MAP THE MEAL GAP 2025

Technical Brief

An Analysis of County and Congressional District Food Insecurity and County Food Cost in the United States in 2023

Contents

TECHNICAL BRIEF

The following methodological overview provides a description of the methods and data used to establish the county- and congressional district-level food insecurity estimates, the food budget shortfall, the cost-of-food index, and the average cost of a meal. Following each section, we provide information on the central results for our methods.

RESEARCH GOALS

The primary goal of the *Map the Meal Gap* analysis is to accurately assess food insecurity at the community level. The methodology we use was developed to be responsive to the following questions:

- Is the methodology directly related to the need for food?
    - Yes, it uses the U.S. Department of Agriculture (USDA) food insecurity measure.
- Does it reflect the many determinants of the need for food?
    - Yes, along with income, our model uses information on unemployment rates, median incomes, and other factors that have been shown to be associated with food insecurity. Beginning in 2020, disability prevalence, another key risk factor for food insecurity, was included in the model.
- Can it be broken down by income categories?
    - Yes, we can look at food insecurity for individuals with incomes below and above state-specific thresholds for federal nutrition programs.
- Is it based on well-established, transparent methods?
    - Yes, the methods across the different dimensions are all well established.
- Can we provide the data without taxing the already limited resources of food banks?
    - Yes, the estimates are all established by the Feeding America National Office.
- Can it be consistently applied to all counties in the U.S.?
    - Yes, the estimates rely on publicly available data for all counties (and congressional districts).
- Can it be readily updated on an annual basis?
    - Yes, the publicly available data are released annually.
- Does it allow one to see the potential effect of economic downturns?
    - Yes, by the inclusion of relevant measures of economic health in the models. For example, in response to the novel coronavirus (Covid-19), the *Map the Meal Gap* model was used to develop projections of local-level food insecurity based on predicted changes to unemployment and poverty. More information on this approach can be found here.

SUMMARY OF METHODS

CHILD, OVERALL AND RACE/ETHNICITY FOOD-INSECURITY RATES

METHODOLOGY

We begin by analyzing the relationships between food insecurity and its determinants (i.e., unemployment, poverty, disability, homeownership, and median income) as well as the percentage of the population that is Black and the percentage of the population that is Hispanic. We also include state and year fixed effects to portray unobserved factors. We then use the coefficient estimates from this analysis combined with information on the same variables defined at the county and congressional district levels to generate estimated food insecurity rates for all individuals and for children for every county and congressional district in the country.

DATA SOURCES

The relationship between food insecurity and selected variables is assessed at the state level using Current Population Survey (CPS) survey data. The variables used were selected because of their availability at the county, congressional district, and state level. The following variables are used: unemployment rates, median income, poverty rates, homeownership rates, percent of the population that is Black, and percent of the population that is Hispanic. Beginning with 2018 estimates released in 2020, *Map the Meal Gap* also includes disability rates and uses an adjusted poverty variable that excludes college students to better reflect the socioeconomic status of communities with sizeable student populations (described below). County and congressional district level data are drawn from the American Community Survey (ACS), except for county unemployment data, which are drawn from the Bureau of Labor Statistics (BLS). For the child food insecurity estimates, we use data restricted to households with children for all variables except the unemployment rate and disability rate, which are defined for the full population of the county.

Map the Meal Gap 2022 Model Updates

Map the Meal Gap includes overall local food insecurity rates by race and ethnicity among the following populations for which data are available: Black (all ethnicities), Hispanic, and white, non-Hispanic. The underlying variables used to produce estimates for these groups are consistent with those used to produce overall and child estimates and are specific to each population (e.g., unemployment rate among Black individuals instead of among the overall population). The models used to produce food insecurity estimates for these populations do not include variables reflecting the share of the population that is Black, the share that is Hispanic nor the share that is white.

Like with overall and child food insecurity, we analyze the state-level relationships between food insecurity and its subgroup-specific variables for each race and ethnicity subgroup. Then following the same steps for the full population, we combine the coefficient estimates from this analysis with information on the same variables defined at the county and congressional district levels to generate estimated food insecurity rates for Black, Latino, and white individuals. Due to small sample sizes at either the state or county level, estimates for these groups are not available for every state, county, or congressional district.

Map the Meal Gap 2020 Model Updates

In 2020, Feeding America made two improvements to the model used to estimate local food insecurity. The estimates now account for disability status and reflect a refined definition of poverty. These changes both improve the accuracy of the estimates and align the model with the most up-to-date research on the key determinants of food insecurity.

Accounting for Disability Status

The first improvement to the model is the inclusion of a variable reflecting the disability status of household members. According to the U.S. Census Bureau, persons with a disability report difficulty with one or more of the following six functions: hearing, vision, cognition, ambulation, self-care, and independent living (U.S. Census Bureau, 2021). Research by the USDA and others has demonstrated disability status is one of the most important risk factors for whether a household is food insecure (recent work includes, e.g., Coleman-Jensen et al., 2020; Guo et al., 2020; Heflin et al., 2019; Henly et al., 2023; Samuel, et al., 2023). The U.S. Census Bureau has been collecting data on disability status for household members since 2009 in the CPS—long enough to now be considered for inclusion in the model.

Refining the Measure of Poverty

In addition to accounting for disability status, the model includes a refined poverty variable to reflect the socioeconomic status of community residents more accurately. Research shows that in areas with high proportions of college students, poverty rates are overstated (Benson & Bishaw, 2018). One indicator of this is that the parental income of students attending universities is substantially higher than the national average (Blagg et al., 2017). As a result, the official poverty measure does not accurately reflect the resources available to college students.

We use 5-year estimates from Table B14006 of the ACS to calculate the numerator of the non-student poverty rate by subtracting the number of undergraduate students reporting income below the poverty level from all persons reporting income below the poverty level. We then divide that number by the total population minus all students irrespective of their incomes.

FOOD BUDGET SHORTFALL

METHODOLOGY

Responses from food-insecure households to CPS questions about a food budget shortfall are calculated at the individual level and then averaged to arrive at a weekly food budget shortfall As discussed in *Household Food Security in the United States in 2023* (Rabbitt et al., 2024), households experiencing food insecurity experience this condition, on average, seven months of the year. The national average shortfall is weighted by the "cost-of-food index" to derive a localized estimate.

FI persons * Shortfall in dollars* 52 weeks * (7/12) =	$ reported needed by the food insecure to meet their food needs

DATA SOURCES

The CPS data includes two questions relevant for this determination. First, a question asks if a household needed more, less, or the same amount of money to meet their basic food needs. Second, those that respond "more" are asked an additional question about how much more money they need to meet their basic food needs. These questions are posed after questions about weekly food expenditures but before the food security module.

FOOD BUDGET SHORTFALL 2025 UPDATES

Due to a methodology change for calculating the national average food budget shortfall in 2025 (2023 data) national and local food budget shortfall estimates from 2023 or later are not comparable to estimates prior to 2024 (2022 data).

Using CPS data, the previous methodology (a) assigned values of zero if households were not in the universe for the shortfall question or had missing data and (b) used household-level data and weights. The new methodology excludes households not in the universe for the questions or with missing data, and uses individual weights.

COST-OF FOOD INDEX

METHODOLOGY

To establish a relative price index that allows for comparability between counties, NielsenIQ assigns every sale of UPC-coded food items in a county to one of the 24 food categories in the USDA Thrifty Food Plan (TFP, 2021). These categories are then weighted to the TFP market basket based on pounds purchased per week by age and gender. For the current analyses, pounds purchased by males age 20 - 50 are examined. While other Thrifty Food Plans for different ages and/or genders may have resulted in different *total* market basket costs, *relative pricing* between counties (our goal for this analysis) would not be affected. The total market basket is then translated into a multiplier that can be applied to any dollar amount. This multiplier differs by county, revealing differences in food costs at the county level.

