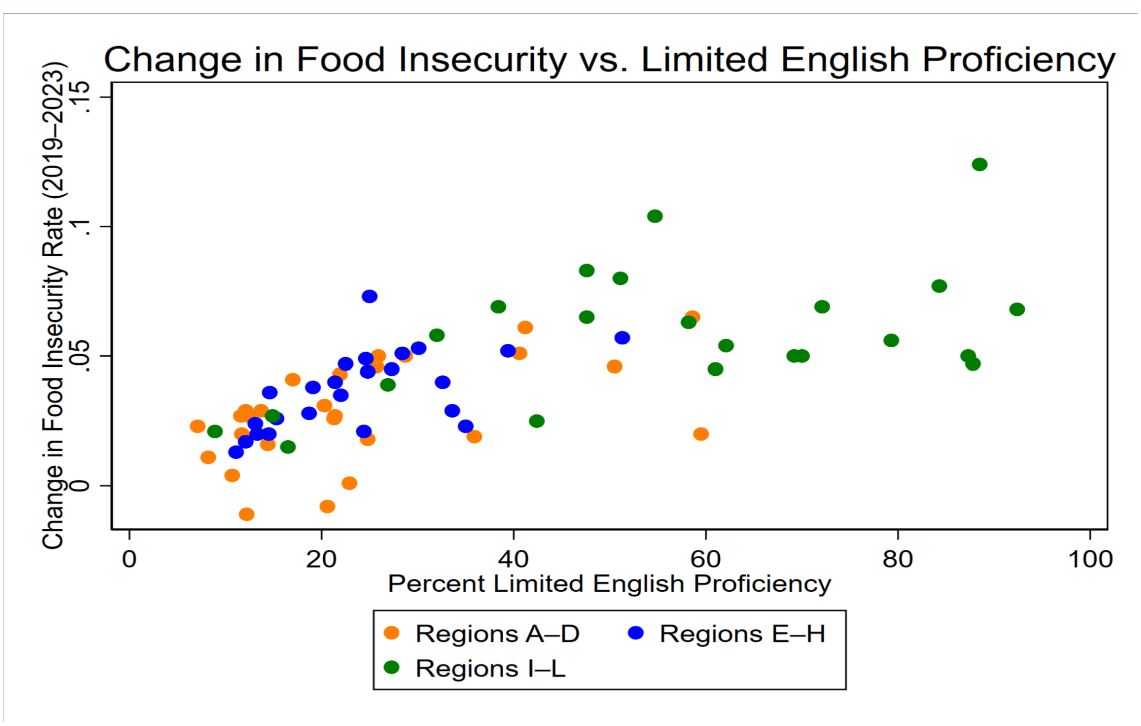
Why It Matters:
Adequate access to primary care is critical for preventive services, chronic disease management, and reducing avoidable hospitalizations.

Context in Literature:
Regions with fewer primary care providers face higher mortality rates and worse overall health outcomes.

