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The Role of Community Food Services in Reducing US Food Insufficiency in the COVID-19 Pandemic

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We use state-level Census Household Pulse Survey data to examine the role of community food services such as food banks and pantries in reducing food insufficiency during the COVID-19 pandemic in the United States. Food insufficiency increased for all income classes during the pandemic, and especially for the lower and middle classes. We adopt a fixed effects filtered estimator to estimate the coefficients on time-invariant regressors in a fixed effects panel model. Estimation results suggest community food services contribute to mitigating food insufficiency, especially for the middle class and in the early months of the pandemic.

Key words: fixed effects filtered estimator, food bank, food insecurity, food pantry, Household Pulse Survey

Introduction

Among the lasting images of the COVID-19 pandemic in the United States, long lines of individuals and cars at food banks will likely be prominent. In addition, public media accounts (e.g., Reiley, 2020b; Smith, 2020; Stewart and Heisler, 2020) and a growing number of academic studies (e.g., Morales, Morales, and Beltran, 2021; Neff, 2020; Ziliak, 2021; Ahn and Norwood, 2021; Gundersen et al., 2021) have documented short-term increases in household food insecurity associated with the economic collapse caused by the pandemic. This raises questions about whether food banks, food pantries, and related aggregators can play a role in reducing food insecurity during a pandemic in a high-income country such as the United States.

While the causes and outcomes of food insecurity have received considerable attention over the past decade in the academic literature (Bernell, Weber, and Edwards, 2006; Gundersen, Kreider, and Pepper, 2011; Gundersen and Ziliak, 2015, 2018; Long et al., 2020), the role of community food services (CFS)—food banks, food pantries, and related aggregators—in contributing to food security has received less consideration, especially in the United States (Gundersen et al., 2016). This is surprising because the concept of food banks originated in this country (Tarasuk, Fafard St-Germain, and Loopstra, 2020). Other public food programs such as the Supplemental Nutrition Assistance Program (SNAP) and the Women, Infants, and Children Program (WIC) have received significantly more attention (Wilde, 2001; Wu, Saitone, and Sexton, 2017). SNAP has been found to be an effective and responsive program that especially helps low-income individuals, who often spend a large share of their income on food

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(Rosenbaum, Dean, and Neuberger, 2020; Hungerford, Effland, and Johansson, 2021). The limited evidence available for the United States suggests that food banks and similar private food giveaway programs are less effective in reducing hunger than public programs such as SNAP, although Gundersen et al. (p. 2 2016) suggest that "both public and private food assistance programs serve as important mechanisms to tackle the problem of hunger and food insecurity in the United States." Byrne and Just (2021) find that for a sample of 40,000 households in Larimer County, Colorado, the importance of food banks in alleviating hunger varies over the month, following the schedule of SNAP benefits receipts. Other studies have shown that emergency food systems, depending on the programming, may not compare favorably to SNAP in terms of overhead costs (Ohls et al., 2002; Mabli et al., 2013; Rosenbaum, 2013; Rosenbaum, Dean, and Neuberger, 2020).

Food programs' efficacy (or lack thereof) may be partly due to social stigma associated with their use (e.g., Loopstra et al., 2018). Gundersen, Engelhard, and Hake (2017) study the characteristics of households using food banks in the United States and find that these households face multiple challenges, such as foreclosures and having to decide between paying for bills or food. In Canada, Holmes et al. (2018) indicate that food banks alone are unable to mitigate the effects of economic deprivation more generally, while Tarasuk, Fafard St-Germain, and Loopstra (2020) find that Canadian food banks are used by low-income individuals and as a last resort. This finding is also generally echoed for the United Kingdom by MacLeod, Curl, and Kearns (2019). Bazerghi, McKay, and Dunn (2016) suggest that food banks provide nutritionally less dense food overall, especially in terms of fruits and vegetables, and dairy products (see also Eicher-Miller, 2020; Simmet et al., 2017).

The problem of food insecurity in the specific context of the COVID-19 pandemic has been examined in Gundersen et al. (2021), using Feeding America's Map the Meal Gap data, and Ziliak (2021), who uses the US Census Household Pulse Survey (HPS) dataset as a supplement to food insufficiency rates derived from the Current Population Survey. Ziliak finds that the pandemic more severely impacted seniors than individuals in other age groups. Wolfson and Leung (2020) similarly find that the pandemic has had disparate effects on seniors, according to a web-based survey of nearly 1,500 adults whose incomes were below 250% of the federal poverty line. Ahn and Norwood (2021) used opt-in panels to measure food insecurity in May 2020. They observed that the number of households with children classified as food insecure was 3% higher that year than in 2016 and 2017, while they did not see an increase in food insecurity for all households.

However, research on how the pandemic has impacted food insufficiency conditions for different income classes has been limited or nonexistent. The comprehensive report by Chetty et al. (2020) observes that while high-income individuals reduced spending during the pandemic, it was primarily low-wage workers who suffered the most with persistent layoffs. Using the HPS data, Bauer (2020) shows that low-income households with children are more likely to suffer food insufficiency and enroll in food assistance programs (e.g., SNAP, WIC, and Pandemic Electronic Benefit Transfer) during the pandemic. In our study, we consider food insufficiency not only for individuals in poverty but also for the middle-income class. These individuals also faced job losses and income reductions during the pandemic. While food security may have been a distant concern for these individuals before the pandemic, food banks or other community food assistance could play a critical role in solving short-term emergent food needs resulting from layoffs.

In this study, we evaluate the mitigating effect of free or alternative food sources during a pandemic on food insufficiency and its variation across income classes. Assessing such an effect is complicated by an identification problem in that households are food insufficient and require free food, and they require free food because they suffer from food insufficiency. The US Census Bureau's (2022) HPS provides data on food insufficiency as well as on access to free sources of food, but it is not possible from the data to sort out the causal pathway (even lagging regressors by a week or more is not effective). For example, our preliminary regressions of HPS food insufficiency status on free food variables, including SNAP, consistently yielded positive and statistically significant parameter estimates. Instead of using the free food access variables from the HPS, we therefore draw on the 2019 County Business Patterns data (US Census Bureau, 2019) to shed light on the role of preexisting Community Food Services (CFS) in mitigating food vulnerability in the states during the current pandemic. We use the North American Industrial Classification System (NAICS) code 624210 for CFS, which includes community meals, social services; food banks; meal delivery programs; mobile soup kitchens; and soup kitchens.[1]

This approach is not without problems, but it allows us to claim quasi-exogeneity in that the presence of CFS in a state prior to COVID-19 is independently determined. Moreover, while the number of such establishments per 10,000 persons may have changed between 2019 (the most recent year for which data are available at the time of this writing) and March 2020, we suggest that once we control for the main driving forces, such as the spread of the disease and unemployment, which can affect both food insufficiency and CFS capacity, the 2019 CFS establishments per 10,000 persons variable is a reasonable proxy for the amount of experience a given state has with CFS and related establishments and its capacity to deliver free food through such a venue.

A dense presence of CFS in a state may also reflect or be correlated with other anti-hunger innovations in terms of providing food to those in need, promoting enrollment in the SNAP program, and advertising available resources. Further, it may be important even to the middle class to maintain these emergency services as they may need them unexpectedly. More generally, in this case our CFS measure may be picking up not only the effects of CFS but also on related factors.

Using HPS data, we compute as our dependent variable a food insufficiency measure, FI, which reflects the change in food insufficiency status during the pandemic relative to the prepandemic period (i.e., before March 2020). Using information about survey respondents' income, we are also able to explore differences in the independent role of CFS establishments on food insufficiency across income classes. For some of the key independent variables that are time invariant over progressive weeks of the pandemic, we adopt the fixed effects filtered (FEF) estimator recently proposed by Pesaran and Zhou (2018) to the panel data. Our results suggest that CFS establishments contribute to mitigating food insufficiency, and the effect is especially significant for the middle-class during the pandemic. Moreover, this effect is generally robust when we include alternative regressors, such as receipt of SNAP benefits or free food from other sources.

Model Specification and Estimation Method

Our objective is to assess whether the presence of CFS made a difference during the pandemic in terms of household food sufficiency, given the relative lack of literature on the roles of CFS more generally. To accomplish this, we posit the following regression model. For state i at time t,

$$FI_{it} = \alpha_i + \theta \cdot CFS_i + \boldsymbol{X}_{it}'\beta + \boldsymbol{Z}_i'\gamma + \varepsilon_{it}. \tag{1}$$

The primary model is a panel data model at the state level, using weekly data from the HPS except as noted. The dependent variable, FI_{it}, represents a change in food insufficiency status due to the COVID-19 pandemic. This is the percentage of individuals reporting insufficient food in their households during the last 7 days but sufficient food before March 13, 2020. Therefore, this dependent variable is equivalent to a differenced variable in which unobserved preexisting individual-specific effects and state-specific effects before the pandemic are removed. With this "differenced" dependent variable, we ensure that a change in food insufficiency status is primarily due to the pandemic and estimate a relatively parsimonious model focusing on the effect of CFS, having accounted for unobserved covariates that could cause omitted variable problems.

[1] This category is defined as comprising "establishments primarily engaged in the collection, preparation, and delivery of food for the needy. Establishments in this industry may also distribute clothing and blankets to the poor. These establishments may prepare and deliver meals to persons who by reason of age, disability, or illness are unable to prepare meals for themselves; collect and distribute salvageable or donated food; or prepare and provide meals at fixed or mobile locations. Food banks, meal delivery programs, and soup kitchens are included in this industry" (see https://www.census.gov/naics/?input=62421+&year=2022&details=624210).

The primary regressor is CFS establishments per 10,000 persons in 2019, which is time invariant during the weeks under study. A key advantage of using this regressor is that there is little doubt about its exogeneity as it is determined 1 year ahead. We consider it as a proxy for the level of preparedness of a state's emergency food services before the pandemic. The contemporaneous count or actual capacity of the CFS organizations during the pandemic may vary from the 2019 level because some may have temporarily closed due to lack of emergency food stock or staff and volunteer availability issues (Reiley, 2020a). To control for the contemporaneous impacts of the disease, we use daily COVID-19 cases per 1,000 persons, unemployment insurance claims, and a time trend as control variables for time-varying concurrent factors in the regression analysis.

