

Featured Article

Food Insecurity during COVID-19

Craig Gundersen*, Monica Hake, Adam Dewey, and
Emily Engelhard

Craig Gundersen is ACES Distinguished Professor at the Department of Agricultural & Consumer Economics at the University of Illinois. Monica Hake and Adam Dewey are senior research managers at Feeding America. Emily Engelhard is managing director of thought leadership at Feeding America

*Correspondence may be sent to: E-mail: cggunder@illinois.edu

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Abstract *For a decade, Feeding America’s Map the Meal Gap (MMG) has provided sub-state-level estimates of food insecurity for both the full population and for children. Along with being extensively used by food banks, it is widely used by state and local governments to help plan responses to food insecurity in their communities. In this paper, we describe the methods underpinning MMG, detail the approach Feeding America has used to make projections about the geography of food insecurity in 2020, and how food insecurity rates may have changed due to COVID-19 since 2018. We project an increase of 17 million Americans who are food insecure in 2020 but this aggregate increase masks substantial geographic variation found in MMG.*

Key words: COVID-19, food insecurity, hunger, Map the Meal Gap, poverty.

JEL codes: I31, Q18.

Introduction

This year represents the tenth anniversary of Feeding America’s Map the Meal Gap (MMG). On an annual basis, MMG provides county- and congressional district-level estimates of food insecurity for both the full population and for children and, upon request, subcounty-level results at, for example, the zip code level. Along with being extensively used by food banks to direct scarce resources to those most in need, it is now widely used by state and local governments to help plan responses to food insecurity in their communities.

For MMG, food insecurity rates are calculated with an imputation method that uses information from the Current Population Survey (CPS) and the American Community Survey (ACS). Since the Core Food Security Module (CSFM) is in the December CPS and the resulting data is not publicly released until September of the following year and the ACS is not released until December, this has meant that MMG, released in the spring, is based on data that is roughly eighteen months old. Given that post-Great Recession, rates

have remained relatively stable from year to year, as have geographical differences within and across states, this release schedule has not produced issues regarding timeliness. Of course, COVID-19 has changed all of this and, given the sharp projected increases in unemployment (and, hence, food insecurity) the levels of food insecurity across the United States are likely to be far higher in 2020 than in 2018.

In this article, after describing the methods underpinning MMG, we detail the approach Feeding America has used to make projections about the geography of food insecurity in 2020 and how this may differ from 2018. Central to these projections is that the methods used in MMG allow for us to do this when information about predictions of the underlying variables are available. We then turn to a description of multiple aspects of this changed geography of food insecurity.

Approach

Food Insecurity

The official measure of food insecurity in the US as established by the USDA uses responses to eighteen questions about food hardships due to financial constraints experienced by households (ten for households without children and eighteen for households with children). Examples of survey questions include: Did you or the other adults in your household ever cut the size of your meals or skip meals because there wasn't enough money for food?. Were you ever hungry but did not eat because you could not afford enough food? and Did a child in the household ever not eat for a full day because you could not afford enough food? (the most severe question). (For the complete set of questions, see Coleman-Jensen et al. 2019.)

The responses for some of these questions are yes or no. In other cases, respondents are asked if something happened never, sometimes, or often. A response of sometimes or often is counted as an affirmative response. Other questions ask respondents if something happened almost every month, some months but not every month, or in only one or two months. A response of almost every month or some months but not every month is counted as an affirmative response. Based on these responses, households are delineated into three categories: A household is said to be food secure if they respond affirmatively to two or fewer questions; low food secure if they respond affirmatively to three to seven questions (three to five questions for households without children); and very low food secure if they respond affirmatively to eight or more questions (six or more questions for households without children). Food insecure households are those without access at all times to enough food for an active, healthy life for all household. The questions employed in MMG to define food insecurity are the same as those used by the USDA since 2001 to define food insecurity.

Methods

We proceed in two steps to estimate the extent of food insecurity in each county (congressional district).