Appendix 1-C. Supplementary Graphs & Bivariate Plots

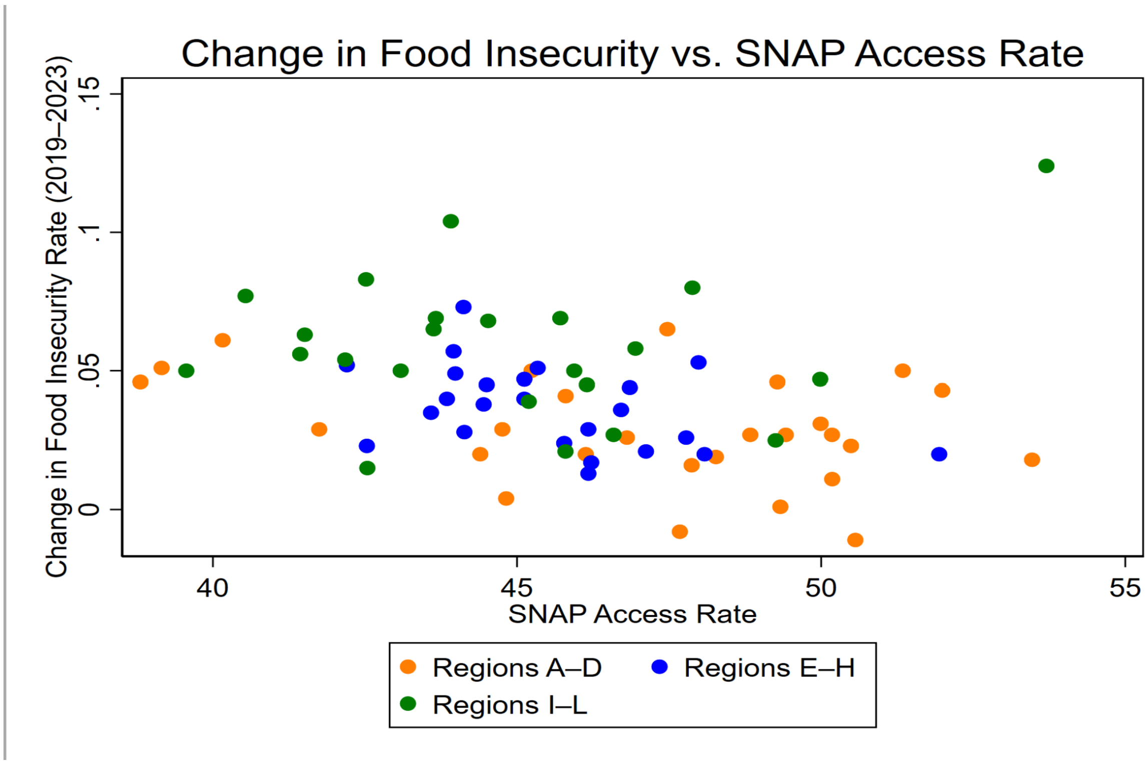
1. Change in Food Insecurity vs. Limited English Proficiency (LEP)

This scatterplot examines the relationship between LEP rates and changes in food insecurity across counties. Regions A–D, E–H, and I–L are color-coded to highlight geographic patterns.



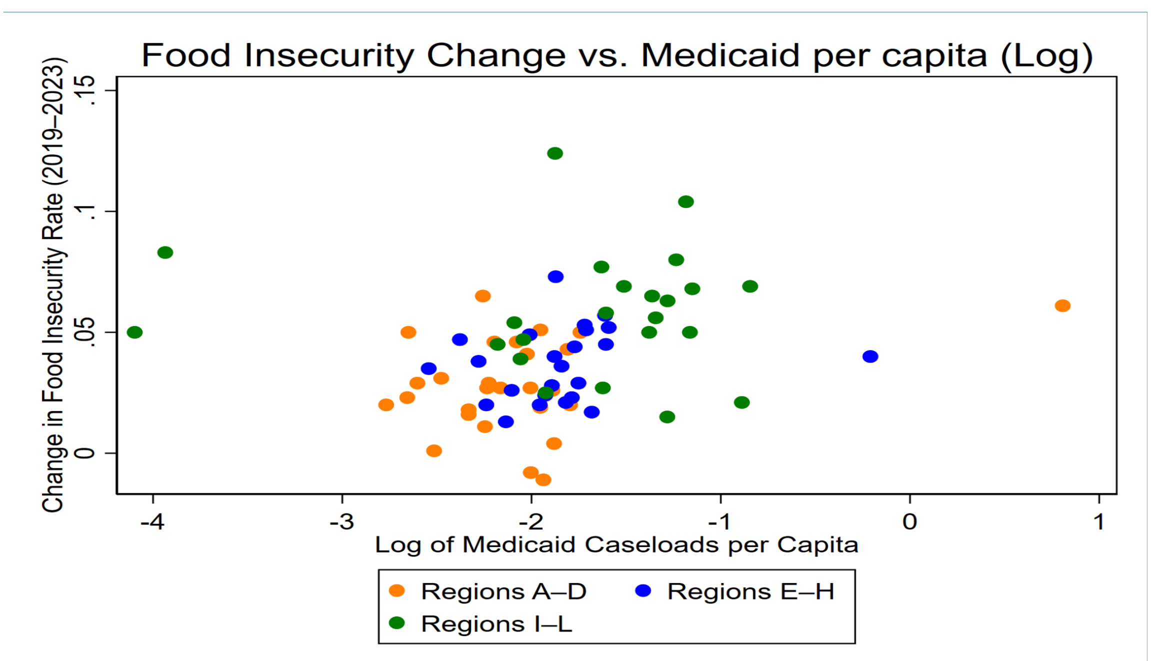
2. Change in Food Insecurity vs. SNAP Access Rate