DATA SOURCES

NielsenIQ establishes the cost of the TFP using in-store scanning data and Homescan data.

NATIONAL AVERAGE MEAL COST

METHODOLOGY

The average dollar amount spent on food per week by food-secure individuals is divided by 21 (three meals per day * seven days per week). Food expenditures for *food-secure* individuals were used to ensure that the result reflected the cost of an adequate diet. We then weight the national average cost per meal by the "cost-of-food index" to derive a localized estimate.

DATA SOURCES

Before respondents are asked the food security questions on the CPS, they are asked how much money their household usually spends on food in a week.

NATIONAL AVERAGE MEAL COST 2025 UPDATES

Due to a methodology change for calculating the national average meal cost in 2025 (2023 data) national and local food budget shortfall estimates from 2023 or later are not comparable to estimates prior to 2022.

Using CPS data, the previous methodology (a) assigned values of zero if households were not in the universe for the shortfall question or had missing data and (b) used household-level data and weights. The new methodology excludes households not in the universe for the questions or with missing data, and uses individual weights.

FOOD INSECURITY RATE ESTIMATES

METHODS

Full Population of Counties (and Congressional Districts)

We proceed in two steps to estimate the extent of food insecurity in each county. In what follows, the descriptions are for counties but, except where otherwise noted, they also apply to congressional districts. Food insecurity estimates for a given year (e.g., 2022) correspond to the geographical boundaries for that same year (e.g., 2022).

Step 1: Using state-level data from 2009-2022, we estimate a model where the food insecurity rate for individuals at the state level is determined by the following equation:

$$FI_{st} = \alpha + \beta_{UN}UN_{st} + \beta_{POV}POV_{st} + \beta_{MI}MI_{st} + \beta_{HISP}HISP_{st} + \beta_{BLACK}BLACK_{st} + \beta_{OWN}OWN_{st} + \beta_{DSBL}DSBL_{st} + \mu_t + \upsilon_s + \varepsilon_{st} \quad (1)$$

where *s* is a state, *t* is year, *UN* is the unemployment rate, *POV* is the poverty rate, *MI* is median income, *HISP* is the percent of households where the respondent is Hispanic, *BLACK* is the percent of households where the respondent is Black, *OWN* is the percent of individuals who are homeowners, *DSBL* is the percent of individuals who live in a household where at least one person reports having a disability, μ_t is a year fixed effect, υ_s is a state fixed effect, and ε_{st} is an error term. This model is estimated using weights defined as the state population. The set of questions used to identify whether someone is food insecure (i.e., living in a food-insecure household) are defined at the household level. A household is said to be food insecure if the respondent answers affirmatively to three or more questions from the Core Food Security Module (CFSM) in the December Supplement of the CPS for the years 2009-2022. For these analyses, we weight the data by the population size of each state. A complete list of questions in the CFSM is found in APPENDIX C.

Our choice of variables was first guided by the literature on the determinants of food insecurity. We included variables found in prior research to influence the probability of someone being food insecure. (For an overview of that literature in this context see Gundersen & Ziliak, 2018.) Next, we chose variables that are available both in the CPS and at the county level in the ACS or other sources (described below). The model does not include variables that are not available at both the state and county level.

Of course, these variables do not portray everything that could potentially affect food-insecurity rates. In response, we include the state and year fixed effects noted above, which allow us to control for unobserved state-specific and year-specific influences on food insecurity.

Step 2: We use the coefficient estimates from *Step 1* plus information on the same variables defined at the county level to generate estimated food insecurity rates for individuals defined at the county level. This can be expressed in the following equation:

$$FI^*_c = \hat{\alpha} + \widehat{\beta_{UN}}UN_c + \widehat{\beta_{POV}}POV_c + \widehat{\beta_{MI}}MI_c + \widehat{\beta_{HISP}}HISP_c + \widehat{\beta_{BLACK}}BLACK_c + \widehat{\beta_{OWN}}OWN_C + \widehat{\beta_{DSBL}}DSBL_C + \widehat{\mu_{2022}} + \hat{\upsilon}_s \quad (2)$$

where *c* denotes a county. The variables *POV*, *MI*, *HISP*, *BLACK*, *OWN* and *DISBL* are based on ACS 5-year estimates for the county-level models and from 1-year estimates for the congressional district-level models.[1] The variable *UN* is based on annualized average BLS estimates[2] for the county-level results and ACS 1-year estimates for the congressional district results.[3] From our estimation of *(2)*, we calculate both food insecurity rates and the number of food-insecure persons in a county. The latter is defined as $FI^*_c * N_c$ where N is the population.

The overall and child models used in *Map the Meal Gap* have historically included race and ethnicity as variables in the model. Methodologically, we include these two variables because they meet the criteria that we have laid out for inclusion in the model.[4] Additionally, the inclusion of these variables is meant to reflect discrimination, unfair practices or conditions that perpetuate cycles of poverty and hunger (Bowen, Elliott & Hardison-Moody, 2021; Odoms-Young, Bruce, 2018). Including these variables may account for significant risk factors that affect these populations beyond what is accounted for in the other variables in the model.

[1] For 2020, we used 2016-2020 5-year ACS data to produce food insecurity estimates for congressional districts, as the U.S. Census Bureau did not release 2020 1-year ACS data in 2022 due to data quality concerns related to Covid-19.

[2] For 2022 Connecticut county equivalents, we used 2022 ACS 1-year unemployment rate estimates because the Bureau of Labor Statistics had not yet adopted the new county equivalents for Connecticut in their annual unemployment rate dataset.

[3] For 2020, we used 2016-2020 5-year ACS data for unemployment to produce food insecurity estimates for congressional districts.

[4] To be considered for inclusion in the MMG model, variables must be available for a minimum of ten years, available at the state, county and congressional district level, and have a documented relationship with food insecurity rates.

Data Imputations for Overall and Child ACS data

In the event ACS data on the independent variables for individual counties or congressional districts are missing or negative, we assign the average value for the given variable, where the average is defined with respect to all counties or congressional districts in the U.S. For those independent variables with values of 0 or 100%, we only impute if a discontinuity is found—an indication that those data may not be accurate. For example, in 2022 only one county out of 3,144 had a homeownership rate of 0% and the next highest was 15.8%. If a discontinuity is found, then the 0 or 100 value is imputed using the national average as defined above.

Income Bands within Counties (and Congressional Districts)

We also estimate the percentage of the overall population in food-insecure households who are income eligible for SNAP (see APPENDIX A for a list of SNAP gross income limits for each state) and the estimated percentage of the child population in food-insecure households who are income eligible for free or reduced-price meals (i.e., below 185% of the federal poverty level).

For the overall population, we proceed with a two-step estimation method. The structure of the equations is slightly different than above. Equation *(1)* is instead specified as follows:

$$FIC_{st} = \alpha + \beta_{UN}UN_{st} + \beta_{HISP}HISP_{st} + \beta_{BLACK}BLACK_{st} + \beta_{OWN}OWN_{st} + \beta_{DSBL}DSBL_{st} + \mu_t + \upsilon_s + \varepsilon_{st} \qquad (1')$$

and equation *(2)* is specified as:

$$FIC^*{}_c = \hat{\alpha} + \widehat{\beta_{UN}}UN_c + \widehat{\beta_{HISP}}HISP_c + \widehat{\beta_{BLACK}}BLACK_c + \widehat{\beta_{OWN}}OWN_C + \widehat{\beta_{DSBL}}DSBL_c + \widehat{\mu_{2022}} + \widehat{\nu_s} \qquad (2')$$

Equation *(1')* is estimated through limiting the sample to those with incomes within a particular income range (e.g., below 130 percent of the poverty line) but *UN*, *BLACK*, *HISP*, *OWN*, and *DISBL* are defined for all individuals. We do so since these variables are only available in the ACS for all income levels. We estimate FIC based on households below each of the thresholds noted in TABLE 1. With this information, we proceed with the following two steps. First, we identify the number of food insecure persons with incomes below the SNAP threshold. Second, the number of food insecure persons with incomes above that threshold is defined as the total number of food insecure persons minus the number of food insecure persons below the SNAP threshold.

