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Food Insufficiency and Mental Health during the COVID-19 Pandemic

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Food Insufficiency and Mental Health during the COVID-19 Pandemic

Abstract

Millions of Americans experienced a sudden loss of income along with hunger early in the COVID-19 outbreak. Using Household Pulse Survey from the Census Bureau, we find a significant impact of the pandemic on both food sufficiency and mental health, with heterogeneous effects of food insufficiency and income loss on mental health across different groups. Larger effects were found in mortgage paying-households, among males, and in non-metro areas. Results indicate the need for effective and timely policies targeting disadvantaged groups to maintain or improve their mental well-being during an economic crisis such as that caused by the pandemic.

Keywords: food sufficiency, mental health, unemployment, COVID-19, Household Pulse Survey

1. Introduction

The COVID-19 pandemic and the associated economic collapse created unprecedented challenges for Americans, including for their mental health, job opportunities, and food security. Researchers have in response sought to understand how the pandemic affected key economic outcomes, such as food security (Amare et al. 2021) and employment (Dang and Nguyen, 2021). In addition, adverse effects of the pandemic on mental health, including crises within the healthcare system and different communities have also been studied (Choi et al. 2020). Researchers have also started to study the effects of food insecurity (Gundersen and Ziliak, 2015) and labor markets shocks on mental health (Polsky and Gilmour, 2020) separately. However, these studies have not estimated the simultaneous effects of hunger and job/income loss on mental health or compared the magnitude of each mechanism on mental health during the pandemic.

In this paper, we employ weekly household-level survey data from April 23, 2020 to March 29, 2021 to investigate the effect of food insufficiency and economic shocks, defined as income loss and unemployment, on the mental health of adults during the COVID-19 pandemic. Our results suggest that food insufficiency and income loss increase the incidence of mental health disorders. However, unemployment also decreases reported anxiety. Further, the size of the food insufficiency effect on poor mental health is larger than that of income loss and unemployment. The negative impact of food insufficiency on mental health is persistent in all groups. Highly educated people and middle-class respondents are less likely to be food insufficient and unemployed than lower-educated and low-income counterparts, but they are more likely to be anxious. Subsample analyses show heterogeneous effects of food insufficiency and economic shocks across groups during the pandemic and reveal disadvantaged groups. Though previous literature shows that women were more vulnerable to be depressed (Casey et al. 2004), we find that, in households, males were more likely to be more anxious if their households experienced food security problems. No significant effects of economic shocks on mental health were found in the top 15 Metropolitan areas, but they did exist in non-metro areas. Even when we include Supplemental Nutrition Assistance Program (SNAP) and unemployment insurance application as control variables, the negative effect of food insufficiency on mental health persists, suggesting a limited impact of public benefits to reduce mental health through decreasing food insufficiency. These findings provide policy implications for identifying the most vulnerable groups and for providing prompt mental health assistance during shocks such as those created by economic or public health crises.

This paper contributes to the literature in three ways. First, we make a unique contribution by examining the relationships among food insufficiency, economic hardship and mental health during the COVID-19 pandemic. Though several papers analyze food security or labor market outcomes in the COVID-19 context (Jablonski et al. 2021; Ahn and Norwood, 2021; Restrepo et al. 2021, Ziliak 2021), few if any focus on mental health and its relations with food sufficiency and economic shocks. Second, with detailed near real-time household-level survey data, we can identify specific disadvantaged groups and test for heterogeneous effects by using subsample regression analyses which are especially relevant for policymakers regarding food and health support programs. Lastly, we add evidence on how public benefits such as SNAP and unemployment insurance affect mental health by reducing economic shocks and food insufficiency.

The paper is organized as follows. Section 2 provides the background. Section 3 introduces the estimation method, section 4 displays data source and summary statistics of main variables. Section 5 presents the regression results and policy implications, and the last section discusses the limitations of this paper and concludes.

2. Background

The COVID-19 virus spread rapidly around the world after it was first reported in December 2019. In addition to direct health impacts, the pandemic led to significant reductions in food security (Amare et al. 2021; Adjognon et al. 2021), including in the U.S. (Zheng et al. 2021), where the share of food insecure households increased sharply. Ahn and Norwood's (2021) internet survey found 15.4% of household to be food insecure in May 2020, confirming the rising food insufficiency rate reported by the Census Bureau. Food insufficiency, a concept similar to food insecurity (USDA ERS), indicates that a household is sometimes or often unable to acquire enough food (U.S. Census Bureau) over a predetermined period. Before the pandemic, the overall U.S. food insecurity rate was 10.9%, the lowest it had been over the last twenty years (Feeding America, 2021). However, Household Pulse Survey (HPS) data showed that during November and December 2020 (Figure 1), Americans experienced the highest food insufficiency rate, over 12%, compared to the start of the pandemic. At the same time, the COVID-19 pandemic greatly challenged Americans by upending labor markets, with many businesses shut down and massive job losses (Petrosky-Nadeau and Valletta, 2020), and the U.S. unemployment rate during the pandemic reached a level not seen since the Great Depression (Long and Van Dam, 2020). In addition to these aggregate impacts on the entire population, studies also have been conducted on subgroups. Using survey data from six countries, Dang and Nguyen (2021) concluded that women were more likely to experience unemployment and income loss during the outbreak compared to men. Doorley et al. (2021) likewise pointed to gender gaps in labor markets and income during the pandemic, and Cajner et al. (2020) found using weekly payroll data that nominal wages had been cut since the beginning of the pandemic. Based on Paker et al. (2020), 43% of Americans experienced a job loss or pay cut due to COVID-19, and low-income and Hispanics experienced a higher rate of income loss (Despard et al. 2020).