This scatterplot displays the association between SNAP access rates and changes in food insecurity. Counties are grouped and color-coded by region segments to emphasize spatial disparities.



3. Change in Food Insecurity vs. Medicaid Caseloads per Capita (Log Transformed)

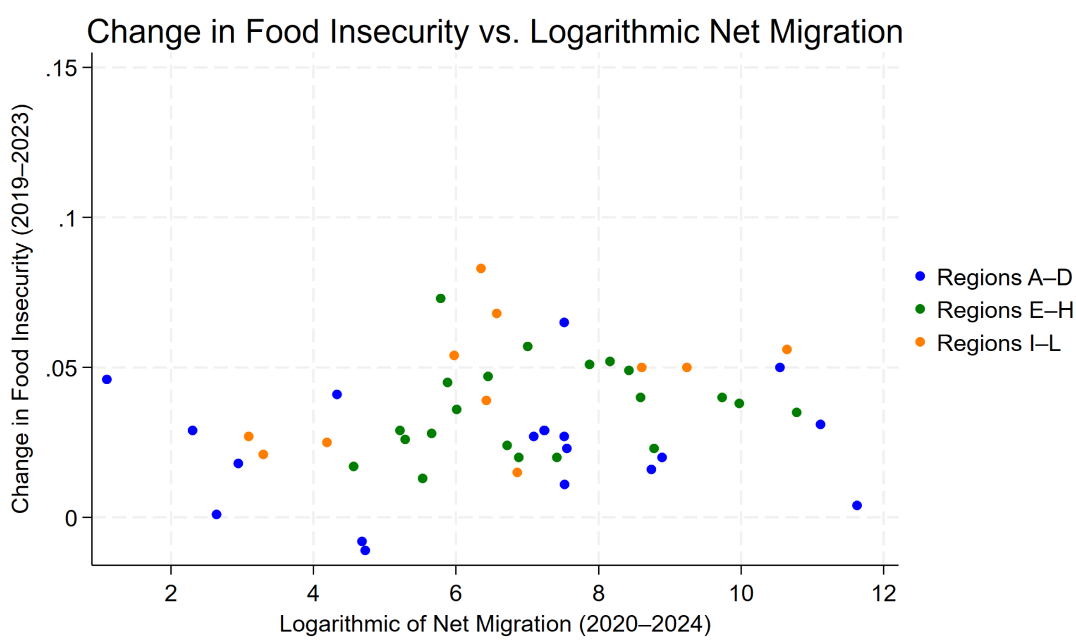
This scatterplot shows the log-transformed Medicaid caseloads per capita against food insecurity changes. Log transformation was applied due to extreme right skew in the original distribution.



To improve interpretability and account for extreme skew in the Medicaid caseloads per capita variable, we applied a natural logarithmic transformation prior to visualization. As shown in the descriptive statistics, the original variable exhibited significant right skew (skewness = 6.57, kurtosis = 50.37), with a small number of counties having disproportionately high Medicaid enrollment per capita. These outliers compressed the variation among the remaining counties, obscuring potential relationships in scatterplot visualizations. By taking the log of Medicaid per capita, we normalized the distribution, allowing clearer identification of underlying patterns between Medicaid participation and changes in food insecurity across counties. This transformation ensures that the scatterplot more accurately reflects structural differences without being dominated by extreme values.