The coefficient on the 2019 CFS variable can be estimated with either a pooled or a random effects panel data model. We cannot use a fixed effects model, because the variable is deleted by the demeaning operation that subtracts all variables in the model by their group (i.e., state) mean values. However, a pooled or a random-effects model may have other kinds of omitted variable problems. A key assumption for these models to yield consistent estimates is that unobserved state-specific effects are uncorrelated with all regressors. However, even though the FI variable removes preexisting unobserved state-specific effects, it cannot purge unobserved effects during the pandemic. For example, the response of each state to the pandemic varied, with some states implementing stringent social distancing rules and others having somewhat relaxed restrictions, which influences how severely the pandemic would affect people's lives and how well existing food banks and food pantries were able to reach individuals in need. The intensity of these rules is difficult to quantify and usually controlled with state dummy variables in a fixed effects panel model that, on the other hand and as noted, fails to estimate the coefficient on the time-invariant CFS variable.

To achieve these two goals—controlling for unobserved state-specific factors and estimating the coefficient on a time-invariant variable—we use a new panel model estimator proposed by Pesaran and Zhou (2018). Their approach accommodates the inclusion of both time-varying and time-invariant regressors, as we have in equation (1) (i.e., $\boldsymbol{X}_{it}$, and $(CFS_i, \boldsymbol{Z}_i)$). Further, we let $\alpha_i = \alpha + \eta_i$, where η_i represents the unobserved state-specific factors during the pandemic. Pesaran and Zhou propose a two-step estimation method to obtain a consistent estimate of the coefficients on time-invariant variables when η_i is suspected to be correlated with any regressor in the model. The first step is a fixed effects models with only time-varying regressors, from which we retrieve the residuals. The second step is an ordinary least squares (OLS) estimation in which the dependent variable is the group-mean of the residuals from the first step, and the regressors are time-invariant variables. In essence, the second step is a "between" panel data model, referred to as a fixed effects filtered (FEF) estimator. Given that time-invariant variables are not correlated with unobserved fixed effects,[2] and under fairly standard assumptions listed in Pesaran and Zhou, the FEF estimator is consistent. The authors provide the equation for computing the variance–covariance matrix of the second-step estimators.

Data Sources and Variable Description

Dependent Variable

The dependent variable is the percentage of adult individuals (over 18 years old) who suffered insufficient food during the pandemic but not before. We create this dependent variable from the two questions in the HPS, using the individual-level Public Use Files (PUF). One question asks whether respondents had enough food to eat in their households prior to March 13, 2020, and the other question asks the same question for the last 7 days. Based on food scarcity rates published on

[2] As the dependent variable is a difference before and after the pandemic, all unobserved state-specific factors before the pandemic are removed. Because all included time invariant variables are predetermined before the pandemic, we can reasonably assume that they are exogenous.

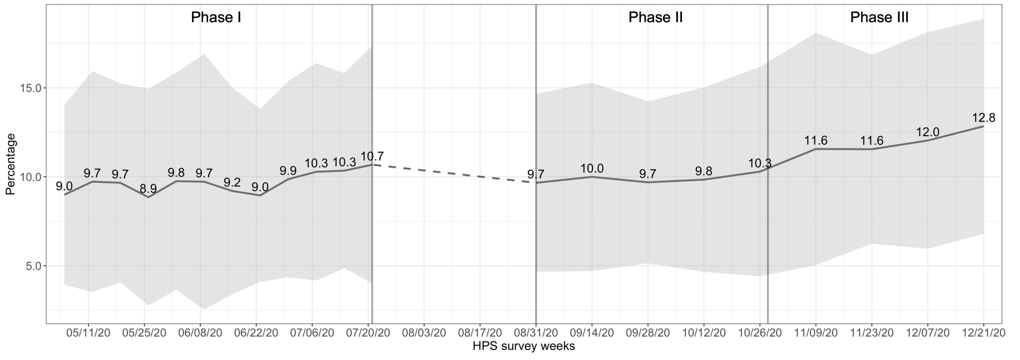

Figure 1. Trend of National Average Food Insufficiency Rates

Notes: The food insufficiency rate is defined as the percentage of people in the total adult population who answered that they "sometimes" or "often" had not had enough food in the last 7 days. The solid center line is the average of food insufficiency rates across 50 states (plus Washington, DC), and the shaded area represents the range of 2 standard deviations above and below the average. The dashed segment represents weeks when the survey was not conducted.
Source: Household Pulse Survey and authors' calculation.

the Household Pulse Survey Data Tools website,[3] we define current food insufficiency as reporting sometimes or often not having enough food in the last 7 days, and similarly define previous food insufficiency before March 13, 2020. The percentage of current and previous food insufficiency (i.e., food insufficiency rate) is the ratio between the weighted count of respondents who reported to be food insufficient to the weighted count of total respondents who answered the food insufficiency questions.[4] Each respondent is assigned a personal weight in the HPS so that the weighted count is an estimate of individuals in food insufficiency in the population.[5] Figure 1 shows the average current food insufficiency rate across all 50 states and Washington, DC. While this rate increases and declines between weeks, an overall rising trend is evident.

We do not directly use the difference between the current food insufficiency rate and the previous food insufficiency rate as the dependent variable because we are concerned about omitting unobserved personal characteristics with these two aggregated ratios. Instead, aggregating from the individual-level data, we calculate the percentage of individuals who did not have a food insufficiency problem before the pandemic but suffered from one in the preceding week. We aggregate the weighted count of respondents who reported having insufficient food in the last 7 days but reported the opposite in the question relating to the time prior to March 13, 2020. With this weighted count as the numerator, we compute the percentage where the denominator is the weighted count of respondents who answered both questions. Since the question for food insufficiency before the pandemic is only available through weeks 1–21 of the survey, we compute the dependent variable and confine our regression analysis to this period.

Similarly, we compute the change in food insufficiency status by each income class. The HPS asks households about their income each week in eight income classes ranging from below $25,000 to greater than $200,000. For each income class, we compute the percentage of people who were food insufficient in the last 7 days but not before March 13. The denominator of these percentages is the weighted count of respondents who answered all three questions regarding previous and current food insufficiency and household income.

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[3] See the Household Pulse Survey Interactive Data Tools at https://www.census.gov/data-tools/demo/hhp/.
[4] The Census Bureau advocates using the actual number of respondents to specific questions as the denominator instead of total number of respondents to the whole survey. We compared our calculation of current food insufficiency with those published in the Household Pulse Survey Interactive Data Tools and confirmed their correctness.
[5] A caveat: Although the HPS survey asks about the food sufficiency status of the entire household, given that we calculate a weighted count based on the number of individuals in households, it is more appropriate to interpret the resulting food insufficiency rate in terms of the percentage of individuals in the population and not households.

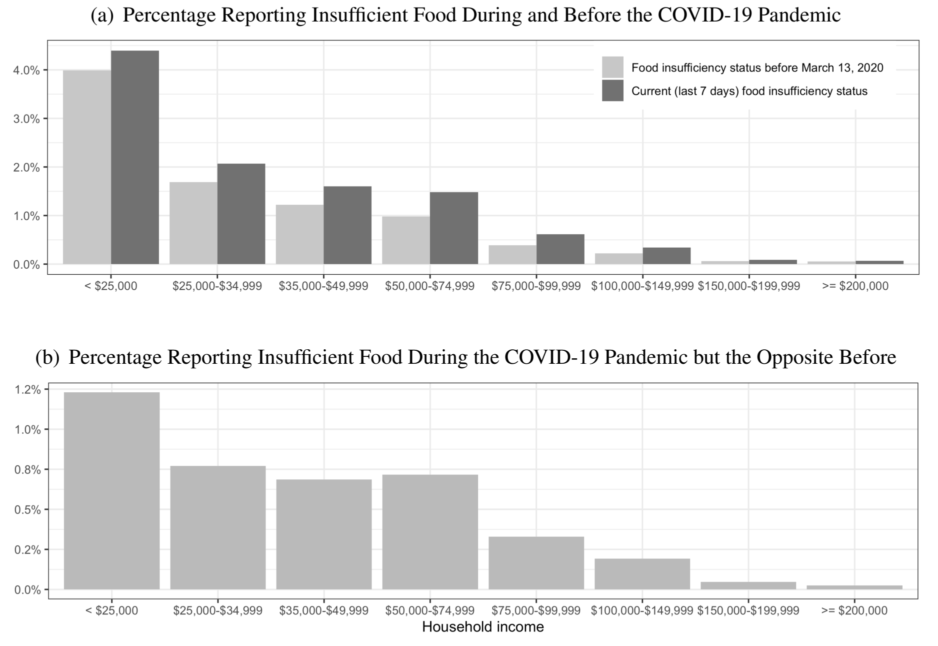

Figure 2. Food Insufficiency Rates by Income Class

Notes: The height of each bar represents the average value of each variable over 21 weeks of the Household Pulse Survey at the national level. The denominator of all percentage variables is total adult population.
Source: Household Pulse Survey and authors' calculation.