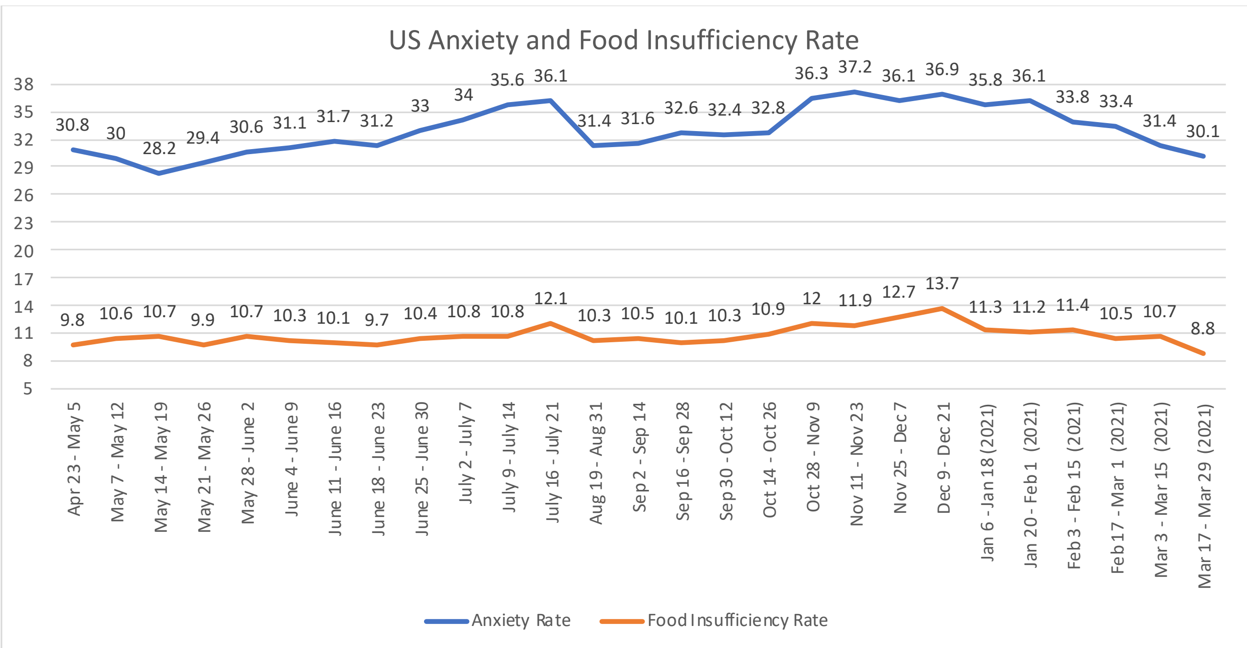

Figure 1: U.S. Average Food Insufficiency and Anxiety Rate

(Source: U.S. Census Bureau Household Pulse Survey)

Mental health, another important concern during the pandemic, has attracted economists and policy makers' interest because it not only imposes significant emotional and financial burden on patients and their families, but also indirect costs to the public (Mendolia 2011; Davlasheridze et al. 2018). Figure 1 shows that over 30% of adults felt anxious in July 2020, and the anxiety rate was above 35% in November and December of 2020 (U.S. Census Household Pulse Survey). The effect of food sufficiency/security on mental health had been noted by several researchers. For instance, Jones (2017) used nationally representative survey data from the 2014 Gallup World Poll (GWP) and concluded food insecurity is a key contributor to poor mental health. Being food insecure was linked to an increased risk of mental illness (Fang et al. 2021). Wei et al. (2018) found malnourished older adults are more depressed. Weinreb et al. (2002) focused on homeless and low-income families and found hunger has a negative effect on both physical and mental health of children. Gundersen and Kreider (2009) employed nonparametric bounding methods and found a significant negative effect of food insecurity on child mental health. Mental health and emotions were also negatively affected by economic shocks (Björklund, 1985; Hamilton et al., 1997). Compared to employed workers, working-aged unemployed individuals had higher odds of suicide (Blakely et al., 2003), and higher unemployment rates lead to higher suicide rates (Breuer, 2015). Addressing endogenous concerns using two-stage least squares, Mandal and Roe (2007) found a negative effect of involuntary unemployment on mental health. Using data from the US Health and Retirement Study surveys, Mandal et al. (2011) found that people who had experienced a job loss were more likely to have symptoms of depression. Our paper fills a gap in the literature by simultaneously estimating the relationships among food insufficiency, economic hardship and mental health and compares the magnitudes of effects of these shocks on mental health.

3. Model

3.1 Conceptual Framework

We model mental health within the household production function framework (Becker 1965; Hamermesh, 2007; Huffman, 2011). A representative household is assumed to gain utility from the production of mental health, and from direct consumption of food and leisure. The inputs of production include market-purchased goods based on household and state characteristics. The household is both a producing and consuming unit and maximizes utility subject to an income constraint. The output produced by the household is consumed directly and not sold in the market. Household utility is then summarized by a strictly concave utility function:

$$U = U(H, F, L; \boldsymbol{X}, \boldsymbol{S}) \quad s.t.\ P_F \cdot F + W \cdot L = I$$

where H is mental health status, F is food, and L is leisure; these inputs may also confer direct utility (Mullahy and Roberts, 2010). X is a vector of household characteristics and S a set of state characteristics. P_F is the price of food and W is the price of leisure. I is total household income. Here, we assume the production function for mental health of household is as following:

The mental health production technology: $H = H(F, L, X, S)$

The Lagrangian for the constrained utility maximization is

$$\begin{aligned}\Phi = U(H(F, L, X, S), F, L; \mathrm{X}, \mathrm{S}) \\ +\lambda(I - \mathrm{P}_F \cdot F - W \cdot L)\end{aligned}$$

where λ is the Lagrange multiplier, indicating the marginal utility of income. Then we obtain the implicit household optimal demand function for F and L by taking first order conditions with respect to F and L in the constrained utility maximization problem. After substituting the optimal demands for *F* and *L* (F^* and L^*) into the mental health production function, we obtain the general form of the household's mental health supply as following.

$$H^* = H\,(F^*, L^*, X, S, I, P_F, W)$$

In this paper, we estimate the mental health supply as shown above. Since the true production level of mental health cannot be observed in the HPS data, we assume that if latent $H^*{}_i$ is less than a certain threshold, that the household experiences anxiety. Here, we treat mental health H_i, as the outcome of a production function, where a lower value means lower mental health and more frequent anxiety. F^* is food, where a lower value of F^* means more severe hunger problem. Hence, the first hypothesis is: $dH/dF^*>0$; in other words, less food and higher food insufficiency causes worse mental health. Z^* *(work)* equals *T* minus L^*. The second hypothesis is: $dH/dZ^*>0$ which means job loss or unemployment leads to worse mental health status. *I* is income in our model so we expect $dH/dI>0$ which means that if a household experiences income loss then it is more likely to have poorer mental health.