A simple example for a county with a SNAP threshold of 160% of the poverty line helps to illustrate this. Suppose in a county of 100,000 persons: 20,000 persons are identified as food insecure, 14,000 are identified as food insecure with incomes below 160% of the poverty line. In this case, there are 14,000 food insecure persons with incomes under 160% of the poverty line and 6,000 with incomes above 160% of the poverty line (i.e., 20,000-14,000). These values are then expressed as percentages: 70% below 160% of the poverty line (i.e., 14,000/20,000) and 30% above 160% of the poverty line (i.e., 6,000/20,000).

We use the same methods to estimate SNAP eligibility among the overall food insecure population in congressional districts as well as eligibility for free or reduced-price school meals among food insecure children.

Black, Latino, and White Populations of Counties (and Congressional Districts)

Consistent with the approach used to generate local food insecurity estimates for the overall and child populations at the county and congressional district levels, a two-step process estimates the percentage of certain racial/ethnic groups that live in food-insecure households.

In the first step, individual state-level files from the Current Population Survey (CPS) are created separately for Black individuals; Hispanic individuals; and white, non-Hispanic individuals. A household is deemed as "Black", "Hispanic" or "white, non-Hispanic" based on the respondent's answers to two sets of questions. The first set of questions asks whether a respondent is of Hispanic, Latino or Spanish origin along with more details, and the second set ask about race. An individual is categorized as Black if they select "Black or African American" as their only race. Said another way, individuals reporting multiple races including "Black" would not be included in the estimates, although persons reporting that they are "Black" may be Hispanic or non-Hispanic. An individual is categorized as "white, non-Hispanic" if they only report "white" for their race and "non-Hispanic" to the question about Hispanic ethnicity. A person is designated as "Hispanic" if they report "Hispanic" to the question about Hispanic ethnicity, although the person may be of any race. Consequently, the data for the racial and ethnic groups are not mutually exclusive. We emphasize that a household that is composed of individuals with different race/ethnicities will all be categorized by the reports of the respondent. For example, suppose the respondent is Black, the respondent's spouse is white, and a child in the household is multiracial. This household would be considered "Black" and every person in the household would be considered to be in a

"Black household". This is consistent with how the USDA classifies race/ethnicity in their annual report on food insecurity (e.g., Rabbitt et al., 2024).

Then, unemployment data by race/ethnicity from the Bureau of Labor Statistics (BLS) are merged to the CPS data. Data for the years 2009 to the most recent data year are created for each subgroup.

Disaggregating data can lead to smaller samples, which can consequently lead to less accurate estimates. We have taken some precautions to address this issue. In the CPS, "state year" observations are dropped 1) where there are fewer than 10 unweighted observations in the CPS and 2) in years for which unemployment information is not available from BLS. States with six or fewer years were dropped from the sample. (Note that states with seven or more years were included even if for some years the state was dropped from our estimations.) For Black individuals, this results in the following states being dropped from the analyses: Hawaii, Idaho, Iowa, Maine, Montana, New Hampshire, North Dakota, South Dakota, Utah, Vermont, and Wyoming. For Hispanic individuals, the following states were dropped: Maine, North Dakota, Vermont, and West Virginia. For white non-Hispanic individuals, all states were included.

Next, separately for each of the three racial/ethnic subgroups, state-level food insecurity is regressed on the subgroup-specific independent variables: the poverty rate, unemployment rate, median income, homeownership rate, and disability rate. The state-level coefficients from these regressions are then applied to subgroup-specific data at the county and congressional district level from the American Community Survey (ACS) to estimate the local subgroup-specific food insecurity rate. Note that the poverty rate used in our race/ethnicity estimates is not the non-student poverty variable used to estimate overall and child food insecurity since the latter variable isn't available by subgroup. Rather, the overall poverty rate for each specific subgroup is used.

It should be noted that estimates for additional groups like Asian American, Native Hawaiian, and Pacific Islander (AANHPI) or Native American individuals are not included in these and many other studies for reasons that include smaller population sizes or insufficient data collection processes that create barriers to achieving reliable estimates.

Missing Data and Data Discontinuities

Additionally, we drop observations where any of the independent variables in the ACS have missing values or where their values are 0% or 100% (except for median income, which is only dropped if it is missing). We drop those with values of 0% or 100% because there is a discontinuity at those values—an indication that those data are not accurate. For example, there are twelve counties where Hispanic individuals face an unemployment rate of 0.3%, five where the rate is 0.2%, four where it is 0.1%, and 800 where it is 0%. Additionally, counties where values of 0% or 100% occur tend to be smaller. For example, the average Hispanic population of the 800 counties with Hispanic unemployment rates of 0% is 418 persons while the average Hispanic population in counties with unemployment rates above 0% is 26,510. We also drop observations with populations below 500 people.

Model Differences

There are two main differences between the models for race and ethnicity and the other models used in *Map the Meal Gap* to estimate local food insecurity among the overall and child populations.

First, the race/ethnicity models do not include the percent Black or the percent Hispanic as covariates, whereas the overall and child models currently do. For the results for white, non-Hispanic individuals, the covariate cannot be included because by design, there are no Hispanic or Black individuals in the sample. For the results for Hispanic individuals, these variables are not included because the overwhelming majority of Latino individuals also identify as white—less than 4% of Latino individuals also identify as Black in the past 10 years. The same reasoning holds for Black individuals. We will continue to explore the inclusion and exclusion of these variables in the model in the coming months and years.

Secondly, the model for race and ethnicity uses the overall subgroup-specific poverty rate in both stages of the estimation process, while the overall and child *Map the Meal Gap* model uses the non-undergraduate poverty rate at the ACS stage. Currently, the data to construct the non-undergraduate poverty rate by subgroup is not available in the ACS. This difference won't affect results for most counties, although in the counties where there is a high undergraduate population and a high proportion of the relevant sub-population, the estimated subgroup-specific food insecurity rates tend to be slightly higher than they otherwise would have been when using the non-undergraduate poverty rate.

While all local estimates within the *Map the Meal Gap* study are approximations, smaller sample sizes for the race and ethnicity estimates do increase uncertainty around the precision of the results. This uncertainty can be quantified using ranges of values known as confidence intervals and corresponding levels of significance (i.e., 90%) that represent how likely it is that the true value of the quantity we are estimating falls within that range. The higher the level of significance, the wider the confidence interval. The table below shows the average 90% confidence intervals for our county food insecurity estimates by available race/ethnicity groups. It should be noted that values are not weighted by population and reflect percentage points.

TABLE 1: 90% Confidence Intervals for County Food Insecurity Rates, 2023

Population	Mean	Median	Min	Max
Latino (Hispanic) (all races)	7.8	7.5	2.4	35.4
Black (all ethnicities)	8.3	7.4	4.4	35.3
Child	4.7	4.4	2.3	12.6
Overall	3.3	2.8	1.2	13.1
White, non-Hispanic	1.9	1.8	0.9	5.7

As shown above, the average (mean) 90% confidence interval for the estimated percentage of the overall population (all ages and races/ethnicities) experiencing food insecurity across all U.S. counties in 2023 is 3.3 percentage points (+/- 1.65 points). In other words, on average, we can say with 90% certainty that the actual food insecurity rate among the overall population for a given county in 2023 was within 3.3 percentage points of the estimated value (there's a 10% chance that the true value was outside of this range).