Step 1. Using state-level data from 2009 to 2018, we estimate a model where the food insecurity rate for individuals at the state level is determined by the following equation:

$$\begin{aligned}
FI_{st} = & \alpha + \beta_{UN}UN_{st} + \beta_{POV}POV_{st} + \beta_{MI}MI_{st} + \beta_{HISP}HISP_{st} \\
& + \beta_{BLACK}BLACK_{st} + \beta_{OWN}OWN_{st} + \beta_{DSBL}DSBL_{st} + \mu_t + v_s + \varepsilon_{st}
\end{aligned} \tag{1}$$

where s is a state, t is year, UN is the unemployment rate, POV is the nonundergraduate student poverty rate, MI is median income, $HISP$ is the percentage of Hispanics, $BLACK$ is the percentage of African Americans, OWN is the percentage of individuals who are homeowners, $DSBL$ is the percentage of individuals who report a disability, μ_t is a year fixed effect, v_s is a state fixed effect, and ε_{st} is an error term. This model is estimated using weights defined as the state population. In previous iterations of MMG we used data back to 2001 but the disability variable is only available since 2009 and, hence, the model is estimated from 2009 to 2018.

Our choice of variables was first guided by the literature on the determinants of food insecurity. We included variables that have been found in prior research to influence the probability of a household being food insecure. (For an overview of that literature in this context see Gundersen and Ziliak 2018.) While the food insecurity measure is defined at the household level, we assume all members of a food-insecure household are food insecure, consistent with the approach found in, e.g., table 1 of Coleman-Jensen et al. (2019). Next, we chose variables that are available both in the CPS and the ACS.

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:

$$\begin{aligned}
FI^*_c = & \hat{\alpha} + \hat{\beta}_{UN}UN_c + \hat{\beta}_{POV}POV_c + \hat{\beta}_{MI}MI_c + \hat{\beta}_{HISP}HISP_c + \hat{\beta}_{BLACK}BLACK_c \\
& + \hat{\beta}_{OWN}OWN_c + \hat{\beta}_{DSBL}DSBL_c + \hat{\mu}_{2018} + \hat{v}_s
\end{aligned} \tag{2}$$

where c denotes a county. The variables POV , MI , $HISP$, $BLACK$, OWN , and $DSBL$ are based on 2014–2018 ACS five-year measures and UN is based on 2018 BLS one-year measures.

This year for MMG we made two primary changes. First, we added the percent of the population that has a disability to reflect the profound impact that disability status has on food insecurity. (See, e.g., Balistreri 2019; Brucker and Coleman-Jensen 2017; Noonan, Corman, and Reichman 2016; Sonik et al. 2016.) Second, the poverty variable now only includes nonundergraduate students. This is because the true resources available to undergraduates are, on average, not reflected in the poverty rate. Consistent with this are the much lower food insecurity rates among college students in comparison to noncollege students of similar ages (Gundersen 2021).

The above methods allow us to establish a base measure of food insecurity for all counties for the full population and for children. Using this base measure, we establish what we believe will happen to food insecurity in the US in 2020 because of the COVID-19 pandemic. To do so, we consider what will occur if two of the variables in the model above, the unemployment rate and the poverty rate, increase along the lines predicted by expert opinions. (The other variables in our model are unlikely to change due to COVID-19.) In our most recent estimates of the upper-bound impact (as of July 13, 2020),

Table 1 Base Food Insecurity Rates and Projected Changes in 15 Highest Counties, Full Population