4. Change in Food Insecurity vs. Net Migration (Log Transformed)

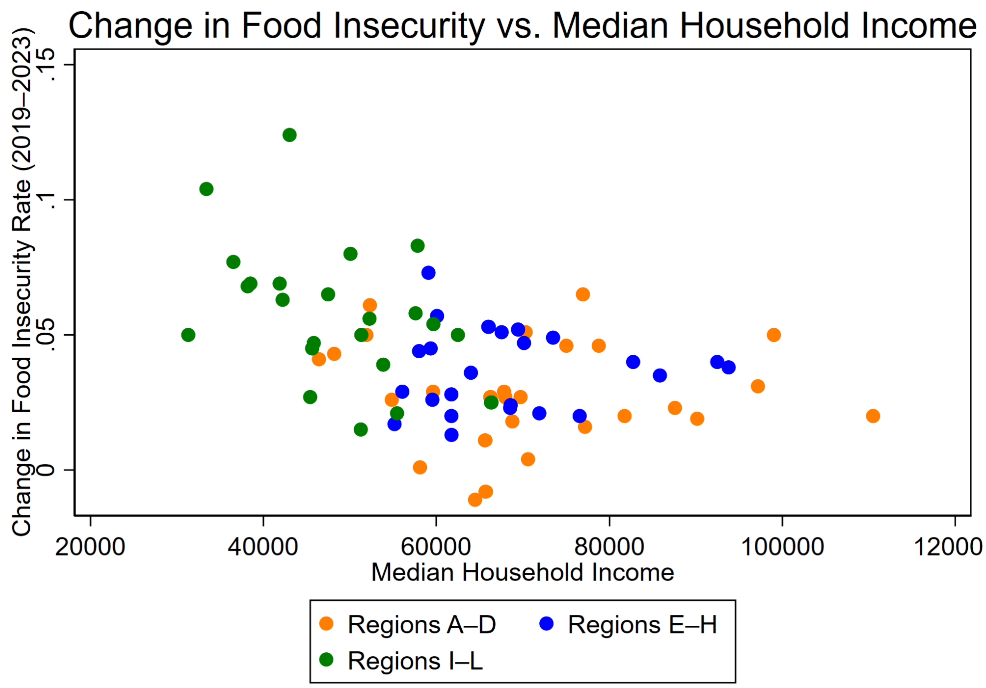
This scatterplot visualizes the log of net migration in relation to changes in food insecurity. A log scale was used to reduce the impact of outliers and improve interpretability.



Note: Since the original *Net Population* variable included both negative and positive values—representing net migration losses and gains across counties—it could not be directly log-transformed due to mathematical limitations. To address this, we applied a log-shift transformation by adding a constant value of 545 to all observations (equal to the absolute minimum value plus one), ensuring all values were positive before transformation. This adjustment allowed us to apply a natural log transformation while preserving the relative differences across counties. The resulting variable, *log_net_pop_shifted*, enables a clearer visual interpretation of the relationship between net migration and changes in food insecurity, especially by reducing the distortion caused by extreme outliers.