Just as the confidence intervals for overall food insecurity rates can be narrower for some counties (as low as 1.2 points) and wider for others (as high as 13.1 points), the intervals specific to our race/ethnicity estimates can vary as well. Whereas our food insecurity rates for white, non-Hispanic individuals have the narrowest confidence intervals on average (1.9 points), our estimates for Black individuals have the widest intervals (8.3 points), followed by those for Latino persons (7.8).

Confidence intervals tend to be wider when the values of the independent variables used in our local food insecurity models are far from the national average. For example, a county with an unemployment rate of 20% (the unweighted national county average unemployment rate for 2023 was 3.7%) is likely to have not only a higher estimated rate of food insecurity than the national average (the unweighted national county average food insecurity rate for 2023 was 15.5%), but also a much wider confidence interval.

While the race and ethnicity estimates should be interpreted with these confidence intervals in mind, we believe that understanding historical variations within and across populations and places is critical. Only then can we develop effective strategies to change the policies and practices that put people at risk of hunger.

Child Populations of Counties (and Congressional Districts)

To estimate child food insecurity rates at the county and congressional district levels, we proceed in essentially the same manner as for the full population. However, a few notes are needed regarding the specific procedures used for child food insecurity.

First, we define the variables for households with children rather than for all households. For example, the poverty rate is defined only for households with children. The only exceptions are for the unemployment rate and disability prevalence variables, which are defined for all households. For the unemployment measure, we use the variable for the full population because the sub-state unemployment rates as constructed by BLS are not broken down by whether or not an adult lives in a household where children are present.

Second, we define child food insecurity in the following manner. There are three measures of food insecurity related to children (Rabbitt et al. 2024, Table 1B). The one we use is "children in food-insecure households," which includes children residing in households experiencing low or very low food security among children, adults, or both. To be in this category, a household with children must respond affirmatively to at least three of the 18 questions in the CFSM in the CPS. The count of children who are food insecure is based on the number of children in food-insecure households, and the food insecurity rate is the ratio of the number of children in food-insecure households to the total number of children in the relevant geographic area. This measure is distinct from two other measures found in Rabbitt et al. (2024): households with food insecure children and households with very low food secure children, albeit all children falling into either of these two categories would also be categorized as being in a food insecure household.

Third, we estimate the percentage of children in food-insecure households with incomes above and below the 185% of the federal poverty level; in other words, we approximate how many children facing hunger are likely income eligible for free or reduced-price school meals. Although we use a similar approach to estimate the percentage of all food-insecure individuals that are income eligible for SNAP, here we use a single income threshold of 185% of poverty, which does not vary by state.

Senior and Older Adult Populations of States, Metropolitan Areas (CBSAs), and Various Subpopulations
Estimating food insecurity for senior populations uses a different methodology from other populations estimated in the *Map the Meal Gap* study. Estimates for seniors and older adults are produced directly from responses to the Current Population Survey, while estimates from *Map the Meal Gap* are derived using models based on the relationship between state-level food insecurity and select economic and demographic variables.

The study utilizes multiple data sources to generate food insecurity estimates for older adults and seniors. The primary dataset is the Current Population Survey – Food Security Supplement (CPS-FSS) for 2018-2023, which provides information on household food security status, demographic characteristics, income, and socioeconomic factors. County-level population data from *Map the Meal Gap* is merged with a 2013 county-to-CBSA crosswalk that is available from the Census Bureau. The CPS-FSS identifies CBSAs (2023 populations of one million people or more) for select areas and uses the 2013 definitions. For the county-to-CBSA crosswalk, the study applies patches for statistical geographies in Connecticut that changed between 2013 and 2023. Additionally, the study incorporates Census poverty threshold data[5], which are updated annually and vary by household size and the number of dependent children.

DATA

The information at the state level (i.e., the information used to estimate equations *(1)* and *(1')*) is derived from the CFSM in the December Supplement of the CPS for the years 2009-2023. While the CFSM has been on the CPS since 1996, we draw from this time range because it reflects the inclusion of the disability status question within the CPS.

The CPS is a nationally representative survey conducted by the Census Bureau for the Bureau of Labor Statistics, providing employment, income, and poverty statistics. In December of each year, around 50,000 households respond to a series of questions on the CFSM (full questionnaire is found in APPENDIX C), in addition to questions about food spending and the use of government and community food assistance programs. Households are selected to be representative of civilian households at the state and national levels and thus do not include information on individuals living in group quarters, including dormitories on college campuses, nursing homes, or assisted living facilities. Using information on all persons in the CPS for which we had information on (a) income and (b) food insecurity status, we aggregated information up to the state level for each year to estimate equation *(1)*. We aggregated in a similar manner for equation *(1')*; however, only those below a defined income threshold were used in this aggregation. As noted above, the values for the full sample for the other variables outside of income are used.

Use of Data at the County and Congressional District Level
For information at the county level (i.e., the information used to estimate equations *(2)* and *(2')*), we used information from the ACS 5-year estimates and BLS 1-year unemployment[6]. The ACS is a sample survey of three million addresses administered by the Census Bureau. To provide estimates for areas with small populations, this sample was defined over a five-year period. The unemployment rate at the county level, however, is from 2023.

For information at the congressional district level, including unemployment data (i.e., the information used to estimate equation *(2)*), we used information from the ACS 1-year estimates. In 2020, we used 5-year ACS estimates due to the unavailability of 1-year district estimates stemming from data quality issues related to Covid-19.

The tables below detail the various independent variable data sources, their definitions, and the geography levels at which those data were referenced. Note for several independent variables (unemployment, race or ethnicity populations) different tables were refenced for different geography levels. All of the ACS data were accessed via the Census Bureau API, while the BLS data were downloaded from the linked page.

[5] https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-poverty-thresholds.html
[6] For 2022-presentConnecticut county equivalents, we used ACS 1-year unemployment rate estimates because the BLS has not adopted the new county equivalents for Connecticut.

TABLE 2: Overall Variables

Table	Definition	Congressional District	County
ACS Table S1810	Disability rate	✓	✓
ACS Table DP04	Homeownership rate	✓	✓
ACS Table B19013	Median income	✓	✓
ACS Table DP05	Percent Black and percent Hispanic	✓	✓
ACS Table B14006	Poverty rate	✓	✓
ACS Table B17002	Ratio of income to poverty level		✓
ACS Table C17002	Ratio of income to poverty level	✓	
ACS Table S2301	Unemployment rate	✓	
[BLS Local Area Unemployment Statistics, Annual Average Data, County]	Unemployment rate		✓
ACS Table DP05	Total population	✓	✓

TABLE 3: Child Variables

Table	Definition	Congressional District	County
ACS Table B01001B	Black or African American (alone) child population		✓
ACS Table S0901	Black or African American child population (one race); Hispanic or Latino child population (any race)	✓	
ACS Table S1810	Disability rate	✓	✓
ACS Table B01001I	Hispanic or Latino child population		✓
ACS Table B25115	Homeownership	✓	✓
ACS Table B19125	Median family income	✓	✓
ACS Table S1701	Poverty rate	✓	✓
ACS Table B17024	Ratio of income to poverty level	✓	✓
ACS Table S2301	Unemployment rate	✓	
[Bureau of Labor Statistics, annual average unemployment rates]	Unemployment rate		✓
ACS Table B09001	Total child population	✓	✓