3.2 Econometric Model

This paper estimates the separate effects of food insufficiency and economic shocks on mental health status and compares their magnitudes during the pandemic. Our dependent variable is binary, whereby anxiety is an indicator of household mental health disorder, anxiety $\in \{0,1\}$, where 1 indicates the household experienced an anxiety symptom in the past 7 days. Placing the dependent indicator variable on the left-hand side of the equation, we use a Linear Probability Model (LPM) to predict the probability of anxiety.

$$y^*_{ist} = FI_{\boldsymbol{ist}}{}'\boldsymbol{\alpha} + \boldsymbol{economic\ shocks_{ist}}{}'\boldsymbol{\beta} + \mathbf{X}'_{\boldsymbol{ist}}\boldsymbol{\gamma} + \mathbf{S}'_{\boldsymbol{st}}\boldsymbol{\delta} + \epsilon_{ist}$$

The true latent anxiety level y^*_{ist} cannot be observed in the data; instead, we observe only

$$y_{ist} = \begin{cases} 1, \text{if } y^*_{ist} > 0 \\ 0, \text{otherwise} \end{cases}$$

where y_{ist} represents observed anxiety for household *i* in state *s* at time *t*, $FI_{\boldsymbol{ist}}$ is an indicator of whether the members in household experience food insufficiency. $\boldsymbol{economic\ shock_{ist}}$ are indicators measuring whether anyone in a household has a loss in income or the representative household member is currently unemployed. $\boldsymbol{X_{ist}}$ includes a set of household level characteristics, $\boldsymbol{S_{st}}$ is a set of time-varying state-level characteristics. Error terms are normally distributed and represented by ϵ_{ist} with zero mean and they are clustered at the state level in order to control for arbitrary correlation among observations from the same state.

The timing of responses to the arrival of the coronavirus varied across states, and state-level time-variant policies are likely to be correlated with household mental health due to consumption and economic shocks. In order to account for the heterogeneous effects across states, we employ time-variant state-level data. First, inspired by Restrepo et al. (2021), we include Google Mobility Trends at the state level, which show the daily change in visits to places such as residential (Google LLC.) relative to the baseline pre-pandemic period (January 3 to February 6, 2020). Similar to Restrepo et al. (2021), we use the state-level visits for the first day in each HPS week (e.g., the visit value for April 23 is used for the HPS week 1 April 23 to May 5). Second, we include an indicator variable from HealthData.gov to indicate whether the state has stay-at-home and non-essential-business closure orders. Stay-at-home orders and restrictions on entertainment activities increase levels of stress, anxiety and depression in the population

(Marroquín et al. 2020). Then, we include assistance program variables from HPS. For example, HPS asks households whether anyone in household has received benefits from unemployment insurance and Supplemental Nutrition Assistance Program (SNAP). Both SNAP and unemployment insurance have expanded significantly during the pandemic to help vulnerable families.

3.3 An instrumental variable (IV) LPM model

As noted, we expect potential endogeneity in the simple LPM. First, the effect of mental health on food sufficiency/security has been noted by several researchers. For instance, using data from Early Childhood Longitudinal Study, Noonan et al. (2016) find depression increases the likelihood of family food insecurity. Casey et al. (2004) state that the existence of maternal depression is associated with household food insecurity. The correlation test shows FI and anxiety are significantly correlated. For example, the coefficient of correlation between these two variables is 0.18 and it is significant at 1% level. Second, poor mental health will affect income as well as employment: people with more health disorders are more likely to earn less and to be unemployed. Health constraints limit their educational attainment and ability (Case et al. 2005). Alternatively, other unobserved variables influence both independent variables of interest and outcome. Therefore, OLS will provide inconsistent estimates for the parameters of interest.

To correct for endogeneity, we employ IV estimation with endogenous indicator variables (referred to as LPM-IV). In the first step, we estimate a LPM model for each endogenous indicator variable as functions of instruments and other control variables. Then we regress Y on the predicted values of endogenous variables and the covariates. The LPM-IV approach employed in this study is illustrated by the first and second stage as follows, where subscripts *s* and *t* are omitted for simplicity,

$$First\ Stage\colon\ \mathbf{x}_i = \mathbf{z}_{1i}\mathbf{\Pi}_1 + \mathbf{z}_{2i}\mathbf{\Pi}_2 + \mathbf{v}_i$$

$$Second\ Stage\colon\ y_i = \hat{\boldsymbol{x}}_i\boldsymbol{\beta}_1 + \mathbf{z}_{1i}\boldsymbol{\beta}_2 + u_i$$

in which $\boldsymbol{x}_i$ is a set of endogenous variables, in our case, FI and economic shocks. $\boldsymbol{z}_{1i}$ is a set of exogenous covariates in the second stage, $\boldsymbol{z}_{2i}$ is a set of instrumental variables. This approach generates consistent estimates compared to OLS.

A valid instrument has to fulfill two important conditions: (i) relevance, i.e., it has to be significantly correlated with the endogenous variable and, (ii) the exclusion restriction, i.e., the instrument has to affect mental health only through food insufficiency, income loss, or unemployment. The four instruments used in this paper to control for three endogenous dummies (food insufficiency, unemployment and income loss) are (1) neighboring states' same month average food insufficiency rate (2) neighboring states' last month average food insufficiency rate (3) neighboring states' same month unemployment rate (4) neighboring states' last month average unemployment rate. To justify or motivate the use of these instruments, many studies show states' interdependence and the existence of state spending spillovers (Figlio et al. 1999; Baicker 2001). For instance, a state's public expenditure can be modelled as being related to its neighboring states' spending by applying a spatial lag model (Case et al. 1993). We also find that neighboring states' food insufficiency rate and unemployment rate are strongly correlated with household's food and employment status. On the other hand, a single household mental health status will not affect neighboring states' food insufficiency rate and unemployment rate.

Importantly, we only include households where members are unemployed due to exogenous reasons (more details discussed in the Data section). Policy variables such as state non-essential business closure and stay-at-home orders are also included to mitigate the concern that these policies jointly affect both neighboring states' unemployment and food insufficiency rates and also households' mental health. Further, we control for state fixed effects and state-specific linear trends in the robustness check to account for unobserved state-level characteristics. In addition, as the COVID cases and vaccine rates may be correlated with both our instruments and respondent's mental health, we control for state-level COVID cases and vaccination rates from Centers for Disease Control and Prevention (CDC)[1] as robustness check as well.

We perform standard F tests and Hansen J tests to check the validity of our instruments. The Cragg-Donald Wald F statistic is 50.8 which rejects the null hypothesis of weak instruments. The p-value of Hensen J overidentification test is 0.879, which does not reject the null hypothesis of exogeneous instruments. Hence, we find no direct evidence against the validity of instruments.