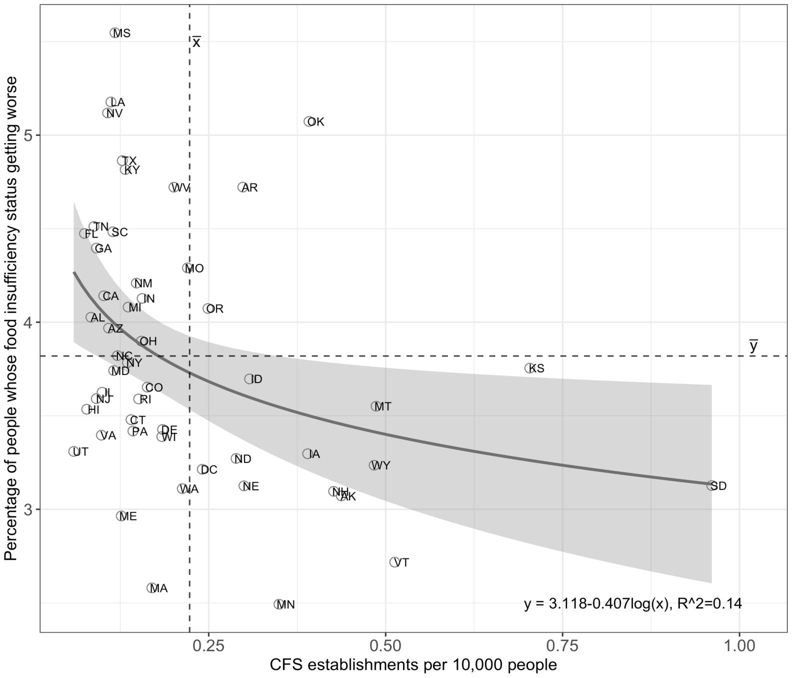

Figure 3. Scatterplot for Change in Food Insufficiency versus Community Food Services per 10,000 Persons

Notes: Vertical and horizontal dashed lines are the respective average values in *x* and *y* axes.
Source: Household Pulse Survey, 2019 County Business Patterns, and authors' calculation.

Figure 2 compares the current and previous food insufficiency rate by income class (Panel A) and shows the percentage of increased food insufficiency (Panel B). The lowest income class, with a household income of less than \$25,000, has the highest food insufficiency before and after the pandemic, and the rate decreases almost monotonically with higher income classes. However, as shown in the lower panel, the percentage of people who only recently fell into food insufficiency increases slightly in the income class of \$50,000–\$74,999 compared to the class immediately below. The percentage drops dramatically for income classes beyond \$75,000. This observation has an important implication for the estimation results.

Time-Invariant Regressors

Our key regressor is the number of CFS establishments per 10,000 persons from the Census Bureau's 2019 County Business Patterns. The variable is transformed with the logarithmic function, given that the scatterplot and a simple pilot regression suggest a log-linear model is appropriate (see Figure 3). The southern states, which have relatively more people living in poverty and thus should have more demand for CFS, have fewer such establishments than expected. South Dakota has 1.03 food banks per 10,000 individuals, the proportionately largest number, while Utah has only 0.06, suggesting noticeably different experiences with and usage of such facilities across the states. Figure 3 shows a scatterplot of CFS per 10,000 persons versus the percentage of individuals whose food insufficiency status worsened during the pandemic. The food insufficiency variable is the average over all weeks for each state. A simple regression line indicates that these two variables are negatively associated, suggesting that CFS may have the expected effect on alleviating food insufficiency; the subsequent regressions are intended to assess whether this effect persists when we control for other factors.

Two other time-invariant variables included in the regression are the 2019 state poverty rate and White alone (not Hispanic or Latino) racial percentage data from US Census Bureau, as an inverse measure of the presence of minorities, who were especially hard hit by the pandemic. These are 5-year estimates from the 2015–2019 American Community Survey (US Census Bureau, 2020). We expect a higher poverty rate to be associated with higher food insufficiency, while the presence of more White and fewer minority households is associated with lower food insufficiency, all else equal.

Time-Varying Regressors

As for time-varying regressors, we include the 7-day moving average of daily new COVID-19 cases per 1,000 persons, the percentage of initial claims for unemployment insurance (UI) in total employment, the percentage of households with children under the age of 18 during the weeks of the survey, and a time-trend variable. The COVID-19 case numbers are from the *New York Times* (2021) database; the data on initial claims for unemployment insurance are from the US Department of Labor (2021); and total employment is from the US Bureau of Labor Statistics (2021). The variable for households with children under 18 is time varying because it is calculated from the HPS, in which the pool of respondents changes from week to week.

In the robustness analysis, as explained in the next section, we use the time-invariant variable of small CFS establishments—defined as having fewer than five employees—to capture potential differences in the effect of varying establishment sizes across states and the time-varying variables for SNAP recipients and individuals resorting to other free food sources, which are both from the HPS. Table 1 reports descriptive statistics for all variables in this study.

The role of time-varying regressors in the FEF estimation is to purge the primary time-varying determinants of food insufficiency. The intensity of new COVID-19 cases and the increase in unemployed workers are the main driving forces of hardship during the pandemic. The effect of households with children under 18 can be twofold. On the one hand, children would increase the burden of households' expenses, thus raising the possibility of food insufficiency; on the other

Table 1. Descriptive Statistics

Variable	Unit	Mean	Std.	Min.	Median	Max.
Dependent variable						
Individuals with worsening food insecurity	%	3.82	1.59	0.10	3.62	10.44
By income class						
< $25,000	%	1.17	0.84	0.00	0.99	5.61
$25,000–$34,999	%	0.76	0.61	0.00	0.63	5.34
$35,000–$49,999	%	0.68	0.57	0.00	0.54	5.34
$50,000–$74,999	%	0.67	0.58	0.00	0.54	5.30
$75,000–$99,999	%	0.30	0.38	0.00	0.19	5.25
$100,000–$149,999	%	0.17	0.24	0.00	0.09	3.16
$150,000–$199,999	%	0.04	0.14	0.00	0.00	2.15
≥ $200,000	%	0.02	0.07	0.00	0.00	0.87
Time-invariant independent variables						
CFS establishments	No. per 10,000 persons	0.22	0.18	0.06	0.15	0.96
Small CFS establishments	No. per 10,000 persons	0.18	0.17	0.02	0.11	0.89
Non-Hispanic White	%	67.67	16.18	21.66	71.06	92.96
Poverty rate	%	12.16	2.64	7.50	11.80	19.50
Time-varying independent variables						
UI initial claims/total employment	%	0.89	0.72	0.06	0.70	5.96
Daily new COVID-19 cases	No. per 1,000 persons	0.20	0.25	0.00	0.10	1.74
Households with children under 18	%	38.29	3.86	24.96	38.26	50.66
Individuals receiving SNAP	%	10.75	3.81	2.38	10.62	25.06
Individuals getting free food from sources other than CFS	%	8.95	3.22	1.70	8.52	25.60
Time trend	n/a	11	6.06	1	11	21

Notes: Household Pulse Survey from weeks 1–21, 2015–2019 American Community Survey, 2019 County Business Patterns, US Department of Labor, *New York Times* COVID-19 database, and authors' calculations.

hand, the US Department of Agriculture offered free meals to children in school, and other eligible children in the household, during the entire 2020–2021 school year, which would have helped some households overcome food deficits during the pandemic (US Department of Agriculture, 2020). The time-trend variable controls for unobserved time-varying factors.

Results

We estimate equation (1) with the FEF estimator for all income classes and each income class separately. Table 2 presents the results of all estimations in our baseline specification, where the first column shows the result for all income classes combined and the remaining columns the results for eight individual income classes. The upper panel shows the first step of a fixed effects model, where the observations include 50 states and Washington, DC, in all 21 weeks of the HPS; the lower panel shows the second step of a between-effects model with the averaged residuals from the first step as the dependent variable, and the observations consist of 50 states and Washington, DC.

The overall effect of CFS organizations on mitigating food insufficiency is statistically significant with all income classes combined, with a coefficient of −-0.249. This means that with each 1% increase in the number of CFS organizations per 10,000 persons, the percentage of people

Table 2. Regression Results for Fixed Effects Filtered Panel Models

		Income Classes							
	All Samples	**< $25,000**	**$25,000–$34,999**	**$35,000–$49,999**	**$50,000–$74,999**	**$75,000–$99,999**	**$100,000–$149,999**	**$150,000–$199,999**	**≥ $200,000**
First step: Fixed effects model with time-varying regressors (N = 1,071)									
UI initial claims/total employment	0.118	0.008	0.044	0.041	−0.012	0.048*	−0.004	−0.011	0.005*
	(0.105)	(0.070)	(0.041)	(0.034)	(0.030)	(0.025)	(0.012)	(0.009)	(0.003)
Daily new COVID-19 cases per 10,000 persons	0.665***	0.057	0.100	0.206*	0.209**	−0.029	0.019	0.099	0.004
	(0.254)	(0.148)	(0.103)	(0.125)	(0.091)	(0.078)	(0.040)	(0.072)	(0.014)
% households with children under 18	−0.022	−0.012	−0.006	0.002	−0.008	−0.002	0.007***	−0.003	−0.001
	(0.016)	(0.010)	(0.008)	(0.009)	(0.009)	(0.005)	(0.002)	(0.002)	(0.001)
Time trend	0.081***	0.009	0.018***	0.020***	0.015***	0.012***	0.007***	0.000	0.001***
	(0.013)	(0.007)	(0.005)	(0.005)	(0.005)	(0.003)	(0.002)	(0.002)	(0.000)
R^2	0.158	0.008	0.036	0.070	0.058	0.021	0.044	0.033	0.012
Second step: Between model with time-invariant regressors (N = 51)									
log(CFS per 10,000 persons)	−0.249**	−0.018	−0.023	−0.047*	−0.114***	−0.022	−0.006	−0.015**	−0.005
	(0.117)	(0.061)	(0.033)	(0.027)	(0.029)	(0.022)	(0.016)	(0.006)	(0.004)
% non-Hispanic White	−0.003	0.001	0.001	0.001	−0.001	−0.001	−0.002***	−0.001*	0.000
	(0.006)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Poverty rate	0.198***	0.132***	0.050***	0.015**	0.020***	−0.005	−0.010***	−0.004**	−0.001
	(0.021)	(0.014)	(0.007)	(0.007)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)
Intercept	0.902***	−0.177**	0.017	−0.029	0.454***	0.280***	0.086***	0.232***	0.040***
	(0.275)	(0.078)	(0.033)	(0.023)	(0.028)	(0.013)	(0.004)	(0.002)	(0.000)
R^2	0.672	0.714	0.463	0.151	0.403	0.087	0.370	0.323	0.147

Notes: The dependent variable in the first-step regression is the percentage of people who experienced worsened food insufficiency. The second step uses the residuals from the first step, averaged for each state. Except for the percentage of non-Hispanic White, which takes a decimal value, all other variables take the unit described in Table 1. Values in parentheses are standard deviations. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