TABLE 4: Race & Ethnicity Variables

Table	Definition	Congressional District	County
ACS Table B25003B	Homeownership rate for Black individuals	✓	✓
ACS Table B25003I	Homeownership rate for Hispanic individuals	✓	✓
ACS Table B25003H	Homeownership rate for white, non-Hispanic individuals	✓	✓
ACS Table S1810	Race or ethnicity specific disability rate	✓	✓
ACS Table S1903	Race or ethnicity specific median income	✓	✓
ACS Table S1701	Race or ethnicity specific poverty rate	✓	✓
ACS Table S2301	Unemployment rate	✓	✓
ACS Table DP05	Race or ethnicity specific total population	✓	✓

RESULTS

We now turn to a brief discussion of the results from the estimation of equation *(1)* and *(1')*. These results for the full population are presented in APPENDIX TABLE 1. In this table, we present coefficient estimates for selected variables and the corresponding standard errors for the full population and for various income categories. In APPENDIX TABLE 2, we present the results for children and in APPENDIX TABLE 3, we present the results for Black individuals, Latino individuals, and white, non-Hispanic individuals.

Concentrating on column (1) in Appendix Table 1, as expected, the effects of unemployment, poverty and disability prevalence are especially strong. Holding all else constant, a one percentage point increase in the unemployment rate leads to a 0.46percentage point increase in estimated food insecurity, while a one percentage point increase in the poverty rate leads to a 0.332 percentage point increase. Furthermore, holding all else constant, a one percentage point increase in the disability rate leads to a 0.198 percentage point increase in estimated food insecurity. The results for the various income categories (i.e., columns (2) through (6)) are broadly similar to those found for the full population.

It should be noted that the *Map the Meal Gap* model is a predictive model that is designed to approximate how many individuals are food insecure at the local level. It is not designed to explain why any individual in any given community may be experiencing food insecurity. While the model may suggest causality in some cases, the coefficients need to be interpreted with caution. We include the explanation in the preceding paragraph for illustrative purposes only.

In the past, we have conducted a series of tests of the *Map the Meal Gap* results to see how well the models performed. Our tests included the following: we compared county results aggregated to metropolitan areas with food-insecurity values for these metro areas taken from the CPS; we compared county results averaged over several years for counties that are observed in the CPS; we compared results with and without state fixed effects; and we compared county results aggregated to the state level with food insecurity values for states taken from the CPS; and we compared results with and without the inclusion of the percent Black and percent Hispanic variables. (For a broader discussion of *Map the Meal Gap* along with information on some further analyses of the robustness of the *Map the Meal Gap* results, see Gundersen et al., 2014 and Gundersen et al., 2017.)

A Note on Compatibility of Local Food Insecurity Estimates

Local food insecurity estimates from *Map the Meal Gap* are primarily designed to make comparisons across similar geographies in a given year (e.g., County A to County B in 2021 or State A to State B in 2020). Users are encouraged to exercise caution when comparing estimates over time (e.g., County A in 2021 to County A in 2020), especially when differences are small since they may not be statistically different. In fact, most geographies will see statistically insignificant changes in estimated food insecurity from one year to the next, especially when the national changes in food insecurity rates are small. That said, the magnitude of those changes may be relatively large and potentially meaningful. Users should consider how differences for one geography compare to differences for other comparable geographies (e.g., how much did estimated food insecurity in County A change from 2020 to 2021 relative to all other counties in the state). Users may also want to look at comparable estimates from more than two years when available (e.g., County A in 2021 compared to County A in 2020 and 2019).

With the caveats above in mind, county and service area food insecurity estimates from *Map the Meal Gap* 2025 (2023 data) may be compared to data from any *Map the Meal Gap* study from 2020 (2018 data) and later, and not to data from studies prior to 2020. . District and state food insecurity estimates from *Map the Meal Gap 2022* (2020 data), however, are not directly comparable to estimates from *Map the Meal Gap 2024* (2022 data), *Map the Meal Gap 2023* (2021 data) or *Map the Meal Gap 2021* (2019 data). Our 2020 congressional district and state estimates were calculated using ACS 5-year (2016-2020) data, not the ACS 1-year data used in previous and subsequent studies. The U.S. Census Bureau did not release 2020 ACS 1-year data in 2022 due to data quality concerns related to Covid-19. District and state estimates for 2020 can, however, be used to make comparisons across similar geographies (e.g., District A to District B in 2020 or State A to State B in 2020) but should not be used for comparisons over time (e.g., District A in 2020 to District A in 2019).

We do not recommend comparing food insecurity estimates for any geography from *Map the Meal Gap 2020* (2018 data) or later, to estimates from *Map the Meal Gap* 2019 (2017 data) or any previous year. The methodology changed in 2020 with the updated poverty variable and new disability variable. Estimates from *Map the Meal Gap* 2013 (2011 data) through *Map the Meal Gap* 2019 (2017 data) are more directly comparable.

FOOD BUDGET SHORTFALL

METHODS

To better understand the food needs of the food-insecure population, we sought to estimate the shortfall in their food budgets. To do so, we use the following question taken from the CPS Food Security Supplement:

In order to buy just enough food to meet (your needs/the needs of your household), would you need to spend more than you do now, or could you spend less?

This question is asked prior to the 18 questions used to derive the food-insecurity measure and, consequently, is not influenced by their responses about food insecurity. Out of those responding "more," the following question is posed:

About how much MORE would you need to spend each week to buy just enough food to meet the needs of your household?

Restricting the sample to households experiencing food insecurity over the previous 12 months, and assigning a value of "0" to households that report needing zero dollars (i.e., those who could spend "the same" each week), as well as to those that report needing "less money", we divide by the number of people in the household to arrive at a per-person figure per week. This value is denoted as PPC.

Not all food-insecure households reported needing additional food every day of the week. The phrasing of the questions above, however, suggests that responses are given with respect to a week during which the household needed to "spend more." Therefore, we have assumed that these responses incorporate both the days of the week during which the household was able to meet its food needs and the days of the week where more money was needed. This assumption is supported by the dollar amount reported, which amounts to approximately 6.2 meals per week (assuming three meals per day, this is fewer than two days per week). The inclusion of food-insecure households that reported needing $0 more per week also supports this assumption. These respondents were assumed to be responding from the perspective of a recent week, one in which they did not require additional money.

Visually, this theoretical week would then look like this:

Day 1	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**
Enough food	Enough food	Enough food	Enough food	Enough food	Not enough food	Not enough food

Similar to how households do not experience food insecurity every day of the month in which they report food insecurity, households may not experience food insecurity every month of the year. As reported by the USDA, in the annual report *Household Food Security in the United States*, "on average, households that were food insecure at some time during the year were food insecure in 7 months of the year" (Rabbitt et al., 2024, pg. 15).

Visually, using the above illustration as a typical week, a sample year would look like this:

Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**
Jul	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**

With this information, we are then able to calculate the dollar figure needed per county, per year as follows: $PPC*52*(7/12)*FI_{cs}*N_{cs}$. This calculation incorporates the number of weeks in a year (52), the average number of months of the year in which someone experiences food insecurity (7 out of 12), and the number of food insecure persons.

DATA

To calculate the dollars needed for a food-insecure person to meet their food needs, we used information from the 2022 CPS.