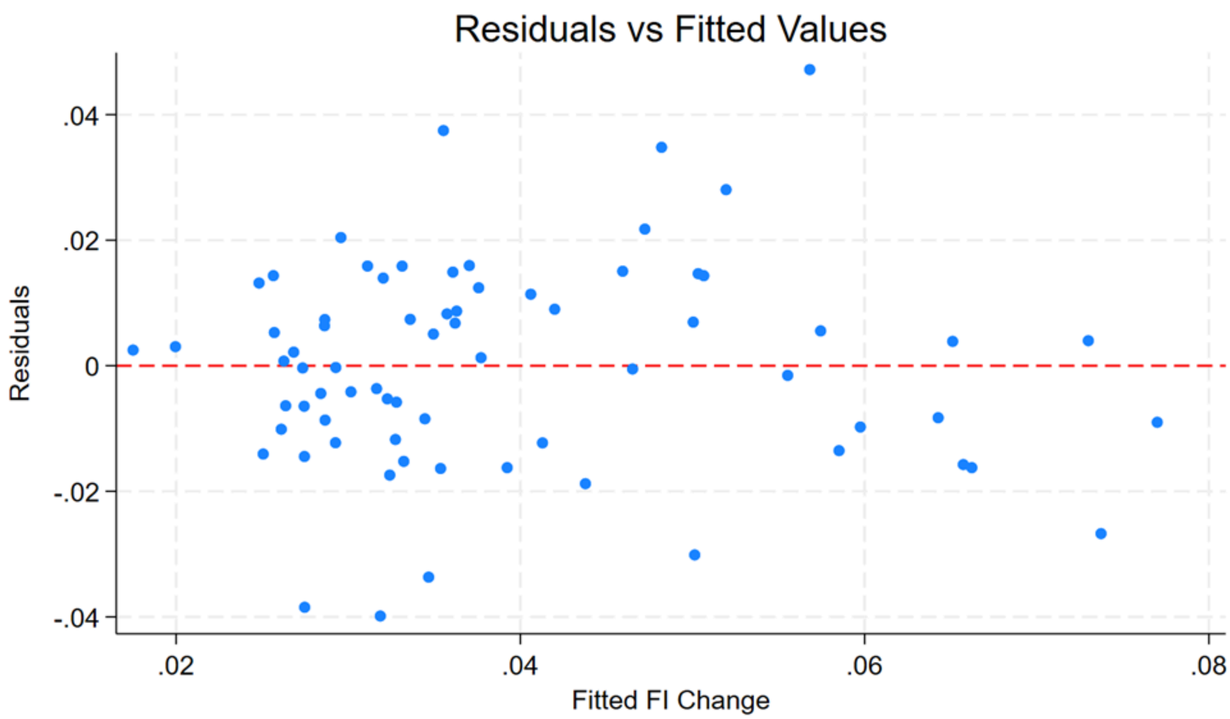
5. Change in Food Insecurity vs. Median Household Income

This scatterplot explores the relationship between household income levels and food insecurity trends, with counties color-coded by region clusters to illustrate contextual differences.



Appendix 2-A. Residual Plots for Table 1 Regression Model

The plot examines a residuals-versus-fitted plot to assess model validity, which showed residuals randomly scattered around zero, suggesting that linearity and homoscedasticity assumptions are reasonably met. While some widening of variance is observed at higher predicted food insecurity changes, this can be addressed with robust standard errors. These outliers may also warrant closer examination for potential and policy relevance.



Appendix 2-B. Counties with High Residuals in Food Insecurity Model with Failed Interaction

This list shows some counties where food insecurity increased more than expected between 2019 and 2023. Each county's actual change in food insecurity is compared to the predicted change from a regression model. The key columns are the actual change (Change_FI_Rate), the model's predicted change (fi_hat), and the difference between the two (fi_resid). A residual above 0.03 means the county saw a noticeably greater rise in food insecurity than the model anticipated, suggesting that other factors not captured by the model may be at play.

County	**Observed Change in FI Rate**	**Predicted Value (fi_hat)**	**Residual (fi_resid)**
Karnes	0.073	0.0355301	0.0374699
Uvalde	0.083	0.0482042	0.0347958

Dimmit	0.104	0.0568134	0.0471866
Kenedy	0.124	—	—
Bexar	—	—	—
Kleberg	—	0.0395283	—