4. Data

The Census Bureau started the HPS on April 23, 2020, as a real-time survey of American households, through an online platform to measure social and economic impacts. Data from this weekly survey provide insights into how employment, health, food security, childcare, and education change nationally during the COVID-19 pandemic. Our analysis uses 27 weeks of household-level public-use data files, over the survey collection periods from April 23, 2020 to

[1] https://data.cdc.gov/Case-Surveillance/United-States-COVID-19-Cases-and-Deaths-by-State-o/9mfq-cb36/data

March 29, 2021. Results before July 22, 2020 of the survey were released weekly. All later results were released every two weeks, in order to maintain continuity, the HPS continues to call these two-week collection periods “weeks” (U.S. Census Bureau HPS). As the HPS replaces the survey sample in every interviewing week, we cannot use panel regression methods and instead a pooled cross-sectional dataset is used in the regression. We apply the HPS household weight to account for nonresponse and coverage of the demographics of the interviewed persons in the household to obtain household-level estimates (Restrepo et al. 2021).

The survey includes several categorical indicators to measure food sufficiency, income loss, employment and mental health status. The dependent variable used in this study shows whether the households have experienced anxiety or not. Based on definitions in the HPS, the respondent in a household has anxiety symptoms if they feel anxious "more than half the days" or "nearly every day"[2].

"Frequency of anxiety over previous 7 days

1) Not at all

2) Several days

3) More than half the days

4) Nearly every day"

[2] We assume only one respondent in a household is interviewed since HPS randomly chooses home addresses to participate in this survey and each home address is only interviewed once.

Food insufficiency is our first independent variable of interest. Based on HPS definitions, members in households are food insufficient if they "sometimes" or "often" do not have enough to eat.

"Household food sufficiency for last 7 days

1) Enough of the kinds of food (I/we) wanted to eat

2) Enough, but not always the kinds of food (I/we) wanted to eat

3) Sometimes not enough to eat

4) Often not enough to eat."

Two other variables of interest are economic shocks. The first one is WRKLOSS, which is a binary answer in the survey to indicate whether anyone in the household has experienced a loss of employment income since March 13, 2020. The second is ANYWORK, and this variable shows the respondent's current employment status in the last 7 days (1=unemployed, 0=employed).

To mitigate concerns on endogeneity, we first focus on the effect of involuntary unemployment, i.e., the sample that only includes respondents who currently do not have a job because of:

"8) My employer experienced a reduction in business (including furlough) due to the coronavirus pandemic;

10) My employment closed temporarily due to the coronavirus pandemic;

11) My employment went out of business due to the coronavirus pandemic;".

Otherwise, if the respondents are not employed because they are fearful of working or needing to care for someone with coronavirus symptoms or other food/mental health-related reasons, an endogeneity problem may arise in the estimation. The second way of controlling endogeneity is including instrumental variables, the neighboring states' average food insufficiency rate from HPS and neighboring states' average insured unemployment rate from US Department of Labor Unemployment Insurance Weekly Claims Data. Though this unemployment rate only provides a lower bound of total unemployment, it is updated weekly and does reflect state-level job loss status (Blaustein 1979).[3] The HPS also provides control variables to capture respondent and household characteristics. They are respondents' age, gender, race, marital status, Hispanic origin, education, household size, number of children and total household annual income level in 2019.

Table 1 shows summary statistics of the overall sample, along with separate tabulations for those reporting and not reporting anxiety. Most variables from the HPS are categorical and indicator variables. For the dependent variable, 32% of the entire sample feel anxious more than half the days or nearly every day. Six percent of households report food insufficiency in the overall sample. [4] Compared to the no-anxiety households, households with anxiety have a higher share of hunger with 12% reporting food insufficiency. In the overall sample, 43% of respondents report they have experienced a loss in income, and 8% of the sample remain

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[3] We also use the monthly state-level unemployment rate from U.S. Bureau of Labor Statistics which is a more commonly used unemployment measure. Results barely change with this replacement.

[4] This number is different from that in Figure 1 because Figure 1 represents the entire sample from the HPS; the sample we use in the analysis is less than the full sample as we exclude individuals who voluntarily left their jobs or have missing data.

unemployed currently. Compared to the group with no anxiety symptoms, the anxiety group has a larger share of female, Hispanic, and not-married populations, and a smaller share of Asian and highly- educated populations. At the state level, the average of the contemporaneous monthly neighboring states' unemployment rate is 7.8%. On average, due to the stay-at-home order of many states, visits to residential places were higher than the pre-pandemic baseline (January 3 to February 6, 2020).

Table 1: Summary Statistics

	All		Anxiety=yes		Anxiety=no		t-test	
	mean	sd	mean	sd	mean	sd	t-test	p-value
Dependent Variable								
Anxiety	.32	.47	1		0			
FI and Economic Shocks								
Food Insufficient	.06	.24	.12	.32	.03	.18	-164.5	<0.001
Income loss	.43	.5	.53	.5	.38	.49	-147.9	<0.001
Unemployment	.08	.27	.11	.32	.07	.25	-85.9	<0.001
Household Characteristics								
Household size	3.01	1.51	2.99	1.51	3.02	1.5	10.1	<0.001
Number of Children	.81	1.11	.8	1.1	.82	1.11	5.5	<0.001
Income $50,000 - $74,999	.16	.37	.18	.38	.15	.36	-31.6	<0.001
Income $75,000 and above	.62	.49	.54	.5	.66	.47	116.9	<0.001
Respondent Characteristics								
Age	45.0	11.5	42.9	11.5	46.1	11.4	130.4	<0.001
Age square	2161.1	1031.4	1974.5	1004.3	2249.7	1032.2	128.2	<0.001
Male	.41	.49	.34	.47	.45	.5	102.4	<0.001
Married	.59	.49	.52	.5	.62	.48	98.7	<0.001
Hispanic	.1	.3	.11	.31	.09	.29	-19.7	<0.001
White	.82	.38	.83	.38	.82	.39	-16.3	<0.001
Black	.08	.27	.08	.27	.08	.27	7.2	<0.001
Asian	.05	.23	.04	.19	.06	.24	47.1	<0.001

Other	.05	.21	.05	.23	.04	.2	-30.4	<0.001
Bachelor's degree or above	.59	.49	.57	.5	.61	.49	37.1	<0.001
State Characteristics								
Residential mobility	11.2	3.8	11.28	3.7	11.2	3.8	-1.1	0.273
Stay-at-home order	.12	.33	.13	.33	.12	.33	-3.9	<0.001
Non-essential-business order	.22	.41	.22	.41	.22	.42	8.0	<0.001
Assistance Program								
SNAP	.05	.23	.08	.27	.04	.2	-20.4	<0.001
Ump Insurance	.18	.38	.23	.42	.15	.36	-72.4	<0.001
Instruments								
This month neighboring states' FI	10.25	1.81	10.32	1.82	10.22	1.81	-25.4	<0.001
Last month neighboring states' FI	10.08	1.86	10.12	1.87	10.06	1.86	-14.8	<0.001
This month neighboring states' UI	7.78	4.37	7.66	4.34	7.83	4.38	17.8	<0.001
Last month neighboring states' UI	8.85	4.66	8.73	4.64	8.9	4.67	17.7	<0.001

Source: Dependent Variables, FI and Economic Shocks, Household Characteristics, Respondent Characteristics and Assistance Program groups are directly from Census Bureau Household Pulse Survey; This month neighboring states' FI and Last month neighboring states' FI are authors' calculations based on Census Bureau Household Pulse Survey; Residential mobility is from Google; This month neighboring states' UI and Last month neighboring states' UI are authors' calculations based on U.S. Department of Labor, Employment and Training Administration; Stay-at-home order and Non-essential-business order are from HealthData.gov. Observations are weighted at the household level.