RESULTS

In APPENDIX TABLE 4, we present some descriptive statistics about reports of dollars needed to be food secure from the CPS. As done above, we restrict the sample to those reporting food insecurity. In the first column, we present results on individuals and in the second column, we present results for households. The average cost to be food secure in 2023 was $22.37 per-person per week. When we break things down further by household size, income levels and food-insecurity levels, the results are consistent with expectations. Namely, larger households report needing more money to be food secure than smaller households; individuals with lower incomes report needing more money to be food secure than individuals with higher incomes; and individuals in households with higher levels of food insecurity need more money to be food secure than households with lower levels of food insecurity.

A Note on Comparability of Local Food Budget Shortfall Estimates

Due to a methodology change for calculating the national average food budget shortfall in 2025 (2023 data) national and local food budget shortfall estimates from 2023 or later are not comparable to estimates prior to 2022.

Using CPS data, the previous methodology (a) assigned values of zero if households were not in the universe for the shortfall question or had missing data and (b) used household-level data and weights. The new methodology excludes households with missing data, and uses individual weights.

COST-OF-FOOD INDEX

METHODS

Because the amount of money needed to be food secure is established as a national average, it does not reflect the range of that figure's food-purchasing power at the local level. To estimate the *local* food budget shortfall, we worked with NielsenIQ to incorporate differences in the price of food that exist between counties. To do so, NielsenIQ designed custom product characteristics so that UPC codes for all food items could be mapped to one of the 24 categories described in the USDA's Thrifty Food Plan (TFP), 2021. This is based on 24 categories of food items (examples include "cheese", "fruit juice", and "whole fruits"). Each UPC-coded food item (non-food items, such as vitamins, were excluded) was assigned to one of the categories. Random-weight food items (such as loose produce or bulk grains) were not included but packaged fresh produce, such as bagged fruits and vegetables, were included. Prepared meals were categorized as a whole (rather than broken down by ingredients) and were coded to "pre-prepared entrees." Processed foods (such as granola bars, cookies, etc.) were coded to "other foods and beverages", "refined-grain other", or "refined-grain staple grains" as appropriate.

The cost to purchase a market basket of these 24 categories is then calculated for each county. Sales of all items within each category were used to develop a cost-per-pound of food items in that category. Some categories, such as milk, are sold in a volume unit of measure and not in an ounces unit of measure. Volume unit of measures were converted to ounces by using "FareShare Conversion Tables". Each category was priced based on the pounds purchased per week as defined by the TFP for each of 24 categories by age and gender. We used the weights in pounds for purchases by males 20 - 50 years for this analysis. Other age/gender weights may have resulted in different total market basket costs but are unlikely to have affected relative pricing between counties, which was the goal of the analysis.

The methods used by NielsenIQ do not, in general, include all stores selling food in a county in the annual sample they use to construct the market basket described above. In counties with sufficient population size and corresponding number of stores selling food, the non-inclusion of some stores is unlikely to bias the cost of the market basket. However, in small counties, the exclusion of some or even all stores can lead to pricing of the market basket that is not an accurate reflection of the "true cost." Along with some stores being excluded, some of the stores included may be too small to have sufficient sales of products included in the market basket. In response to these biases, for all counties with less than 20,000 persons, we ascertain the cost of a market basket that is based on the average of prices found in that county and the prices of the contiguous counties. To request a full list of counties for which cost data were imputed, please email research@feedingamerica.org.

To accurately reflect the prices paid at the register by consumers, food sales taxes are integrated into the market basket prices. County-level food taxes include all state taxes and all county taxes levied on grocery items. Within some counties, municipalities may levy additional grocery taxes. Because these taxes are not consistently applied across the county and we do not calculate food prices at the sub-county level, they are not included. Taxes on vending machine food items or prepared foods were not included, as the market baskets do not incorporate those types of foods. For state-level market basket costs, the average of the county-level food taxes was used. Twelve states levy grocery taxes. An additional seven states do not levy state-level grocery taxes but do permit counties to levy a grocery tax. Finally, an additional state does not levy state or county-level grocery taxes but does permit municipalities to levy grocery taxes (more detail about the tax rates used can be found in APPENDIX B).

As suggested above, our interest is in the relative rather than the absolute price of the TFP, so using the value of the TFP (VTFP), we then calculate an index (IVTFP) as follows: $IVTFP = VTFP_{cs}/AVTP$ where AVTP is the weighted average value of the TFP across all counties. We then estimate the annual food budget shortfall among all food insecure persons (AFBS) that incorporates these price differences. This is calculated for each county as $AFBS_{cs} = IVTFP_{cs}*PPC*52*(7/12)*FI_{cs}*N_{cs}$.

DATA

To calculate the differences in food costs across counties, we used information from the NielsenIQ Scantrack service. This includes prices paid for each UPC code in over 65,000 stores across the U.S. All these analyses use data from a 52-week period ending December of the given analysis year (end of month).

NATIONAL AVERAGE MEAL COST

METHODS

With the above information, we have calculated a localized food budget shortfall for all food-insecure individuals in a county area. In many situations, however, food banks have found it useful and meaningful to discuss the "meals" or "meal equivalents" represented by these dollar values. To meet this need, we calculated an approximation of the number of meal equivalents represented by the county-level food budget shortfall as follows.

In the CPS there is a question that asks how much a household usually spends on food in a week:

Now think about how much (you/your household) USUALLY (spend/spends). How much (do you/does your household) USUALLY spend on food at all the different places we've been talking about IN A WEEK? (Please include any purchases made with SNAP or food stamp benefits).

Restricting the sample to households that are food secure, constructing this sample on a per-person basis, and dividing by 21 (i.e., the usual number of meals a person eats), we arrive at a per-meal cost (*PMC)*. We restrict the sample to food-secure households to ensure that the per-meal cost was based on the experiences of those with the ability to purchase a food-secure diet.

Using this information, the number of meals needed in a county can then be calculated as

$$MAFBScs = (IVTFP_{cs}*PPC*52*(7/12)*FI^{*}_{cs}*N_{cs})/(IVTFP_{cs}*PMC)$$

It is important to note that the "meal gap" is descriptive of a food budget shortfall, rather than a literal number of meals.

DATA

To calculate the average meal cost, we used information from the 2022 CPS.

A Note on Comparability of Local Meal Cost Estimates
Due to a methodology change in 2025, meal costs estimated prior to 2023 are not comparable to meal costs estimated for 2023 or later years.

Using CPS data, the previous methodology (a) assigned values of zero if households were not in the universe for the shortfall question or had missing data and (b) used household-level data and weights. The new methodology excludes households with missing data, and uses individual weights.

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TECHNICAL APPENDICES

APPENDIX A: SNAP THRESHOLDS

To be most useful for planning purposes, Supplemental Nutrition Assistance Program (SNAP) thresholds effective October, 2024 were used for all states in this analysis. SNAP thresholds provided are the gross income eligibility criteria as established by the state. Applicants must meet other criteria (such as net income and asset criteria) to receive the SNAP benefit. Children in households receiving SNAP are categorically eligible for such programs as free National School Lunch Program (NSLP). In states with a SNAP threshold lower than 185 percent of the poverty line, persons earning between the SNAP threshold and 185 percent of the poverty line are income-eligible for other nutrition programs such as the reduced-price NSLP, Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), etc.