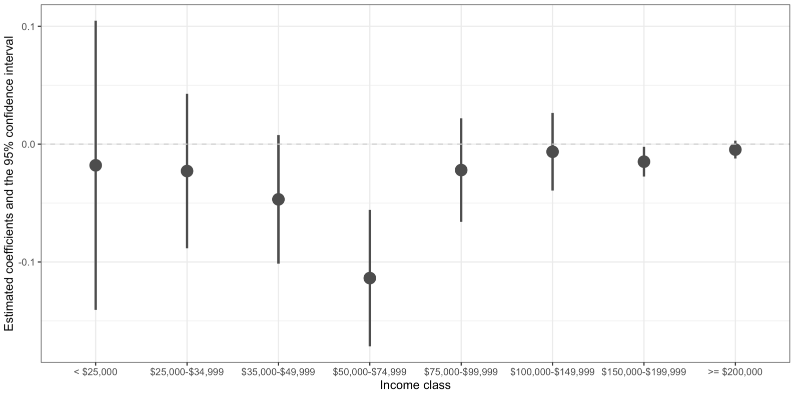

Figure 4. Estimated Effects of Community Food Services per 10,000 Persons on Food Insufficiency by Income Class

Notes: The points represent the estimated coefficients on the community food services (CFS) variable for each income class, and the vertical segments represent the 95% confidence intervals. Wald tests and Student's t-tests based on the bootstrapped coefficients confirm the coefficient for the middle-income class of \$50,000–\$74,999 is statistically lower than for other income classes.
Sources: Authors' calculation.

who newly suffered food insufficiency during the pandemic dropped by 0.249 percentage points. As shown in Table 1, with the mean value of CFS per 10,000 persons being 0.22, a 1% increase amounts to 2.2 CFS organizations per 10 million people. Given that the HPS, on average, covers 232.2 million adult individuals,[6] such an increase would potentially help about 578,200 individuals move out of food hardship status. As we show in the robustness analysis, when we consider other types of food assistance programs, such as SNAP and free food sources other than CFS organizations, although the mitigating effect of CFS is reduced, this coefficient remains negative in almost all alternative specifications, albeit statistically insignificant in some cases.

The mitigating effect of CFS shows a V-shaped pattern across income classes (see Figure 4). For lower and higher income classes, the mitigating effect is insignificant, and the effect increases (or the value of the coefficient decreases) toward the middle-income classes, reaching the highest point at the \$50,000–\$74,999 income class. Given that these income classes perfectly partition all observations, the sum of the coefficients of eight income classes equals the coefficient without the income broken down, which is the property of the least squares estimation. This property enables us to show how the overall effect of CFS is allocated into each income class. In the appendix, we describe the process of testing the hypothesis that the coefficients on the income class of \$50,000–\$74,999 is the lowest among all classes, which withstands all the tests (see Table A1). Also, the V-shaped pattern generally holds in other specifications of the robustness check.

The variation in the mitigating effect of CFS organizations on different income classes reflects the *new* adverse situation faced by individuals in the lower- and middle-income classes. For individuals in the lowest two income classes, with household income below \$34,999, who have experienced food insufficiency and may have relied on CFS organizations for food before the pandemic, the mitigating effect of existing organizations is attenuated during the pandemic, as indicated by the negative but insignificant coefficients. For individuals in the household income class of \$35,000–\$49,999—who mostly work in lower-paid jobs, (e.g., personal care services, restaurants, retail stores, house or car maintenance)[7] and who may fall into food shortage status if they are laid off—the mitigating effect of CFS becomes statistically significant at the 10% level. The mitigating effect of CFS is the highest and most statistically significant for individuals in the \$50,000–\$74,999

[6] The total population is an estimate based on the average number of respondents who answered the questions about food insufficiency in the survey.

[7] See the table of annual wage by occupation in the Bureau of Labor Statistics (https://www.bls.gov/oes/current/oes_nat.htm).

income class, the entry level to the middle-income class in the United States (Bennett, Fry, and Kochhar, 2020). As discussed previously, this income class is also a threshold above which the food insufficiency rate drops substantially. Finally, CFS organizations also have a negative but small effect on higher-income classes; the effect is especially significant for the $150,000–$199,999 income class.

A few notable findings stand out for other regressors in the model. The poverty rate, as expected, has an overall significant and positive effect on food insufficiency. The positive effect persists with all income classes below $74,999, and then the effect becomes negative for higher income classes. The paradoxical positive–negative effect may indicate a divide between the rich and the poor. Non-Hispanic White people or those in the upper income classes are less likely to have an inadequate food situation. Coronavirus cases and initial claims for unemployment insurance overall have positive effects on food insufficiency. The coefficients on households with children under 18 years old are somewhat surprising. Its overall effect is negative but statistically insignificant, and it is significantly positive for the $100,000–$149,999 income class. Free meals for children during the pandemic may, to some extent, explain the negative effect, but the positive coefficient for the high-income class requires further exploration. The time-trend coefficient is positive in all cases, underscoring the rising severity of food insufficiency across all members of society during this pandemic.

Robustness of the Coefficients with Alternative Specifications

We examine the robustness of the coefficients in the baseline model with some alternative specifications. The purpose of the robustness analysis is largely to check whether the overall mitigating effect of CFS organizations persists and the effect remains prominent for the middle-income class under various specifications. The detailed results for the alternative estimation are included in the online supplemental material (see www.jareonline.org). First, we add the squared and cubic terms of the time-varying regressors—UI claims rate, new COVID-19 cases per 1,000 persons, and time trend—given that we consider them capturing the most important determinants of food insufficiency during the pandemic. With a better goodness of fit using the cubic specification in the first-stage estimation of the FEF estimator, the residuals that are fed into the second-stage estimation would be less influenced by time-varying factors. The estimation results of the cubic specification confirm the robustness of the coefficients on the CFS variables while only slightly reducing effects across all income classes.

The second robustness check is to estimate the baseline specification with the three phases of the HPS separately. We observed that in the first week of Phase II (August 19–31) of the survey, some variables change unexpectedly, which we suspect could result from the change in the sampling pool of the survey. Therefore, we separate the baseline regression into three phases to see whether the results vary across phases. We find that in Phases I and II, the results are relatively robust as we still have the greatest mitigating effect for the middle-income class of $50,000–$74,999. However, in Phase III, the coefficients on all income classes become insignificant. On the one hand, this could result from the change in the sampling pool of the survey in Phase III, although we have no evidence for that. On the other hand, the result may imply that the mitigating effect of the CFS institutions is important in the early phases of a pandemic and diminishes at the end of the year when restrictions were lifted and people were able to return to work, which deserves further investigation.

The third robustness check examines the effect of the size of CFS organizations. The County Business Patterns includes various types of CFS organizations, which can be as small as a soup kitchen with a few employees or as big as a large-scale food bank with hundreds of employees. Figure A1 shows the size distribution of CFS organizations in the CBP dataset: 58% establishments have fewer than five employees.[8] As these small CFS interact directly with community residents, we investigate how the baseline coefficients on the CFS variables would change when replacing

[8] The distribution of small CFS per 10,000 persons across states is very similar to what is shown in Figure 3.

the small CFS variable with the original one. In this case, the overall mitigating effect of the small CFS variable becomes smaller than in the baseline model and statistically insignificant. However, the V-shaped pattern of the coefficients for income classes persists, where the coefficients on the middle-income class of $50,000–$74,999 is still negative and statistically significant at the 1% level.[9]

The Influence of SNAP and Other Free Food Sources

SNAP has played a significant role in solving the problem of food insufficiency during the pandemic, as a result of the increased availability of SNAP benefits, expanded access to the SNAP Online Purchasing Pilot, and additional funding that the USDA provided to states from the American Rescue Plan Act (US Department of Agriculture, 2021). Besides CFS organizations and the SNAP program, other organizations (e.g., schools, religious organizations, and other community assistance agencies) have actively provided emergency food aid. Figure A2 shows the percentage of individuals who received SNAP benefits or free food from any sources listed in the HPS. In this figure, we use the number of recipients of SNAP benefits from the USDA SNAP Data Tables and the number of individuals receiving free food from each source from the HPS and calculate their percentage in the total adult population estimated in the HPS. The percentage of SNAP recipients started picking up in March 2020, rising from the prepandemic level of 11% to the highest level of 17% in June. Schools are the main source of free food because of the extended free-meals-to-kids program. Food banks and food pantries are the second largest source of free food, and the percentage for food banks and food pantries sharply increases from May to August and remains around 3% afterward. We also see a rising trend for other free food sources (e.g., family, friends, neighbors, and religious organizations). This figure implies that while the SNAP program provides a long-term stable source of food assistance, food banks and other types of free food sources likely represented a critical responsibility for emergency food aid.

Given the importance of the SNAP program and other types of food assistance, and as a further robustness check, we include the variables for the percentage of individuals receiving SNAP benefits and free food from sources other than CFS organizations—food banks/pantries, soup kitchen, and home-delivered meals—as additional time-varying regressors in the first-stage estimation. Some important caveats are noted for the SNAP recipients variable. Beginning in week 13 (August 19–August 31), the HPS started asking whether anyone in a respondent's household received SNAP benefits, but the SNAP recipients' count is smaller than the administrative records of the USDA SNAP Data Tables. For example, the administrative record for the recipients in September is 43,022,767 persons and 22,265,554 households, but the average count in September in the HPS is only 25,158,116, which could be due to the fact that the respondents of the survey are adults and the administrative record may include other household members. Another concern of using the variables for SNAP recipients and for other free food sources is that they are contemporaneous with the dependent variable so that they may be endogenous themselves. Even when we lagged variables by two survey periods (i.e., 1 month for Phases II and III), the endogeneity concern remains. Given these issues, we only consider the estimation as a robustness check, present the results in the supplemental material, and remind readers to interpret the results cautiously.