5. Results and Policy Implications

5.1 Main Results

Table 2 presents OLS regression results, and results of the LPM-IV. Table 3 presents first-stage results of the LPM-IV. The magnitudes of OLS coefficients on food insufficiency and income loss are smaller compared to the LPM-IV results. The sign of the coefficient on unemployment becomes negative when we address endogeneity. The first stage results indicate that household size and number of children in a household are each positively related to the probability of being food insufficient. Middle and high-income households and highly- educated population are less likely to have food insufficiency, income loss and unemployment. Female, Hispanic and Black are more likely to experience all of these shocks. These are consistent with other findings that vulnerable groups, such as households with income below $50,000 and households with children, are experiencing more food insecurity during the pandemic (Gundersen et al. 2021; Jablonski et al. 2021; Restrepo et al. 2021; Ahn and Norwood, 2021). Certain job types, such as restaurant service and construction, are difficult if not impossible to perform remotely. Workers in these sectors usually have lower income and were also more affected by the pandemic and stay-at-home orders.

Table 2 presents our main results of the LPM-IV. First of all, the effect of food insufficiency is positive, which means that if members of a household sometimes or often do not have enough to eat, then the household has a higher probability of reporting anxiety disorder. This correlation is as expected: being food insecure is associated with poor mental health. Households with severe hunger problems have a higher risk of stress, depression and anxiety. People who have experienced a loss of income are also more likely to report anxiety. A negative income shock causes a person to report anxiety symptoms with a higher probability. However, the effect of unemployment is negative. One explanation is that people who are currently unemployed do not need to face stressful work with potential exposure to the virus, so they will be less anxious. Additionally, the effect of food insufficiency is larger than the effect of income loss (column 2). To be specific, if a household does not have enough to eat, the probability of anxiety is 167 percentage points higher. If someone in a household has experienced income loss, the household has a 89 percentage point higher probability of reporting anxiety. Thus, food insufficiency is more important than income loss and unemployment in inducing anxiety. Column 3 includes selected assistance program variables provided by HPS. Since these questions are not shown in the early weeks of the survey, we have fewer observations in column 3. After controlling for these assistance programs, the coefficient of food insufficiency on anxiety is still significant. However, receiving these benefits make economic shocks like income loss and unemployment have no significant effect on anxiety. These results suggest that the importance of public welfare programs such as SNAP and unemployment insurance in mitigating the negative impacts of economic shocks.

Even though the first stage results suggest that highly-educated, high-income people are less likely to be food insufficient and unemployed, the second stage results also show they have a higher probability of reporting anxiety. On the other hand, even though Hispanic, Blacks and households with more members have higher probability of losing income and employment, and experience hunger, they are less likely to report anxiety based on these results. At the state level, an increase in residential mobility and stay-at-home mandates lead to an increase in anxiety. These mandated reductions in visits to entertainment places making it harder for people to unload their stress though social activities.

Table 2: Main Results

	(1)	(2)	(3)
Dep. Var	OLS	Baseline	Add Assistance
Anxiety		model	Program Variables
Food Insufficiency	0.228***	1.667***	1.707***
	(0.004)	(0.345)	(0.370)
Income Loss	0.106***	0.887***	-0.089
	(0.003)	(0.257)	(0.492)
Unemployment	0.043***	-0.807**	-0.754
	(0.005)	(0.377)	(0.643)
Household size	-0.001	-0.069***	0.003
	(0.001)	(0.019)	(0.034)
Number of children	-0.012***	0.030	-0.033
	(0.001)	(0.019)	(0.034)
Income 50,000-75,000	-0.006*	0.150***	0.108***
	(0.003)	(0.047)	(0.032)
Income >75,000	-0.039***	0.198***	0.097***
	(0.004)	(0.063)	(0.033)
Age	-0.0003	-0.014***	-0.011***
	(0.0006)	(0.002)	(0.002)
Age square	-0.00005***	0.0001***	0.0001***
	(0.00001)	(0.00003)	(0.00003)
Male	-0.080***	-0.065***	-0.072***
	(0.002)	(0.005)	(0.011)
Married	-0.033***	0.003	0.012
	(0.002)	(0.013)	(0.016)
Hispanic	-0.043***	-0.084***	-0.058***
	(0.005)	(0.012)	(0.020)
Black	-0.077***	-0.163***	-0.158***
	(0.004)	(0.034)	(0.035)
Asian	-0.094***	-0.050***	-0.106***
	(0.006)	(0.015)	(0.027)
Other Race	0.007	-0.063***	-0.040***
	(0.005)	(0.022)	(0.015)

Bachelor's degree/above	0.019***	0.153***	0.099***
	(0.002)	(0.033)	(0.015)
Residential Mobility	0.001	0.002	0.005***
	(0.000)	(0.003)	(0.002)
Stay-at-home order	0.009	0.016**	0.041***
	(0.010)	(0.008)	(0.011)
Non-essential business	-0.004	-0.001	-0.002
	(0.006)	(0.014)	(0.014)
Time trend	0.003***	-0.002	-0.001
	(0.000)	(0.001)	(0.001)
Unemployment Insurance			0.174
			(0.211)
SNAP			0.007
			(0.043)
Constant	0.407***	0.240***	0.449***
	(0.016)	(0.081)	(0.054)
Observations	1,039,923	1,039,923	539,731

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 3: First-Stage Results of LPM-IV

		First Stage	
VARIABLES	FI	Income loss	Unemployment
Neighbor month UI	-0.001	0.006**	0.008***
	(0.001)	(0.003)	(0.002)
Neighbor month FI	0.004***	0.004**	-0.0002
	(0.001)	(0.002)	(0.001)
Neighbor Last month UI	0.0004	-0.001	-0.004*
	(0.0007)	(0.002)	(0.002)
Neighbor Last month FI	-0.0003	-0.006***	0.00005
	(0.0009)	(0.002)	(0.001)
Household size	0.008***	0.080***	0.007***
	(0.001)	(0.002)	(0.001)
Number of children	0.006***	-0.070***	-0.005***