Base results		Projected results		% Increase	
	FI rate		FI rate		
Jefferson County, Mississippi	0.304	Jefferson County, Mississippi	0.342	Burke County, North Dakota	157.3
Issaquena County, Mississippi	0.289	Issaquena County, Mississippi	0.339	Renville County, North Dakota	131.4
East Carroll Parish, Louisiana	0.282	East Carroll Parish, Louisiana	0.332	Dickey County, North Dakota	127.0
Kusilvak Census Area, Alaska	0.280	Kusilvak Census Area, Alaska	0.331	Loudoun County, Virginia	124.7
Holmes County, Mississippi	0.278	Holmes County, Mississippi	0.327	Eagle County, Colorado	123.8
Claiborne County, Mississippi	0.271	Oglala Lakota County, South Dakota	0.326	Bowman County, North Dakota	122.2
Perry County, Alabama	0.270	Claiborne County, Mississippi	0.320	Mountrail County, North Dakota	118.2
Oglala Lakota County, South Dakota	0.269	Perry County, Alabama	0.317	Hettinger County, North Dakota	118.2
Humphreys County, Mississippi	0.264	Quitman County, Mississippi	0.316	Billings County, North Dakota	118.1
Greene County, Alabama	0.261	Humphreys County, Mississippi	0.315	Mercer County, North Dakota	115.9
Todd County, South Dakota	0.259	Todd County, South Dakota	0.313	Sargent County, North Dakota	113.9
Phillips County, Arkansas	0.256	Phillips County, Arkansas	0.307	Falls Church city, Virginia	111.7
Quitman County, Mississippi	0.252	Greene County, Alabama	0.307	Dunn County, North Dakota	111.6
Wilkinson County, Mississippi	0.248	Washington County, Mississippi	0.302	Carver County, Minnesota	110.4
Harlan County, Kentucky	0.248	Wolfe County, Kentucky	0.302	Daggett County, Utah	109.5

Notes: The base results are based on imputations derived from the 2009 to 2018 December Supplements of the Current Population Survey and the 2014 to 2018 American Community Survey. The projected results are explained in the text.

we have assumed that the annual average unemployment rate will increase to 11.5% (up 7.6% compared to 2018) and the poverty rate will increase to 16.6% (up 4.8% compared to 2018). When we wrote the first version of this paper, there had not been expert projections of changes in poverty rates due to COVID-19, so we assumed that the proportional change in the poverty rate *viz.* the unemployment rate would be roughly the same as during the Great Recession. To put this into terms of equation (2), we assume the value of UN_C will increase (on average) by 0.076 and the value of POV_C will increase by 0.048.

This increase in the unemployment rate, though, is unlikely to be uniform across all counties in the US. Instead, certain industries and occupations will be disproportionately affected by COVID-19. So, we further adjust the county-level and CD-level unemployment projections for the proportion of the population that is likely to lose their jobs, combining data from the American Community Survey with estimates established in Hatzius et al. (2020).

Findings

At the national level, we project 54 million food insecure Americans in 2020, approximately 17 million higher than in 2018. For children, the food insecurity rates are projected to increase to 18 million, up nearly 7 million from 2018.

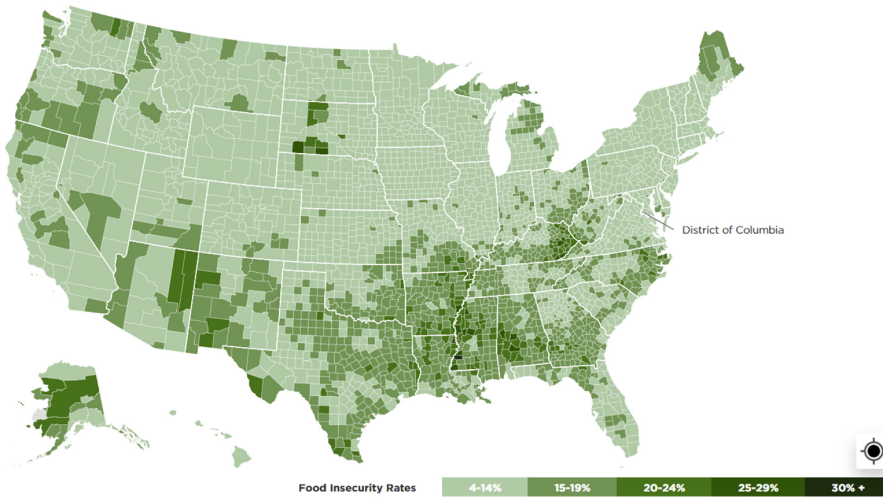
These national estimates, though, mask substantial heterogeneity across the country in terms of the projected impacts of COVID-19. This is not unexpected, given the geographic diversity in the base models for both the full population (figure 1) and children (figure 2). Looking at states, the highest five states are the same whether or not COVID-19 occurred – Mississippi, Arkansas, Alabama, Louisiana, and New Mexico. However, there are some states that will see much higher food insecurity rates. Nevada stands out – pre-COVID-19 it would have been twentieth, but post-COVID-19 it is projected to be eighth. For children, Louisiana and New Mexico are first and second with or without COVID-19, but Nevada is now third (ninth without COVID-19). The substantially higher projected rates for Nevada are primarily due to their reliance on service sector jobs, which have been disproportionately affected by COVID-19.