After controlling for the contemporaneous variable for SNAP recipients, the overall effect of the CFS, −0.122, becomes almost half as much as in the baseline regression and insignificant. This may imply that the role of SNAP benefits reduces the effect of CFS organizations in alleviating food insufficiency. As for income classes, although the coefficients become insignificantly negative, −0.059, for the $50,000–$74,999 middle-income class, the mitigating effect, −0.081 for the $75,000–$99,999 middle-income class, becomes the largest among all income classes, and it is statistically significant. The coefficient on the contemporaneous SNAP variable is significantly positive, partly affirming the endogeneity concern over this variable. When using the lagged variable

[9] In the supplemental material, we also present the results that utilizes employees of CFS organizations instead of establishments. The results are robust in terms of the statistically negative coefficient for the middle-income class.

for SNAP recipients, the overall effect of CFS organizations (-0.225) is again close to the baseline result, and those for the middle-income classes (\$50,000–\$74,999 and \$75,000–\$99,000) become significantly negative (-0.083 and -0.075, respectively). Interestingly, controlling for the effect of other free food sources, we obtain an even higher and significant overall mitigating effect of CFS organizations than in the baseline models. Therefore, while we acknowledge the important influence of the SNAP program and other free food sources, our robustness checks support the main results, especially for the middle-income classes.

Conclusion

The US hunger situation worsened over the course of the COVID-19 pandemic. The objective of our analysis was to assess whether Community Food Services (CFS) have made a difference in household food sufficiency during the current pandemic by adopting a fixed effect filtered estimator that provides consistently estimated coefficients on time-invariant regressors in a fixed effects panel model. Our analysis shows that the current food insufficiency rate during the pandemic is on average higher than before for all income classes. An increase in the food insufficiency rate in the low tier of middle-income classes is especially noteworthy. Our study confirms the timely contribution of the CFS organizations to alleviate food insufficiency and that they may have the most beneficial impact on middle-income households, which suffered a proportionally larger change in their incomes when the pandemic adversely impacted employment and health status. Our result reveals that a small increase in additional support to CFS organizations would have helped hundreds of thousands of individuals deal with hunger issues. Therefore, one may conclude that such entities may be worthy of increased public and private support. However, this also needs to be balanced with the costs of such programs, given that emergency food systems may be less favorable than SNAP in terms of overhead costs. Our result also indicates that SNAP benefits may reduce the mitigating effect of CFS organizations. For future research, it is important to explore the role of pandemic-related emergency relief funding to taxpayers such as that paid under the CARES Act in mitigating the effects of income losses due to unemployment, which likely contributed to the initial decline in household food insufficiency early in the pandemic. The subsequent rise in food insufficiency since the late summer may reflect the fact that households spent all or most of the relief funds received.

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Appendix: Testing the Variation in the CFS Coefficients across Income Classes

We focus on testing whether the mitigating effect of community food services (CFS) for the income class of \$50,000–\$74,999 is significantly the lowest among all classes. Given that we estimate these coefficients in separate equations for each income class, and the main model is a panel fixed effects filtered (FEF) model, we cannot stack the data for each income class together and introduce the dummy variables for income classes because they are invariant for both state and time. However, we take advantage of the fact that the second-stage estimation of the FEF estimator is a simple cross-sectional OLS estimation, which enables us to extract the averaged residuals from the first-stage estimation for each income class, which is the dependent variable of the second stage, and set up an "artificial" dataset by stacking the averaged residuals and the time-invariant regressors for all income classes and introduce the dummy variables for income classes. Then, we estimate a linear regression, $u_{ik} + d_k(\alpha + \theta \cdot CFS_i + \mathbf{Z}_i'\gamma) + v_{ik}$, where d_k is the dummy variable for income class k, and we estimate the model without a constant intercept. Since we cannot compute the exact variance–covariance matrix of the second stage of the FEF estimator with this artificial dataset, we compute the clustered variance–covariance matrix by state and get the almost exact estimation as the main regression results shown in the lower panel of Table 2. To test the equality, we calculate the Wald statistic for the null hypotheses (i.e., $H_0 : \theta_4 = \theta_k, k \neq 4$), and find that the coefficient for the income class of \$50,000–\$74,999 is not equal to the coefficient for any other income class. Because the Wald test does not use the exact variance–covariance matrix of the FEF estimator, to further ensure the validity of the test, we also use the bootstrap method to simulate the samples of the coefficients for each income class, we then use the t-test for the same null hypothesis and the one-sided alternative hypothesis (i.e., $\theta_4 < \theta_k$). The test results in Table A1 confirm that the coefficient for the income class of \$50,000–\$74,999 is statistically lower than those for all other income classes.

Table A1. Tests for Equality of Coefficients on Community Food Services per 10,000 Persons across Income Classes

	Wald Test		Bootstrap t-Test	
	Statistic	p-Value	Statistic	p-Value
Income Class of \$50,000–\$74,999 vs.	1	2	3	4
< \$25,000	3.35	0.07	−44.23	0.000
\$25,000–\$34,999	4.60	0.03	−59.64	0.000
\$35,000–\$49,999	3.65	0.06	−47.82	0.000
\$75,000–\$99,999	7.97	0.01	−77.05	0.000
\$100,000–\$149,999	9.66	0.00	−96.27	0.000
\$150,000–\$199,999	12.06	0.00	−100.26	0.000
≥ \$200,000	14.82	0.00	−112.23	0.000

Notes: Column 1 represents the tests for equality of the coefficient on community food services establishments per 10,000 persons for the income class of \$50,000–\$74,999 with that of each other income class. Wald statistics have a chi-squared distribution. Bootstrap t-tests are based on the bootstrapped coefficients in the baseline regression model for each income class.

Size Distribution of the CFS Organizations in the CBP Dataset

Figure A1 shows the size distribution of the CFS organizations in the 2019 CBP dataset. We use the small CFS establishments with less than five employees per 10,000 in the robustness analysis.

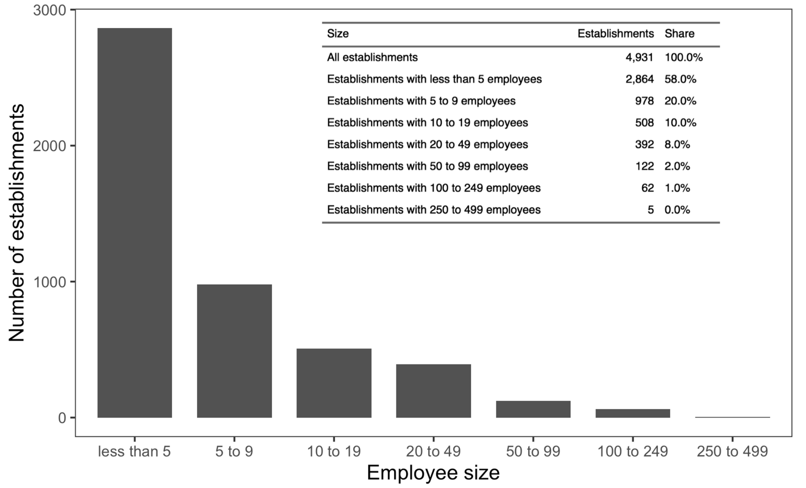

Figure A1. Size Distribution of Community Food Services Establishments
Sources: 2019 County Business Patterns and authors' calculation.

Individuals Receiving SNAP Benefits and Free Food from Various Sources

Figure A2 shows the percentage of individuals receiving SNAP benefits and free food from various sources during the pandemic.

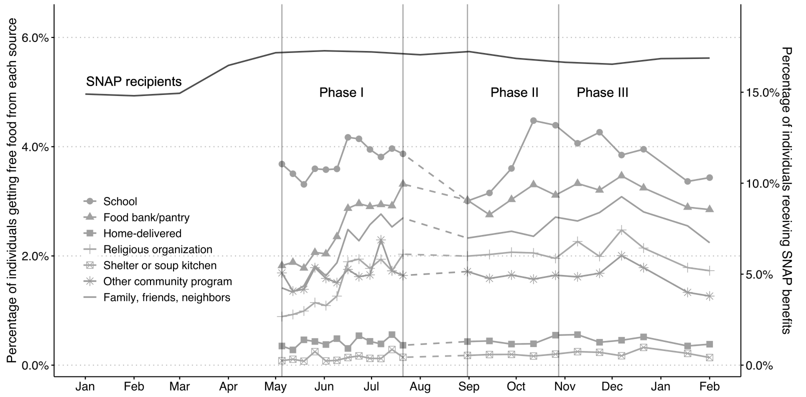

Figure A2. Trend of Adult Population Receiving SNAP Benefits or Free Food from Seven Sources
Notes: The denominator of all percentage variables is total adult population estimated in the Household Pulse Survey.
Source: USDA SNAP tables, Household Pulse Survey, and authors' calculation.

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Online Supplement:* The Role of Community Food Services in Reducing U.S. Food Insufficiency in the COVID-19 Pandemic

Zheng Tian, Claudia Schmidt, and Stephan J. Goetz

This document contains detailed results of the regression estimation for robustness check.

Regressions with a Cubic Specification

In this robustness check, we add the squared and cubic terms of the time-varying regressors–UI claims rate, new COVID cases per capita, and time trend, given that we consider them embedding the most important factors for food insufficiency during the pandemic. Since using the cubic specification usually yields a better goodness of fit, the residuals from the first stage estimation, which are fed into the second stage, would have a lesser influence of time-varying regressors. The estimation results of the cubic specification confirm the robustness of the coefficients on the CFS variables, with only mildly reduced mitigating effects across all income classes. The detailed results are shown in Table S1, and the plot of the coefficients for income classes is Figure S1.