	(0.001)	(0.002)	(0.001)
Income 50,000-75,000	-0.100***	-0.085***	-0.064***
	(0.002)	(0.003)	(0.003)
Income >75,000	-0.129***	-0.168***	-0.093***
	(0.002)	(0.004)	(0.005)
Age	0.007***	0.005***	-0.001
	(0.001)	(0.001)	(0.001)
Age square	-0.0001***	-0.00005***	0.00001*
	(0.00001)	(0.00001)	(0.000008)
Male	-0.003*	-0.011***	0.003*
	(0.001)	(0.002)	(0.002)
Married	-0.031***	-0.004	-0.015***
	(0.002)	(0.004)	(0.002)
Hispanic	0.020***	0.030***	0.016***
	(0.004)	(0.010)	(0.006)
Black	0.071***	0.013**	0.035***
	(0.005)	(0.006)	(0.006)
Asian	-0.001	-0.033***	0.021***
	(0.002)	(0.007)	(0.007)
Other Race	0.041***	0.038***	0.022***
	(0.004)	(0.005)	(0.004)
Bachelor’s degree/above	-0.064***	-0.105***	-0.048***
	(0.002)	(0.005)	(0.003)
Residential Mobility	0.001***	0.003***	0.005***
	(0.0003)	(0.001)	(0.001)
Stay-at-home order	-0.007***	0.014	0.014*
	(0.002)	(0.012)	(0.007)
Non-essential business	-0.005**	0.002	-0.008
	(0.002)	(0.018)	(0.006)
Time trend	0.0004	0.003***	-0.002***
	(0.0003)	(0.001)	(0.001)
Constant	0.0097	0.244***	0.109***
	(0.0127)	(0.047)	(0.026)
Observations	1,039,923	1,039,923	1,039,923

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

5.2 Subgroup Analysis

Table 4 shows the effects in different subgroups, which helps us to identify vulnerable populations that are more affected by economic shocks and food insufficiency. The entire regression results of subgroups are presented in Table A1. To begin with, the magnitude of the coefficient on food insufficiency is larger than that of economic shocks for all groups and significant statistically, while unemployment becomes insignificant in some subgroups. We first examine the mortgage and rent payment subsamples. As many people did not answer this question in the survey, we have fewer observations in these two groups. Both of these groups are significantly affected by food insufficiency and economic shocks. Compared to food sufficient households, the probability of the food insufficient mortgage paying group being anxious increases by 232 percentage points. In contrast, this number is only 101 for the rent- paying group. Examining the assistance program related statistics of these two groups (Table A2), we find that rent payers have a higher share receiving SNAP and mental health care than those with mortgages. One hypothesis is that although the rent paying group experiences food insufficiency, they are eligible for food support programs and receive free food, and so the hunger shock is not as large as that received by mortgage payment groups. When examining economic shocks, income loss causes mortgage payment people report anxiety with higher probability. One explanation is that people are more anxious about paying for the mortgage due to loss of income. One should note that, participation in the assistance programs and mental health care may be affected by anxiety so we could not interpret the differences in those variables as casual effects.

The second comparison is between males and females. Previous research indicates more household food security problems and mental health disorders among women (Casey et al. 2004). However, our subgroup comparison shows the effects of food insufficiency and income loss on anxiety are stronger for men during the pandemic. Column 3 and 4 indicate that anxiety is estimated to be increasing with food insufficiency and job loss among male workers, with the increasing probability of experiencing anxiety by roughly 188 percentage points if his family experienced a food hardship, and 93 percentage points if he has an income loss. During the pandemic, if the household lost the main income source and hence, is more likely to be anxious about the current situation. The difference between gender can also be seen in Table A2: females receive more mental health care and SNAP, which will reduce the effect of hunger on anxiety.

The last two columns compare different effects of food insufficiency and economic shocks between top 15 metropolitan and non-metropolitan residents. Income and job loss increase the probability of being anxious for residents in non-metropolitan areas, but the magnitude of effect is smaller than the food insufficiency. The effect of food insufficiency is significant on both groups but there is a bigger effect for the non-metro households. It is possible that health access prevents residents in non-metro areas from receiving adequate mental care. For example, we find in our data that the share of receiving mental health care in the non-MSA group is smaller than in the MSA group although more residents in the non-MSA area receive free food to reduce hunger (Table A2).

Table 4: Heterogenous Effects of LPM with Instruments

VARIABLES	Mortgage	Rent	Male	Female	Non-MSA	MSA
Food Insufficiency	2.318***	1.006***	1.879***	1.426***	1.704***	1.393**
	(0.396)	(0.296)	(0.391)	(0.275)	(0.398)	(0.687)
Income loss	0.787*	0.667**	0.927*	0.653***	0.935**	0.527
	(0.406)	(0.287)	(0.485)	(0.170)	(0.380)	(0.959)
Unemployment	-0.789**	-0.408**	-0.855	-0.638**	-0.655*	-0.202
	(0.392)	(0.181)	(0.722)	(0.319)	(0.395)	(0.395)
Observations	624,097	325,793	479,698	644,514	720,207	404,005

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

5.3 Robustness Check

We include robustness checks in Table A3. As Restrepo et al. (2021) argued, policy responses to the spread of COVID-19 that related to food and mental health hardship and economic shocks have also varied within states over time. To control for this confounding factor, we add state fixed effect and state-specific time trends in the model (column 1). Column 2 shows the results when we add COVID cases and vaccine rate as state-level controls.[5] Column 3 and 4 show the different measures of mental health disorder: worry and "feeling down." These two binary dependent variables are from the HPS as well. WORRY equals to 1 means the respondent has been feeling worried more than half the days or nearly every day over the last week. DOWN equals to 1 means the respondent has been feeling depressed more than half the days or nearly

[5] Note that we do not observe the residence of the respondents other than the states they live in, so we are unable to match covid vaccination and cases at the county level.

every day over the last week. We see that the effect of variables of interest are similar to those in our primary model, although the impact of unemployment becomes statistically insignificant.