One of the key contributions from MMG is its portrayal of the substantial heterogeneity in local food insecurity that is seen in figures 1 and 2. The responses to COVID-19 will also vary based on geography, although, consistent with the state results, there is likely to be some similarities in terms of county rankings. For the full population (table 1), we display, first, the fifteen counties with the highest rates of food insecurity in the base case and due to our projections. In the base case, the fifteen counties are all in the South or counties with Indian Reservations. The highest is Jefferson County, Mississippi (30.4%) and the fifteenth is Harlan County, Kentucky (24.8%). Without the adjustments for county-level differences in unemployment rates described above, these would be the same orderings after COVID-19 but, due to these adjustments, there are some differences. The five highest remain the same but, for example, Washington County, Mississippi and Wolfe County, Kentucky are now in the top fifteen.

In the final two columns of table 1 we display the projected percent increases in food insecurity for the highest fifteen counties. These are all counties with base rates that are relatively low, which is the reason for the substantial increases. The increases range from 157.3% in the highest (Burke County,

Figure 1 Estimates of Food Insecurity Rates for the Full Population by County, 2018

Notes: These results are based on imputations derived from the 2009 to 2018 December Supplements of the Current Population Survey and the 2014 to 2018 American Community Survey. [Color figure can be viewed at [wileyonlinelibrary.com](#)]



North Dakota) to 109.5% in the fifteenth highest (Daggett County, Utah). These dramatic increases may be one reason for why some food banks reported being especially strained in response to COVID-19.

Table 2 has the same structure as table 1 but for children. As expected, there is overlap in counties between the two. For example, Kusilvak Census Area in Alaska is second highest for children and fourth highest for the full population for both the base case and the rankings after COVID-19. There are some contrasts, though, insofar as Texas has no counties in the top fifteen for the full population but has four in the base case for children and four in the COVID-19 projections. In terms of projected percent increases for children, there are

Figure 2 Estimates of Food Insecurity Rates for Children by County, 2018

Notes: These results are based on imputations derived from the 2009 to 2018 December Supplements of the Current Population Survey and the 2014 to 2018 American Community Survey. [Color figure can be viewed at [wileyonlinelibrary.com](#)]

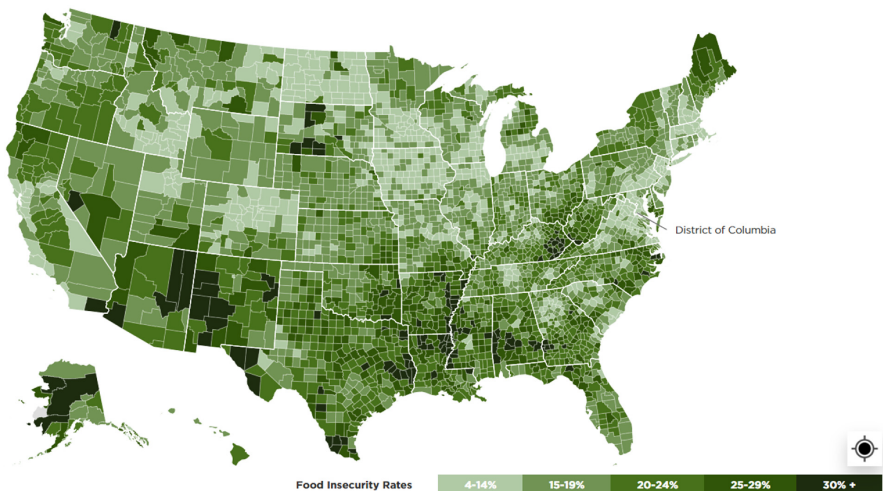


Table 2 Base Food Insecurity Rates and Projected Changes in 15 Highest Counties, Children