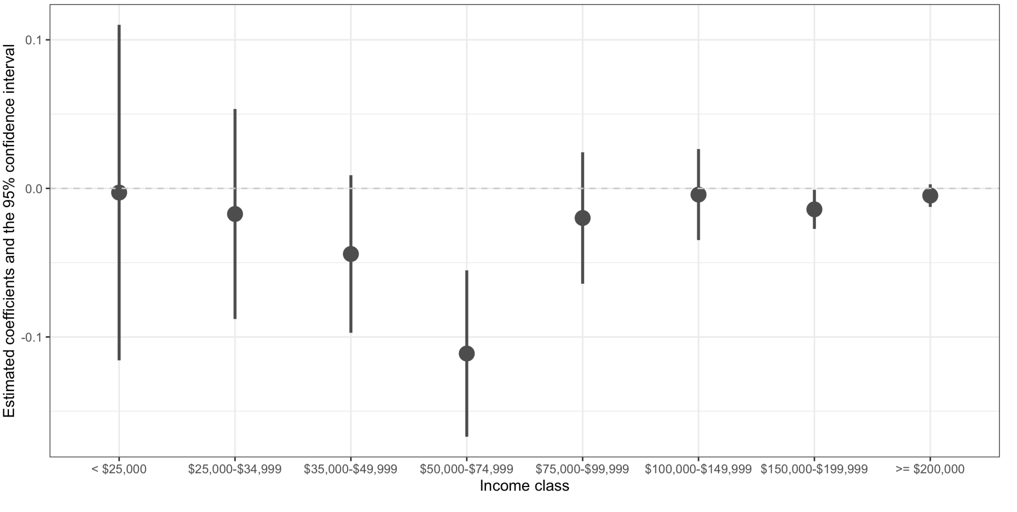

Figure S1. Estimated Effects of CFS on Food Insufficiency by Income Class in the Cube Specification

Notes: (i) The dependent variable in the first-step regression is the percent of people who had worse food insufficiency. The second step is the residuals from the first step averaged for each state. (ii) Except for the percentage of non-Hispanic White that takes the decimal value, all other variables take the unit as described in Table 1. (iii) Standard deviations are parenthesized. (iv) Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).

Table S1. Regression Results with Cubic Terms of Time-Varying Regressors

	All Samples				Income Classes				
	All	< $25,000	$25,000-$34,999	$35,000-$49,999	$50,000-$74,999	$75,000-$99,999	$100,000-$149,999	$150,000-$199,999	>= $200,000
First step: A fixed-effects model with time varying regressors									
UI initial claims / total employment	1.128 ***	0.472 *	0.149	0.173	0.052	0.250 *	0.060	-0.050	0.022
	(0.430)	(0.246)	(0.192)	(0.175)	(0.130)	(0.132)	(0.068)	(0.041)	(0.018)
(UI initial claims / total employment)^2	-0.378 **	-0.148	-0.015	-0.075	-0.004	-0.114 **	-0.035	0.021	-0.008
	(0.173)	(0.093)	(0.085)	(0.077)	(0.058)	(0.056)	(0.029)	(0.017)	(0.007)
(UI initial claims / total employment)^3	0.037 *	0.011	-0.002	0.011	-0.002	0.015 **	0.005	-0.002	0.001
	(0.020)	(0.011)	(0.010)	(0.009)	(0.007)	(0.007)	(0.004)	(0.002)	(0.001)
Daily new COVID-19 cases per capita	3.133 ***	1.214 **	0.338	0.422	0.262	0.190	0.219	0.480 ***	0.007
	(1.106)	(0.532)	(0.498)	(0.458)	(0.434)	(0.317)	(0.169)	(0.156)	(0.059)
(Daily new COVID-19 cases per capita)^2	-4.890 ***	-1.966 ***	-0.240	-0.690	-0.318	-0.210	-0.288	-1.198 ***	0.020
	(1.728)	(0.738)	(0.785)	(0.845)	(0.694)	(0.507)	(0.279)	(0.320)	(0.095)
(Daily new COVID-19 cases per capita)^3	2.145 ***	0.729 **	-0.022	0.406	0.198	0.010	0.082	0.756 ***	-0.013
	(0.770)	(0.316)	(0.331)	(0.420)	(0.309)	(0.218)	(0.127)	(0.177)	(0.039)
Perc. of households with children under 18	-0.018	-0.011	-0.005	0.004	-0.007	-0.003	0.006 **	-0.002	-0.001
	(0.016)	(0.009)	(0.008)	(0.009)	(0.009)	(0.005)	(0.003)	(0.002)	(0.001)
Time trend	0.260 ***	0.084 *	0.072 **	0.063 **	0.070 **	-0.031	-0.002	0.006	-0.002
	(0.075)	(0.044)	(0.032)	(0.030)	(0.034)	(0.023)	(0.010)	(0.006)	(0.004)
(Time trend)^2	-0.018 **	-0.007	-0.006 *	-0.005	-0.006	0.005 **	0.001	-0.001	0.000
	(0.007)	(0.004)	(0.003)	(0.003)	(0.004)	(0.002)	(0.001)	(0.001)	(0.000)
(Time trend)^3	0.001 **	0.000	0.000	0.000	0.000	-0.000 **	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.173	0.023	0.042	0.074	0.061	0.031	0.049	0.141	0.015

	All Samples				Income Classes				
	All	**< $25,000**	**$25,000-$34,999**	**$35,000-$49,999**	**$50,000-$74,999**	**$75,000-$99,999**	**$100,000-$149,999**	**$150,000-$199,999**	**>= $200,000**
Num. obs.	1071	1071	1071	1071	1071	1071	1071	1071	1071
Second step: A between model with time invariant regressors									
log(CFS per capita)	-0.218 **	-0.003	-0.017	-0.044 *	-0.111 ***	-0.020	-0.004	-0.014 **	-0.005
	(0.110)	(0.056)	(0.035)	(0.027)	(0.028)	(0.022)	(0.015)	(0.007)	(0.004)
Perc. of non-Hispanic White	0.000	0.002	0.002	0.001	-0.001	-0.001	-0.002 ***	-0.001 *	-0.000
	(0.005)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Poverty rate	0.193 ***	0.129 ***	0.049 ***	0.015 **	0.019 ***	-0.005	-0.010 ***	-0.004 **	-0.001
	(0.022)	(0.013)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)	(0.002)	(0.001)
Intercept	-0.557 **	-0.848 ***	-0.272 ***	-0.263 ***	0.172 ***	0.332 ***	0.091 ***	0.196 ***	0.036 ***
	(0.273)	(0.075)	(0.034)	(0.023)	(0.027)	(0.012)	(0.004)	(0.002)	(0.000)
R^2	0.640	0.705	0.437	0.138	0.380	0.079	0.362	0.291	0.139
Num. obs.	51	51	51	51	51	51	51	51	51

Regressions with Three Phases of the Household Pulse Survey Separately

The second robustness check is to estimate the baseline specification with the three phases of the Household Pulse Survey separately. We have observed in this studies that from Phase I to Phase II of the survey, some variables change unexpectedly, which we suspect could result from the change in the sampling pool of the survey. Therefore, we separate the baseline regression into three phases to see if the results vary across phases. We find that in Phase I and II, the results are relatively robust for we still have the greatest mitigating effect for the middle-income class of \$50,000-74,999. However, in Phase III, the coefficients on all income classes become insignificant. On one hand, this could result from the change in the sampling pool of the survey in Phase III, although we cannot have a direct evidence for that; on the other hand, the result may imply that the effect of CFS may diminish at the end of the year when restrictions were lifted and people were able to go back to work, which deserve further investigation. To save space, we only present a table (Table S2) for the coefficients on the CFS variables and plot of the coefficients on income classes in Figure S2.

Table S2. Estimated Effects of CFS on Food Insufficiency in Three Phases of the Household Pulse Survey

	All classes	**< \$25,000**	**\$25,000–34,999**	**\$35,000–49,999**	**\$50,000–74,999**	**\$75,000–99,999**	**\$100,000–149,999**	**\$150,000–199,999**	**>= \$200,000**
Phase I	-0.181	0.031	-0.011	-0.071 *	-0.113***	0.006	-0.015	-0.008	-0.000
	(0.113)	(0.070)	(0.050)	(0.038)	(0.040)	(0.029)	(0.024)	(0.006)	(0.004)
Phase II	-0.234	0.044	-0.064	0.049	-0.157**	-0.038	-0.007	-0.029 *	-0.032**
	(0.183)	(0.103)	(0.063)	(0.036)	(0.067)	(0.059)	(0.026)	(0.016)	(0.014)
Phase III	0.021	-0.035	0.128	-0.017	0.057	-0.112	0.053	-0.042	-0.011
	(0.256)	(0.107)	(0.123)	(0.084)	(0.103)	(0.088)	(0.045)	(0.027)	(0.013)

Notes: (i) The model specification is the same for all phases as the baseline model. (ii) Estimated coefficients on other control variables are omitted. (iii) Standard deviations are parenthesized. (iv) Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level