5.4 Policy Implications

Adults in the United States continue to face severe food and mental health hardships during the ongoing pandemic. This calls for prompt actions and cooperation from the government, community, and organizations. First, we find the magnitude of the effect of food insufficiency on mental health is larger than that of either income loss or unemployment. The statement holds even if we control for assistance program and benefit variables such as receiving unemployment insurance and SNAP. Table A4 includes different interaction terms between food insufficiency and programs to compare how these programs mitigate the effect of hunger on mental health. Receiving food assistance does not eliminate the effect of hunger on anxiety. For example, receiving free food will reduce the probability of anxiety by 142 percentage points if the household is food insufficient, while receiving SNAP only reduces the probability by 95 percentage points. Although these results cannot be interpreted as casual effects due to the endogeneity of receiving benefits, these still call for immediate targeting strategies to identify the most impacted populations who have mental health problems due to hunger. Currently, many social benefit programs target low-income, low-educated, and other disadvantaged groups (Dimitri et al. 2015; Swann 2017; You et al. 2021), but we find high-income, highly-educated people require mental health care as well when they face hunger and economic shocks.

Second, our subgroup comparison between metro and non-metro areas shows that people living in non-metro areas are more likely to experience anxiety due to hunger and income loss.

One of the policy implications is the need to address social benefit and health care systems in non-metro areas. The government may provide incentives or subsidized insurance to support rural health care access during the crisis to alleviate the effect of hunger and economic shocks (Raifman et al. 2020; Room 2021). Then, increasing attention could be paid to male's mental health. Men who experience hunger or suffer negative economic shocks may be reluctant to seek mental health assistance and avoid expressing emotions (Cochran and Rabinowitz, 1999; Addis and Mahalik, 2003). Based on our analysis, males experience greater anxiety than females as a result of food insufficiency in a household. Lastly, the need for extended food assistance programs, local emergency feeding programs and policies during the pandemic has been the focus of much discussion (Barrett, 2001; Bartfeld et al., 2015; Bitler et al., 2020; Jablonski et al., 2021), particularly for mortgage payment families (Loibl et al., 2021). Mortgage holders received unemployment insurance benefits at a lower rate than renters (Greig et al., 2021). Due to asset tests restrictions, some mortgage paying families are not able to receive food assistance programs to reduce hunger and stress (Ratcliffe, 2016). For example, they have higher probability of reporting anxiety disorder when they are food insufficient compared to rent paying group. Future research is warranted to analyze and compare the costs and benefits of specific policies in alleviating the negative effects of food insecurity on mental health.

6. Conclusion

This study analyzes the effect of food insufficiency and economic shocks on mental health disorders during the pandemic and compares the magnitudes of effects of these shocks on mental health. Our main hypothesis is that food insufficient households, or households with income loss or unemployment have a higher probability of being anxious. Based on household-level survey data, the results show that food insufficiency and income loss significantly impact mental health. In addition, we find larger magnitude of food insufficiency than income or job loss. Food insufficient households are more likely to experience anxiety symptoms by 167 percentage points. Households experiencing income loss are 89 percentage points more likely to report anxiety. However, the unemployed households are 81 percentage points *less* likely to report anxiety than employed counterparts. After controlling for assistance program variables, the effect of food insufficiency is still significant across all groups, while the impact of income loss and unemployment become insignificant. Based on subgroup regressions, we find males, mortgage payers and non-metro area populations have higher probabilities of reporting anxiety disorder when they are food insufficient, compared to their counterparts.

Although this paper provides important new insights about food and mental health hardship during Covid-19, there are several limitations. First, the interviewed population sample are not identical every week and thus we cannot lag the effect of shocks by one or two weeks. For example, mental disorders may be delayed after hunger, income loss and unemployment. Second, lack of access to food from the supply side is also an important topic in household food security research. Unfortunately, households in the survey are only identified at the state level, not county or zip-code level so we are unable to identify the local food environment. Our analysis prompts some research questions worth further investigation. For example, one could incorporate local food shopping environments such as food retailers, community food assistance such as food pantries or soup kitchens using more detailed data. Future research is warranted to evaluate the costs and benefits of specific policies in alleviating the negative effects of food insecurity and economic shocks on mental health.

Appendix

Table A1: Results of Subgroup Analysis

VARIABLES	(1) Mortgage	(2) Rent	(3) Male	(4) Female	(5) Non-MSA	(6) MSA
Food Insufficiency	2.318***	1.006***	1.879***	1.426***	1.704***	1.393**
	(0.396)	(0.296)	(0.391)	(0.275)	(0.398)	(0.687)
Income Loss	0.787*	0.667**	0.927*	0.653***	0.935**	0.527
	(0.406)	(0.287)	(0.485)	(0.170)	(0.380)	(0.959)
Unemployment	-0.789**	-0.408**	-0.855	-0.638**	-0.655*	-0.202
	(0.392)	(0.181)	(0.722)	(0.319)	(0.395)	(0.395)
Household size	-0.065**	-0.041*	-0.065**	-0.045***	-0.066***	-0.037
	(0.031)	(0.023)	(0.032)	(0.013)	(0.025)	(0.065)
Number of kids	0.032	-0.000	0.030	0.006	0.030	-0.003
	(0.030)	(0.018)	(0.029)	(0.012)	(0.025)	(0.051)
Income 50,000-75,000	0.142*	0.097***	0.152***	0.130***	0.161***	0.142
	(0.079)	(0.029)	(0.055)	(0.039)	(0.049)	(0.102)
Income >75,000	0.212**	0.134***	0.221***	0.147***	0.199***	0.199
	(0.099)	(0.045)	(0.084)	(0.052)	(0.062)	(0.191)
Age	-0.020***	-0.014***	-0.014***	-0.018***	-0.016***	-0.013
	(0.004)	(0.005)	(0.004)	(0.003)	(0.002)	(0.010)
Age square	0.0002***	0.0001**	0.0001***	0.0002***	0.0002***	0.0001
	(0.00005)	(0.00007)	(0.00005)	(0.00003)	(0.00003)	(0.0001)
Male	-0.076***	-0.074***	-0.350	0.173	-0.062***	-0.077***
	(0.007)	(0.006)	(0.513)	(0.284)	(0.007)	(0.011)
Married	0.008	-0.004	0.008	0.001	0.014	0.002
	(0.022)	(0.017)	(0.020)	(0.010)	(0.018)	(0.021)
Hispanic	-0.070***	-0.093***	-0.107***	-0.070***	-0.068***	-0.087***
	(0.018)	(0.013)	(0.016)	(0.014)	(0.024)	(0.019)
Black	-0.149***	-0.155***	-0.177***	-0.165***	-0.164***	-0.166***
	(0.052)	(0.025)	(0.040)	(0.026)	(0.052)	(0.042)
Asian	-0.041	-0.078***	-0.033	-0.074***	-0.047	-0.069
	(0.026)	(0.015)	(0.030)	(0.013)	(0.043)	(0.051)
Other Race	-0.056**	-0.059***	-0.066***	-0.065***	-0.074***	-0.059
	(0.026)	(0.022)	(0.025)	(0.022)	(0.025)	(0.040)
Bachelor degree/above	0.133***	0.125***	0.157***	0.132***	0.166***	0.135
	(0.035)	(0.034)	(0.044)	(0.031)	(0.032)	(0.116)
Residential Mobility	0.003	0.0005	0.001	0.002	0.002	0.000
	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
Stay-at-home order	0.030***	0.002	0.015	0.018**	0.016	0.022