Appendix 2-C. County-Level Residual Summary from Regression Model

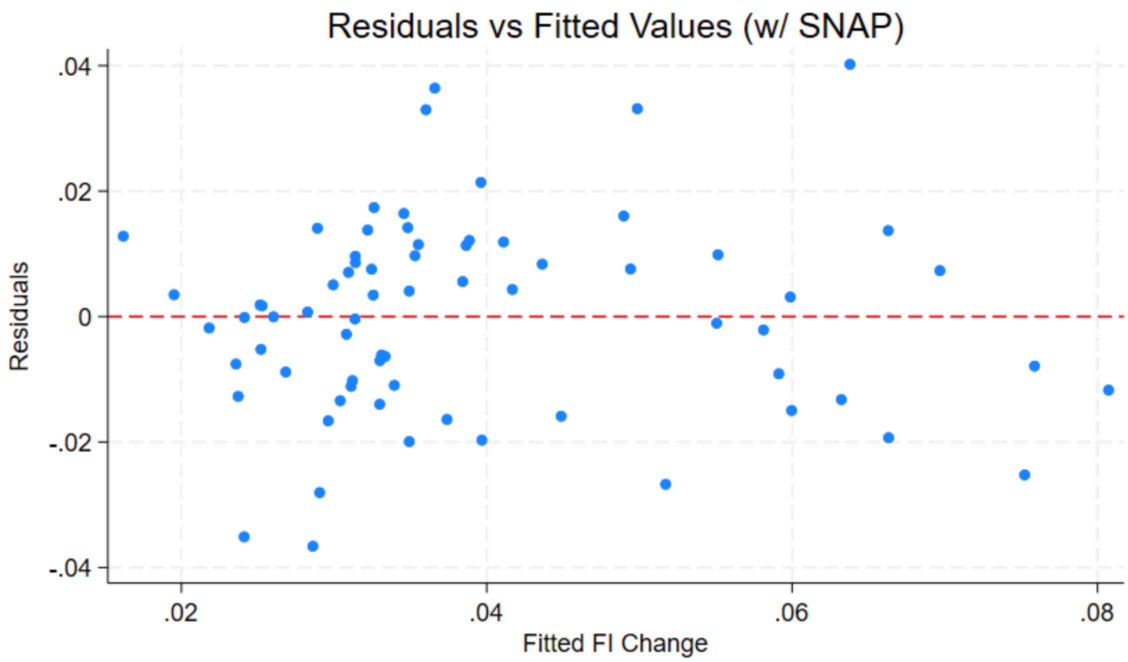
This table highlights select counties that exhibited notable residuals in the regression model predicting changes in food insecurity (FI). Residuals are calculated as the difference between actual and predicted FI change. Positive residuals indicate underperformance—counties where actual FI increased more than predicted.

- *Karnes, Uvalde, and Dimmit all showed underperformance, suggesting possible unmet needs or local factors not captured by the model.*
- *Dimmit County had the largest positive residual (+4.7%), indicating the model significantly underestimated its rise in food insecurity.*
- *Kenedy County was excluded from prediction due to missing data for one or more independent variables.*

County	Actual FI Change	Predicted FI	Residual	Interpretation
Karnes	7.3%	3.6%	**+3.7%**	Underperformed, actual FI is much worse than expected
Uvalde	8.3%	4.8%	**+3.5%**	Underperformed, likely unmet needs
Dimmit	10.4%	5.7%	**+4.7%**	Strongest underperformance in the dataset
Kenedy	12.4%	missing	missing	Not predicted (likely due to missing independent variables)

Appendix 2- D. Residual Plots for Table 2 Regression Model

The residuals-versus-fitted plot for the model including SNAP participation shows residuals mostly randomly scattered around zero, indicating that the assumptions of linearity and homoscedasticity are reasonably satisfied. Slight heteroskedasticity is observed at the higher end of predicted values, but this *can be mitigated by applying robust standard errors. These deviations suggest a few influential cases that may merit further policy-focused investigation.*



Appendix 2-E. Table of Variance Inflation Factor (VIF) Analysis

We again tested our diagnostics of our regression using residual graphs and multicollinearity tests. According to our diagnostics, our residuals show no patterns, although showing mild variance at higher fitted numbers. Furthermore, our Variance Inflation Factor still shows no multicollinearity with VIFs of all variables being less than 10.

Variable	VIF	1/VIF
SNAP Rate for 2023	3.05	0.328219
Median Household Income	2.74	0.365375
Percent of English Proficiency	1.87	0.535937
Uninsured Population	1.78	0.561836
Net Flow Migration	1.35	0.741667
Medicaid Caseloads	1.19	0.836856
Mean VIF	2.00	