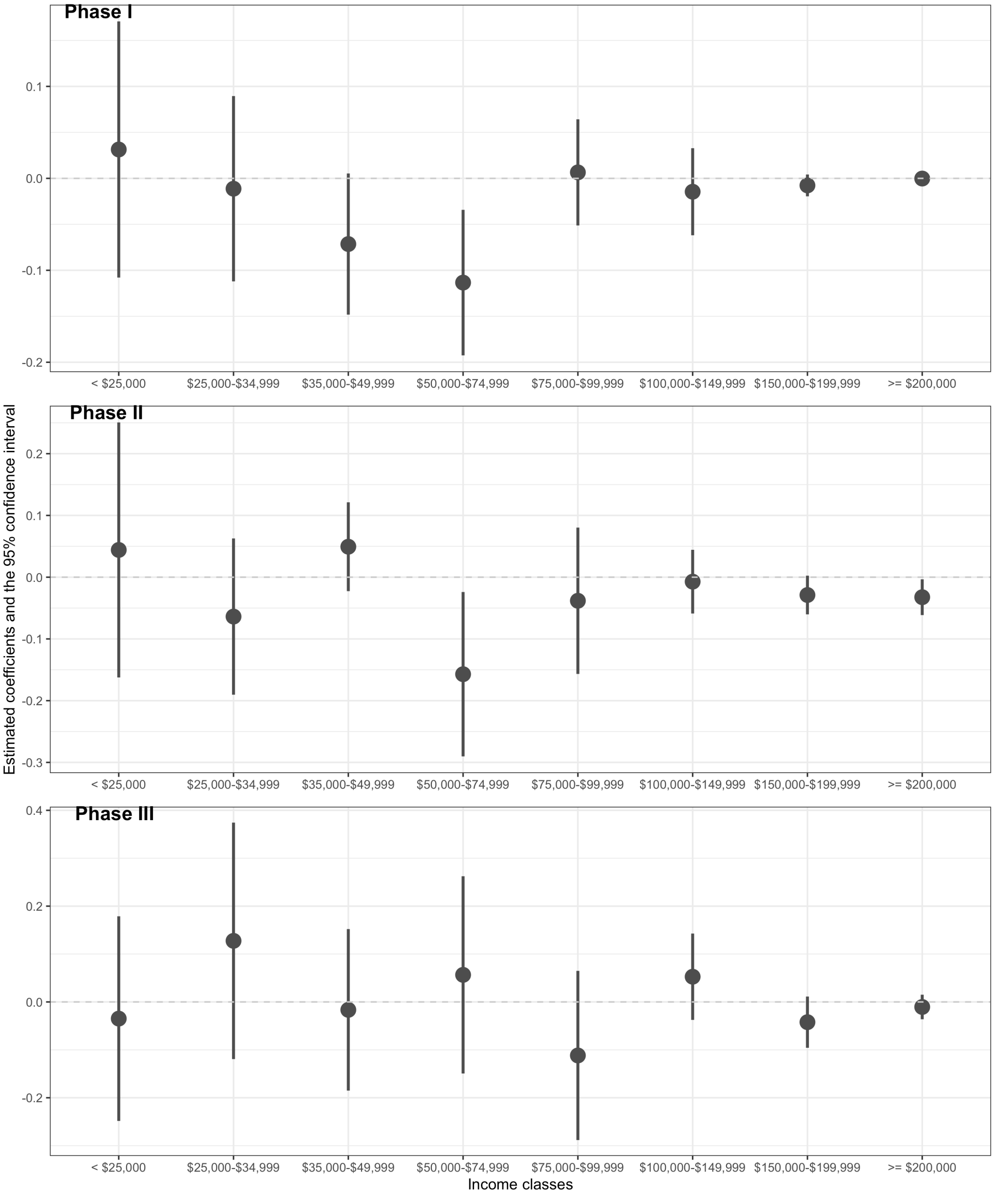

Figure S2. Estimated Effects of CFS on Food Insufficiency by Income Class in Three Phases of the Household Pulse Survey

Notes: The points represent estimated coefficients on the CFS variable for each income class, and the vertical segments represent the 95% confidence intervals.

Source: Authors' calculation.

Regressions with Small CFS Organizations and CFS Employees

The third robustness check is to examine the size of CFS organizations. In the County Business Patterns, NAICS 62421 includes various types of CFS organizations, which can be as small as a soup kitchen with a few employees or as large as a large-scaled food bank having hundreds of employees. The coefficients on the three CFS variable shows that (i) when including small CFS in terms of both establishments and employments, the overall mitigating effect of the CFS variable becomes almost as half as that in the baseline model and statistically insignificant; (ii) However, small CFS in terms of both establishments and employees still have the highest effect for the middle-income class of $50,000-$74,999; (iii) In terms of employees in all size, the overall effect is statistically significant and almost in par with the baseline model, but the largest mitigating effect is on the lowest income class. Except for that, the middle-income class of $50,000-$74,999 still have the second highest effect among the rest of income classes.

Table S3. Estimated Effects of Three CFS Variables on Food Insufficiency

	All classes	**< $25,000**	**$25,000–34,999**	**$35,000-49,999**	**$50,000–74,999**	**$75,000–99,999**	**$100,000–149,999**	**$150,000–199,999**	**>= $200,000**
log(small CFS establishments per capita)	-0.166	0.026	-0.016	-0.045 *	-0.096 ***	-0.002	-0.013	-0.015 ***	-0.004
	(0.102)	(0.052)	(0.030)	(0.027)	(0.027)	(0.018)	(0.015)	(0.005)	(0.003)
log(CFS employees per capita)	-0.255	-0.087	-0.015	-0.038	-0.084 *	-0.036	0.019	-0.007	-0.006
	(0.147)	(0.073)	(0.039)	(0.032)	(0.043)	(0.029)	(0.015)	(0.011)	(0.004)
log(small CFS employees per capita)	-0.113	0.052	-0.010	-0.045	-0.088 ***	0.007	-0.016	-0.009 *	-0.003
	(0.104)	(0.050)	(0.030)	(0.027)	(0.028)	(0.019)	(0.012)	(0.005)	(0.003)

Notes: (i) The model specification is the same as the baseline model except for the CFS variables. (ii) Estimated coefficients on other control variables are omitted. (iii) Standard deviations are parenthesized. (iv) Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

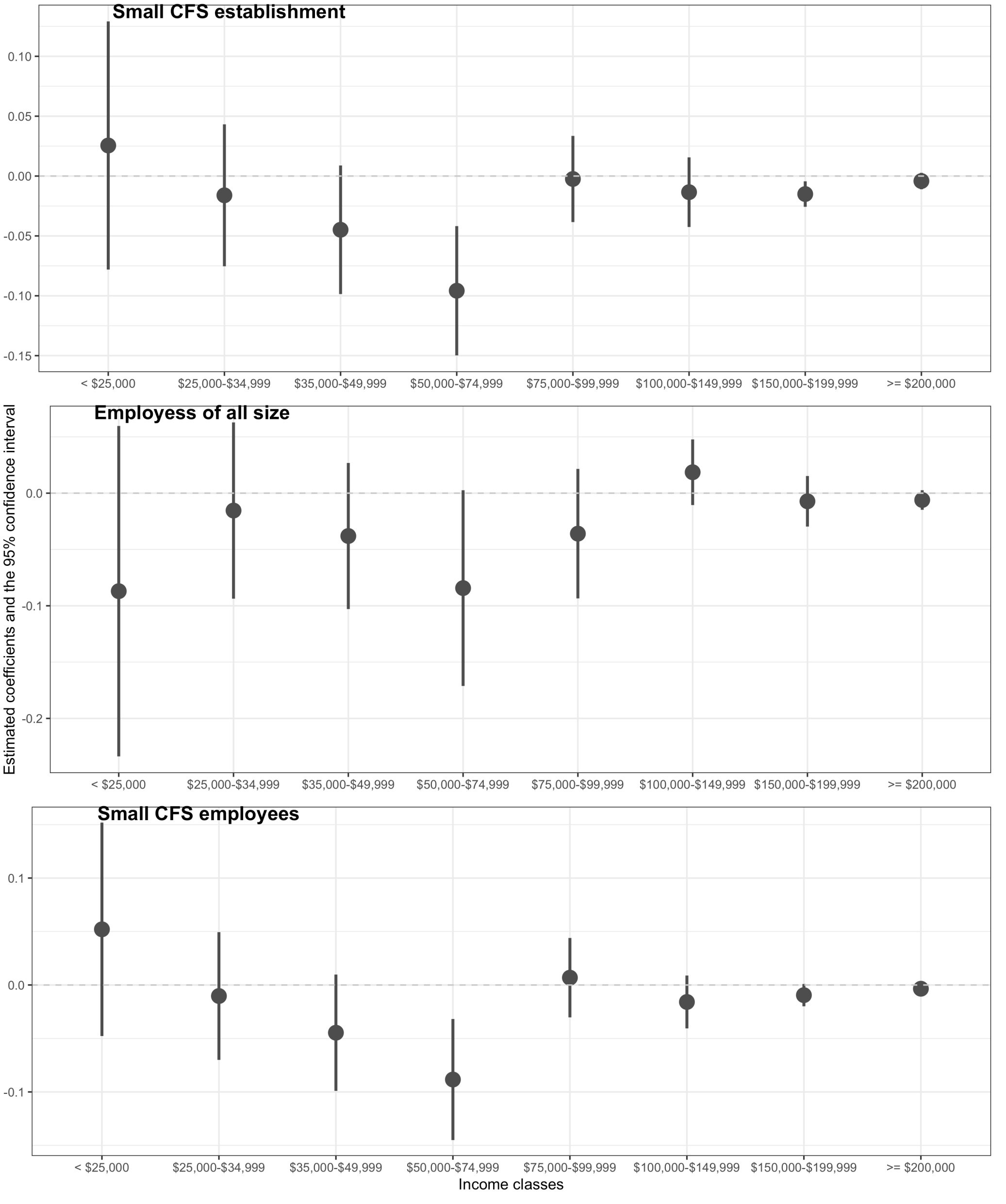

Figure S3. Estimated Effects of Three CFS Variables on Food Insufficiency
Notes: The points represent estimated coefficients on the CFS variable for each income class, and the vertical segments represent the 95% confidence intervals.
Source: Authors’ calculation.

Regressions Controlling for SNAP Recipients

The fourth robustness check is to include the variables for the percentage of individuals receiving SNAP benefits as an additional time-varying regressor in the first stage estimation to see if the mitigating effect of CFS organizations would change when controlling the influence of SNAP. We calculate the percentage of SNAP recipients in all adults from the Household Pulse Survey. However, the variable has some problem. First, only from week 13 (August 19-August 31), the Household Pulse Survey started asking whether anyone in a respondent's household received the SNAP benefits, and given that our dependent variable is available up to week 21, the estimation with the SNAP variable have only observations for 9 weeks that are mostly in Phase II. Second, the count of SNAP recipients in the survey is smaller than the administrative records of the USDA SNAP Data Tables. For example, the administrative record for the recipients in September is 43,022,767 persons and 22,265,554 households, but the averaged count in September in the survey is only 25,158,116, which could be due to the fact that the respondents of the survey are adults, and the administrative record may include other household members. Another concern of using the variables for SNAP recipients and for other free food sources is that they are contemporaneous with the dependent variable so that they may be endogenous themselves. Even though we also tried with lagged variables by two survey periods, roughly a month for Phases II and III, the endogeneity concern may remain. After controlling for the contemporaneous variable for SNAP recipients, the overall effect of the CFS, -0.122, becomes almost half as much as in the baseline regression and insignificant. As for income classes, although the coefficients become insignificantly negative for the middle-income classes of $50,000-74,999, -0.059, the mitigating effect for the income class $75,000-99,999, -0.081, becomes the highest and statistically significant. The coefficient on the contemporaneous SNAP variable is significantly positive, partly affirming the endogeneity concern over this variable. When using the lagged variable for SNAP recipients, the overall effect (-0.225) goes back close to the baseline, and those for the middle-income classes of $50,000-74,999 and $75,000-99,000 become significantly negative (-0.083 and -0.075 respectively). Table S4 shows the coefficients on the SNAP variables, contemporaneous and lagged respectively, and those on the CFS variables, and Figure S4 shows the coefficients on income classes. Due to the smaller sample size that is even smaller with the lagged SNAP variable, the computation of variance-covariance matrices of the 2^{nd}-stage estimation fails in some cases.