SNAP Gross Income Limit (% of poverty) by State, 2024

AK	130%	**MT**	200%
AL	130%	**NC**	200%
AR	130%	**ND**	200%
AZ	185%	**NE**	165%
CA	200%	**NH**	200%
CO	200%	**NJ**	185%
CT	200%	**NM**	200%
DC	200%	**NV**	200%
DE	200%	**NY**	200%
FL	200%	**OH**	130%
GA	130%	**OK**	130%
HI	200%	**OR**	200%
IA	160%	**PA**	200%
ID	130%	**RI**	185%
IL	165%	**SC**	130%
IN	130%	**SD**	130%
KS	130%	**TN**	130%
KY	200%	**TX**	165%
LA	200%	**UT**	130%
MA	200%	**VA**	130%
MD	200%	**VT**	185%
ME	200%	**WA**	200%
MI	200%	**WI**	200%
MN	200%	**WV**	200%
MO	130%	**WY**	130%
MS	130%		

Source: Broad-Based Categorical Eligibility (USDA), October 2024

APPENDIX B: FOOD TAX RATES

States not listed in this appendix do not levy grocery taxes and do not permit counties or municipalities to levy grocery taxes (with the exception of Arizona[7] and Hawaii[8]). In some cases, municipalities may levy additional grocery taxes. These taxes were not included in this analysis. A full list of individual counties' rates is not provided here but is available upon request.

Twelve states levy grocery taxes. In the following three states, no additional grocery taxes are levied at the individual county level. Any additional taxes levied by municipalities were excluded from this analysis.

State	2023 Food Tax (state rate)
ID	6.0%
MS	7.0%
SD	4.2%

In the following nine states, additional grocery taxes are levied at the county or municipal level. Only those rates levied at the county and state level were incorporated into this analysis.

State	2023 Food Tax (state rate)	2023 Food Tax (weighted county average)	2023 Total Food Tax (state + county)
AL	4.00%	2.02%	6.02%
AR	0.13%	1.27%	1.4%
IL	1.00%	0.71%	1.71%
KS	4.00%	1.15%	5.15%
MO	1.23%	1.94%	3.17%
OK	4.50%	0.70%	5.20%
TN	4.00%	2.54%	6.54%
UT	1.75%	1.25%	3.00%
VA	1.00%	1.00%	2.00%

Seven states of the 38 states that do not levy state-level grocery taxes do permit counties and municipalities to levy a grocery tax.[9]

State	2023 Food Tax (state rate)	2023 Food Tax (weighted county average)
AK	0%	0.93%
CO	0%	0.25%
GA	0%	3.47%
LA	0%	2.79%
NC	0%	2.00%
RI	0%	.05%
SC	0%	0.69%

[7] Arizona does not levy state or county-level grocery taxes but does permit municipalities to levy grocery taxes. As a result, no taxes were factored into the food-cost index. It is worth noting, however, that additional burden may be placed on residents of municipalities in which food taxes are in effect.
[8] Hawaii levies a general excise tax on businesses, which can be passed along to consumers.

APPENDIX C: FOOD INSECURITY QUESTIONS IN THE CORE FOOD SECURITY MODULE[10]

ASKED OF ALL HOUSEHOLDS

1. "We worried whether our food would run out before we got money to buy more." Was that **often, sometimes**, or never true for you in the last 12 months?

2. "The food that we bought just didn't last and we didn't have money to get more." Was that **often, sometimes**, or never true for you in the last 12 months?

3. "We couldn't afford to eat balanced meals." Was that **often, sometimes**, or never true for you in the last 12 months?

4. In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (**Yes**/No)

5. (If yes to Question 4) How often did this happen—**almost every month, some months but not every month**, or in only 1 or 2 months?

6. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? (**Yes**/No)

7. In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food? (**Yes**/No)

8. In the last 12 months, did you lose weight because you there wasn't enough money for food? (**Yes**/No)

9. In the last 12 months did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food? (**Yes**/No)

10. (If yes to Question 9) How often did this happen—**almost every month, some months but not every month**, or in only 1 or 2 months?

ONLY ASKED OF HOUSEHOLDS WITH CHILDREN

11. "We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food." Was that **often, sometimes**, or never true for you in the last 12 months?

12. "We couldn't feed our children a balanced meal, because we couldn't afford that." Was that **often, sometimes**, or never true for you in the last 12 months?

13. "The children were not eating enough because there wasn't enough money for food." Was that **often, sometimes**, or never true for you in the last 12 months?

14. In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food? (**Yes**/No)

15. In the last 12 months, were the children ever hungry because there wasn't enough money for food? (**Yes**/No)

16. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (**Yes**/No)

17. (If yes to Question 16) How often did this happen—**almost every month, some months but not every month**, or in only 1 or 2 months?

18. In the last 12 months did any of the children ever not eat for a whole day because there wasn't enough money for food? (**Yes**/No)

[10] Responses in bold indicate an affirmative response. Updates and modifications to the FSS survey instrument were implemented in 2022 (see USDA ERS report *Household Food Security in the United States in 2022* for details). Despite the revisions, USDA ERS found that the underlying food security measurement methodology is unchanged, and the 2022 food security statistics can be compared with food security statistics from prior years.

TABLES

APPENDIX TABLE 1: Estimates of the Impact of Various Factors on Food Insecurity, State Level, 2009-2023

	Full Population	<130% of the poverty line	<160% of the poverty line	<165% of the poverty line	<185% of the poverty line	<200% of the poverty line
	coefficient	coefficient	coefficient	coefficient	coefficient	coefficient
	(s.e.)	(s.e.)	(s.e.)	(s.e.)	(s.e.)	(s.e.)
Poverty Rate	0.332**					
	(0.045)					
Unemployment Rate	0.460**	0.993**	0.864**	0.887**	0.904**	0.896**
	(0.086)	(0.258)	(0.228)	(0.232)	(0.211)	(0.206)
Median Income	-0.001					
	(0.001)					
Percent Hispanic	0.002	0.050	0.073	0.081	0.013	0.031
	(0.054)	(0.187)	(0.173)	(0.170)	(0.148)	(0.144)
Percent Black	-0.043	-0.214	-0.109	-0.137	-0.118	-0.117
	(0.064)	(0.208)	(0.183)	(0.178)	(0.167)	(0.158)
Percent Homeownership	-0.071*	-0.161	-0.115	-0.123	-0.122	-0.140
	(0.032)	(0.116)	(0.096)	(0.097)	(0.086)	(0.085)
Percent Disabled	0.198**	0.601**	0.549**	0.551**	0.533**	0.512**
	(0.052)	(0.165)	(0.147)	(0.146)	(0.126)	(0.124)
2010 (year fixed effect)	-0.012**	-0.028**	-0.018	-0.019	-0.016	-0.020*
	(0.004)	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)
2011 (year fixed effect)	-0.008*	-0.023*	-0.003	-0.013	-0.004	-0.004
	(0.004)	(0.011)	(0.010)	(0.010)	(0.009)	(0.008)
2012 (year fixed effect)	-0.009*	-0.011	-0.007	-0.014	-0.000	-0.007
	(0.004)	(0.011)	(0.010)	(0.010)	(0.009)	(0.008)
2013 (year fixed effect)	-0.005	0.003	-0.002	-0.002	0.010	0.002
	(0.004)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)
2014 (year fixed effect)	-0.006	-0.002	-0.004	-0.002	0.010	0.000
	(0.005)	(0.014)	(0.013)	(0.013)	(0.013)	(0.012)
2015 (year fixed effect)	-0.008	0.002	-0.001	0.000	0.009	-0.003
	(0.005)	(0.016)	(0.014)	(0.014)	(0.013)	(0.012)
2016 (year fixed effect)	-0.012*	-0.006	-0.008	-0.006	0.000	-0.010
	(0.005)	(0.016)	(0.014)	(0.014)	(0.013)	(0.012)
2017 (year fixed effect)	-0.012	-0.015	-0.015	-0.015	-0.006	-0.019
	(0.006)	(0.017)	(0.015)	(0.015)	(0.014)	(0.013)
2018 (year fixed effect)	-0.015*	-0.025	-0.026	-0.026	-0.018	-0.022
	(0.006)	(0.018)	(0.016)	(0.016)	(0.015)	(0.014)