Base results		Projected results		% Increase
	FI rate	FI rate		
East Carroll Parish, Louisiana	0.437	0.525	Falls Church city, Virginia	363.0
Kusilvak Census Area, Alaska	0.432	0.523	Arlington County, Virginia	215.8
Issaquena County, Mississippi	0.411	0.499	Loudoun County, Virginia	210.5
Jefferson County, Mississippi	0.400	0.491	Eagle County, Colorado	201.4
Zavala County, Texas	0.397	0.489	Fairfax city, Virginia	188.7
Sabine County, Texas	0.388	0.482	Teton County, Idaho	175.9
Greene County, Alabama	0.386	0.476	Williamson County, Tennessee	168.3
Oglala Lakota County, South Dakota	0.381	0.474	Teton County, Wyoming	161.7
Perry County, Alabama	0.377	0.472	Fairfax County, Virginia	160.2
Claiborne County, Mississippi	0.370	0.470	Bowman County, North Dakota	157.0
Clay County, Georgia	0.368	0.466	Summit County, Colorado	154.1
Magoffin County, Kentucky	0.366	0.464	Manassas city, Virginia	151.4
Cottle County, Texas	0.360	0.460	Pitkin County, Colorado	150.5
San Augustine County, Texas	0.358	0.460	Dickey County, North Dakota	146.5
Phillips County, Arkansas	0.357	0.458	Kendall County, Illinois	143.6

Notes: The base results are based on imputations derived from the 2009 to 2018 December Supplements of the Current Population Survey and the 2014 to 2018 American Community Survey. The projected results are explained in the text.

some differences with the full population. While North Dakota has ten of the fifteen highest counties for the full population, they have two for children and, conversely, Virginia has one in the full population but six for children including the top three. The range of the percent increase is also higher and wider—from 143.6% for the fifteenth (Kendall County, Illinois) to 363.0% to the highest (Falls Church City, Virginia). (An Excel file with the full set of results for the full population and children including the projected proportional changes and the adjustment for unemployment rate is in the Appendix.)

Conclusion

The proceeding discussion—and the full set of results with updates as needed at <http://map.feedingamerica.org/>—provides an overview of the geographic diversity in food insecurity rates across the U.S. and what may happen due to COVID-19. We conclude with three main points. First, while these projections of increased food insecurity rates are of great concern, they would have been for worse were it not for the resiliency of the agricultural supply chain in the face of COVID-19. (For more on this, see the other articles in this Special Issue.) Given that food prices are a key determinant of food insecurity (e.g., Gregory and Coleman-Jensen 2013; Courtemanche et al. 2019), if there had been price increases due to agricultural supply chain breakdowns, the food insecurity rates we have estimated would have been much higher. In other words, the projected increase in food insecurity is due to projected increases in unemployment and poverty and not problems within the agricultural sector. Future researchers may wish to consider why this success occurred and, in particular, the protections it afforded vulnerable persons. Second, our estimates are based on information from annual food insecurity measures for the full calendar year instead of food insecurity measures that are based on either shorter time frames (e.g., the previous thirty days) and or across years. In addition, these estimates are based on the full set of eighteen questions on the CFSM. Three other papers in this Special Issue employ other methods to ascertain the impact of COVID-19 on food insecurity and, as such, our results are not directly comparable. (See Ahn and Norwood 2021; Restrepo, Rabbitt, and Gregory 2021; and Ziliak 2021.) Third, the accuracy of our projections will not become evident until September 2021 for the national results and March 2022 for the MMG estimates. We look forward to ascertaining the success (or lack of success) of our projections at that time.

Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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