Table S4. Estimated Effects of SNAP Recipients and CFS

	All	**< $25,000**	**$25,000–34,999**	**$35,000–49,999**	**$50,000–74,999**	**$75,000–99,999**	**$100,000–149,999**	**$150,000–199,999**	**>= $200,000**
Using the contemporaneous SNAP variables									
Perc. of people receiving SNAP	0.060	0.082 ***	0.134 **	0.208 ***	0.144 **	0.112 **	0.111	0.123 *	0.008
	(0.037)	(0.026)	(0.055)	(0.064)	(0.066)	(0.052)	(0.073)	(0.066)	(0.024)
log(CFS per capita)	-0.122	0.005	0.009	0.074	-0.059	-0.081 *	0.003	0.003	-0.015
	(0.168)	(0.077)	(0.042)	(0.050)	(0.044)	(0.045)	(0.015)		
Using the lagged SNAP variables									
Lag 2 periods of perc. of people receiving SNAP	-0.051	0.345	-0.299	0.016	-0.046 *	-0.036	0.017	-0.001	-0.013
	(0.056)	(0.283)	(0.243)	(0.024)	(0.028)	(0.024)	(0.017)	(0.015)	(0.016)
log(CFS per capita)	-0.225	0.060	-0.074	0.036	-0.083 *	-0.075 *	0.014	-0.022 ***	-0.012 *
	(0.151)			(0.044)	(0.050)	(0.040)	(0.017)	(0.006)	(0.006)

Notes: (i) The model specification is the same as the baseline model except for the SNAP variables. (ii) Estimated coefficients on other control variables are omitted. (iii) Standard deviations are parenthesized. (iv) Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level. (v) Due to limited samples with the SNAP variable by income class, the variance-covariance matrices for some income classes fail to be computed.

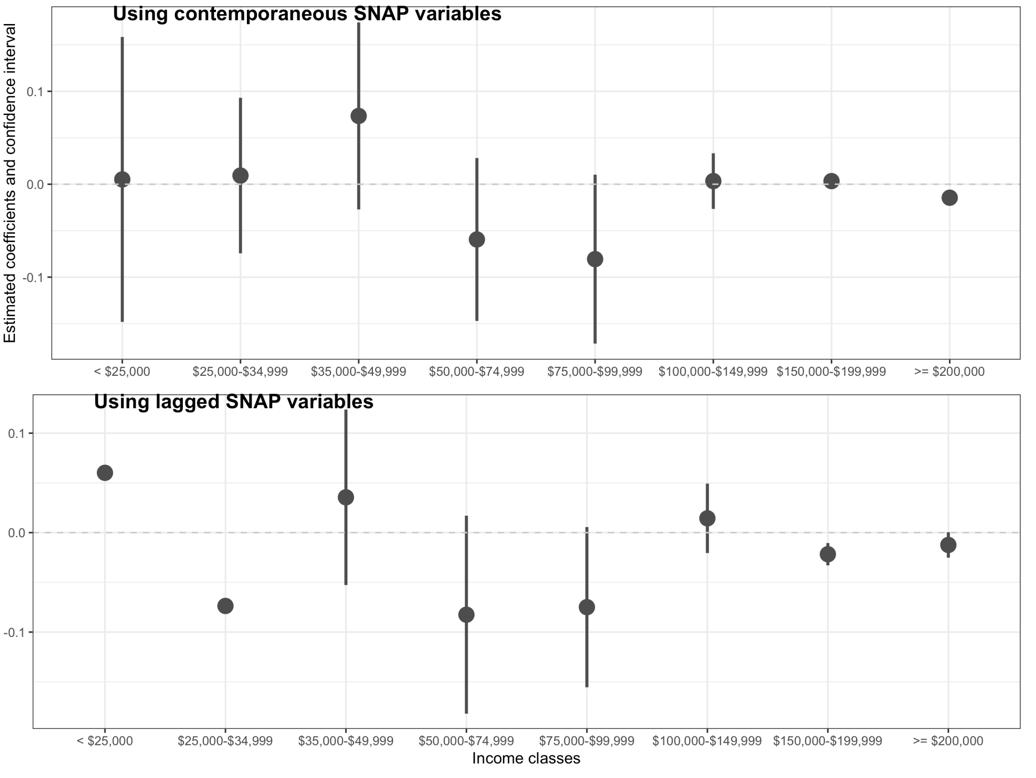

Figure S4. Estimated Effects of CFS Variables When Controlling for SNAP Recipients
Notes: The points represent estimated coefficients on the CFS variable for each income class, and the vertical segments represent the 95% confidence intervals.
Source: Authors' calculation.

Regressions Controlling for Free Food Sources Other than CFS

The fifth robustness check is to include the variables for the percentage of individuals getting free food from sources other than CFS organizations as an additional time-varying regressor in the first stage estimation to see if the mitigating effect of CFS organizations would change when controlling these free food sources. Interestingly, we obtain an even higher and significant overall mitigating effect of CFS organizations than in the baseline models. A caveat is in order: similarly with the SNAP variables, we also concern that the variable for other free food sources is endogenous itself, so we use both contemporaneous and lagged variables. Table S5 shows the coefficients on the variables for other free food sources, contemporaneous and lagged respectively, and those on the CFS variables, and Figure S5 shows the coefficients on income classes.

Table S5. Estimated Effects of Other Free Food Sources and CFS

	All	< $25,000	$25,000–34,999	$35,000–49,999	$50,000–74,999	$75,000–99,999	$100,000–149,999	$150,000–199,999	>= $200,000
Using contemporaneous variables for other free food sources									
Perc. of people getting free food from sources other than CFS	0.006	0.052 ***	0.069 *	0.082 ***	0.047 ***	0.024	0.067 ***	0.005	0.012
	(0.019)	(0.017)	(0.038)	(0.025)	(0.018)	(0.021)	(0.016)	(0.026)	(0.010)
log(CFS per capita)	-0.255 **	-0.024	-0.037	-0.052 **	-0.124 ***	-0.025	-0.012	-0.015 **	-0.007 *
	(0.118)	(0.061)	(0.034)	(0.026)	(0.028)	(0.022)	(0.017)	(0.007)	(0.004)
Using lagged variables for other free food sources									
Lag 2 periods of perc. of people getting free food from sources other than CFS	0.015	-0.000	-0.027	0.000	-0.023	-0.004	-0.005	0.000	-0.005 *
	(0.021)	(0.078)	(0.050)	(0.011)	(0.018)	(0.017)	(0.007)	(0.006)	(0.003)
log(CFS per capita)	-0.279 **	0.004	-0.061 *	-0.047 *	-0.109 ***	-0.022	-0.005	-0.015 **	-0.004
	(0.121)	(0.061)	(0.035)	(0.027)	(0.030)	(0.022)	(0.016)	(0.006)	(0.004)

Notes: (i) The model specification is the same as the baseline model except for the variables for other free food sources. (ii) Estimated coefficients on other control variables are omitted. (iii) Standard deviations are parenthesized. (iv) Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

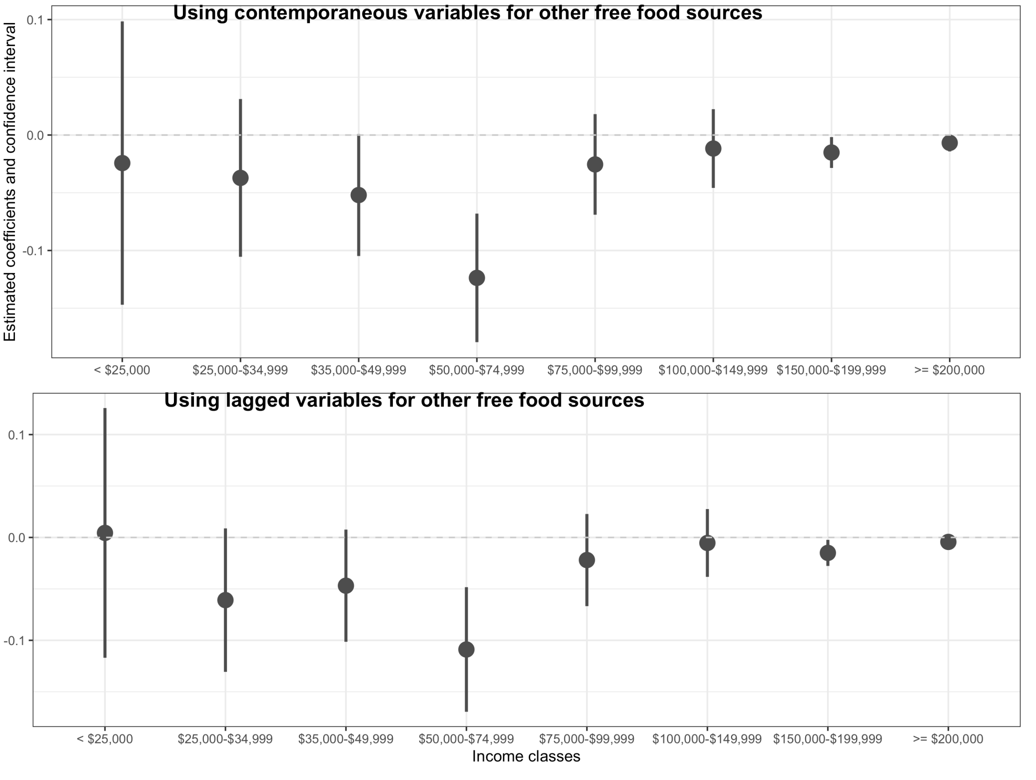

Figure S5. Estimated Effects of CFS Variables When Controlling for Other Free Food Sources
Notes: The points represent estimated coefficients on the CFS variable for each income class, and the vertical segments represent the 95% confidence intervals.
Source: Authors' calculation.