2019 (year fixed effect)	-0.016*	-0.020	-0.027	-0.031	-0.028	-0.027
	(0.007)	(0.018)	(0.016)	(0.016)	(0.016)	(0.015)
2020 (year fixed effect)	-0.034**	-0.058**	-0.055**	-0.056**	-0.054**	-0.052**
	(0.005)	(0.013)	(0.011)	(0.011)	(0.011)	(0.010)
2021 (year fixed effect)	-0.032**	-0.060**	-0.057**	-0.057**	-0.055**	-0.054**
	(0.006)	(0.016)	(0.015)	(0.015)	(0.014)	(0.013)
2022 (year fixed effect)	0.001	-0.005	0.003	-0.002	0.011	0.004
	(0.008)	(0.020)	(0.017)	(0.017)	(0.016)	(0.015)
2023 (year fixed effect)	0.013	0.018	0.014	0.017	0.026	0.019
	(0.008)	(0.018)	(0.016)	(0.016)	(0.016)	(0.015)
Constant	0.101**	0.415**	0.365**	0.362**	0.335**	0.335**
	(0.027)	(0.091)	(0.081)	(0.081)	(0.071)	(0.070)

* p<0.05 ** p<0.01. The omitted year for the year fixed effects is 2009. The data used is taken from the December Supplements of the 2009-2023 Current Population Survey.

APPENDIX TABLE 2: Estimates of the Impact of Various Factors on Child Food Insecurity, State Level, 2009-2023

	Full Population	<185% of the poverty line
	coefficient	coefficient
	(s.e.)	(s.e.)
Poverty Rate	0.265**	
	(0.050)	
Unemployment Rate	0.667**	1.023**
	(0.162)	(0.329)
Median Income	-0.004**	
	(0.001)	
Percent Hispanic	-0.071	-0.175
	(0.053)	(0.110)
Percent Black	0.117*	0.089
	(0.053)	(0.137)
Percent Homeownership	-0.110**	-0.276**
	(0.037)	(0.101)
Percent Disabled	0.318**	0.578**
	(0.091)	(0.197)
2010 (year fixed effect)	-0.025**	-0.045**
	(0.007)	(0.012)
2011 (year fixed effect)	-0.024**	-0.033*
	(0.007)	(0.015)
2012 (year fixed effect)	-0.020**	-0.034*
	(0.007)	(0.014)
2013 (year fixed effect)	-0.017*	-0.016
	(0.008)	(0.014)
2014 (year fixed effect)	-0.014	-0.023
	(0.009)	(0.018)
2015 (year fixed effect)	-0.023*	-0.025
	(0.010)	(0.019)
2016 (year fixed effect)	-0.022*	-0.036
	(0.010)	(0.020)

2017 (year fixed effect)	-0.019	-0.040*
	(0.011)	(0.020)
2018 (year fixed effect)	-0.028*	-0.069**
	(0.012)	(0.024)
2019 (year fixed effect)	-0.027*	-0.068**
	(0.013)	(0.024)
2020 (year fixed effect)	-0.044**	-0.077**
	(0.008)	(0.014)
2021 (year fixed effect)	-0.051**	-0.097**
	(0.012)	(0.022)
2022 (year fixed effect)	0.010	-0.001
	(0.013)	(0.026)
2023 (year fixed effect)	0.020	0.008
	(0.014)	(0.024)
Constant	0.168**	0.491**
	(0.035)	(0.086)

* $p<0.05$ ** $p<0.01$. The omitted year for the year fixed effects is 2009. The data used is taken from the December Supplements of the 2009-2023 Current Population Survey.

APPENDIX TABLE 3: Estimates of the Impact of Various Factors on Sub Group Food Insecurity, State Level, 2009-2023

	All	Black	Hispanic	White, non-Hispanic
	coefficient	coefficient	coefficient	coefficient
	(s.e.)	(s.e.)	(s.e.)	(s.e.)
Poverty Rate	0.332**	0.219**	0.220**	0.265**
	(0.045)	(0.053)	(0.050)	(0.038)
Unemployment Rate	0.460**	0.489**	0.280	0.322**
	(0.086)	(0.172)	(0.173)	(0.085)
Median Income	-0.001	-0.003	-0.008	-0.002*
	(0.001)	(0.005)	(0.004)	(0.001)
Percent Hispanic	0.002			
	(0.054)			
Percent Black	-0.043			
	(0.064)			
Percent Homeownership	-0.071*	-0.196**	-0.025	-0.074**
	(0.032)	(0.049)	(0.039)	(0.025)
Percent Disabled	0.198**	0.065	0.317**	0.125**
	(0.052)	(0.080)	(0.090)	(0.041)
2010 (year fixed effect)	-0.012**	-0.013	-0.019	-0.009**
	(0.004)	(0.013)	(0.011)	(0.003)
2011 (year fixed effect)	-0.008*	-0.015	-0.018	-0.003
	(0.004)	(0.015)	(0.013)	(0.004)
2012 (year fixed effect)	-0.009*	-0.010	-0.045**	-0.001
	(0.004)	(0.013)	(0.012)	(0.003)
2013 (year fixed effect)	-0.005	0.008	-0.039**	-0.002
	(0.004)	(0.015)	(0.012)	(0.004)
2014 (year fixed effect)	-0.006	0.016	-0.046**	-0.004
	(0.005)	(0.015)	(0.015)	(0.005)
2015 (year fixed effect)	-0.008	-0.012	-0.056**	-0.002
	(0.005)	(0.015)	(0.016)	(0.005)
2016 (year fixed effect)	-0.012*	-0.002	-0.060**	-0.010*
	(0.005)	(0.018)	(0.015)	(0.005)

2017 (year fixed effect)	-0.012	-0.003	-0.060**	-0.011*
	(0.006)	(0.019)	(0.017)	(0.006)
2018 (year fixed effect)	-0.015*	-0.008	-0.069**	-0.014*
	(0.006)	(0.020)	(0.017)	(0.006)
2019 (year fixed effect)	-0.016*	-0.020	-0.073**	-0.015*
	(0.007)	(0.021)	(0.018)	(0.006)
2020 (year fixed effect)	-0.034**	-0.021	-0.075**	-0.033**
	(0.005)	(0.017)	(0.015)	(0.004)
2021 (year fixed effect)	-0.032**	-0.022	-0.091**	-0.029**
	(0.006)	(0.018)	(0.014)	(0.005)
2022 (year fixed effect)	0.001	0.028	-0.023	-0.004
	(0.008)	(0.022)	(0.018)	(0.006)
2023 (year fixed effect)	0.013	0.052*	-0.003	0.006
	(0.008)	(0.024)	(0.019)	(0.007)
Constant	0.101**	0.255**	0.204**	0.121**
	(0.027)	(0.045)	(0.041)	(0.022)

* p<0.05 ** p<0.01. The omitted year for the year fixed effects is 2009. The data used is taken from the December Supplements of the 2009-2023 Current Population Survey.

APPENDIX TABLE 4: Breakdowns of Weekly Cost to be Food Secure in 2023

	Individuals	Households
All Food Insecure	$22.37	-
By Household Size	-	-
1 person	-	$41.39
2 person	-	51.61
3 person	-	69.22
4 person	-	61.34
5 person	-	77.89
By Income Categories	-	-
<130% of poverty line	24.99	-
>130% of poverty line	20.56	-
<185% of poverty line	23.85	-
>185% of poverty line	20.12	-
By food security status	-	-
Marginally food secure	12.15	-
Low food secure	18.10	-
Very low food secure	30.57	-

The data used are taken from the December Supplement of the 2023 Current Population Survey.

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