	(0.010)	(0.009)	(0.011)	(0.008)	(0.018)	(0.014)
Non-essential-business	-0.003	0.006	0.005	-0.0004	0.005	-0.004
	(0.014)	(0.010)	(0.017)	(0.010)	(0.011)	(0.019)
Time trend	-0.001	-0.001	-0.002	-0.001	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Constant	0.384**	0.390***	0.466	0.406***	0.205**	0.267
	(0.157)	(0.125)	(0.560)	(0.080)	(0.089)	(0.330)
Observations	624,097	325,793	479,698	644,514	720,207	404,005

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A2: Summary Statistics of Assistance-Related Variables of Subgroups (Mean (Std))

Assistance-related Variables	Mortgage	Rent	T-test (P-value)	Male	Female	T-test (P-value)	Non-MSA	MSA	T-test (P-value)
Free Food	0.061	0.085	48.15	0.058	0.075	47	0.069	0.064	18.75
	(0.240)	(0.279)	(<0.001)	(0.233)	(0.263)	(<0.001)	(0.254)	(0.245)	(<0.001)
Unemployment Insurance	0.183	0.296	73.74	0.198	0.211	30.25	0.195	0.226	-7.35
	(0.387)	(0.456)	(<0.001)	(0.399)	(0.408)	(<0.001)	(0.396)	(0.418)	(<0.001)
SNAP	0.041	0.109	103.95	0.047	0.070	52.4	0.060	0.061	10.45
	(0.199)	(0.311)	(<0.001)	(0.212)	(0.255)	(<0.001)	(0.238)	(0.240)	(<0.001)
Mental Health Care	0.114	0.157	45.4	0.093	0.143	61.75	0.117	0.132	-16.25
	(0.317)	(0.363)	(<0.001)	(0.291)	(0.350)	(<0.001)	(0.321)	(0.339)	(<0.001)

Note: All of assistance-related variables are indicators. Mean of summary statistics show the percent of households in that group receive such assistance. P-values correspond to t tests of equality of means between groups.

Table A3: Robustness Check

VARIABLES	(1) Add state-specific time trend and FE	(2) Add COVID cases +vaccine rate	(3) WORRY	(4) DOWN
Food Insufficiency	1.590***	2.096***	1.827***	1.212***
	(0.406)	(0.807)	(0.427)	(0.366)
Income Loss	0.715**	1.188*	0.549*	0.147
	(0.290)	(0.650)	(0.318)	(0.262)
Unemployment	-0.720*	-1.476	-0.029	0.337
	(0.389)	(1.154)	(0.476)	(0.345)
Household size	-0.056***	-0.092*	-0.048**	-0.016
	(0.018)	(0.050)	(0.022)	(0.018)
Number of kids	0.019	0.046	0.012	-0.014
	(0.022)	(0.038)	(0.023)	(0.018)
Income 50,000-75,000	0.133***	0.176**	0.177***	0.099**
	(0.040)	(0.074)	(0.054)	(0.042)
Income >75,000	0.167***	0.242**	0.223***	0.113**
	(0.045)	(0.114)	(0.070)	(0.053)
Age	-0.013***	-0.019**	-0.012***	-0.010***
	(0.002)	(0.008)	(0.002)	(0.002)
Age square	0.0001***	0.0002*	0.0001***	0.0001***
	(0.00002)	(0.0001)	(0.00003)	(0.00003)
Male	-0.068***	-0.059***	-0.062***	-0.024***
	(0.005)	(0.012)	(0.005)	(0.004)
Married	0.001	0.007	0.022	-0.008
	(0.016)	(0.015)	(0.017)	(0.013)
Hispanic	-0.084***	-0.091***	-0.076***	-0.061***
	(0.011)	(0.019)	(0.013)	(0.011)
Black	-0.155***	-0.174***	-0.150***	-0.121***
	(0.037)	(0.040)	(0.043)	(0.037)
Asian	-0.060**	-0.025	-0.016	-0.030**
	(0.024)	(0.049)	(0.018)	(0.014)
Other Race	-0.058***	-0.076**	-0.065***	-0.038*
	(0.014)	(0.035)	(0.025)	(0.020)
Bachelor degree/above	0.133***	0.180***	0.139***	0.066**
	(0.017)	(0.068)	(0.035)	(0.026)
Residential Mobility	0.001	0.004	-0.002	-0.002
	(0.002)	(0.004)	(0.003)	(0.002)
Stay-at-home order	0.008	0.025*	0.009	0.007
	(0.009)	(0.013)	(0.010)	(0.009)

Non-essential-business	0.010	-0.007	0.003	0.005
	(0.006)	(0.018)	(0.013)	(0.008)
Time trend	0.003	-0.007	-0.0001	0.002
	(0.001)	(0.007)	(0.002)	(0.001)
COVID Cases per capita		8.336		
		(17.200)		
Vaccine rate		0.001		
		(0.002)		
Constant	0.303***	0.252***	0.102	0.248***
	(0.031)	(0.082)	(0.082)	(0.061)
Observations	1,039,923	1,039,923	1,038,316	1,038,367

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table A4: Programs Comparison

VARIABLES	(1) anxiety	(2) anxiety
Food Insufficiency	1.679***	1.883***
	(0.293)	(0.426)
Income loss	0.353	0.891***
	(0.289)	(0.301)
Current unemployed	-1.283**	-0.820*
	(0.609)	(0.444)
FI*Receive SNAP	-0.946***	
	(0.274)	
FI*Receive Free Food		-1.424***
		(0.357)
Household size	-0.030	-0.069***
	(0.021)	(0.022)
Number of kids	-0.004	0.031
	(0.020)	(0.023)
Income 50,000-75,000	0.093***	0.148***
	(0.034)	(0.052)
Income >75,000	0.105**	0.202***
	(0.047)	(0.071)
Age	-0.010***	-0.013***
	(0.002)	(0.002)
Age square	0.0001***	0.0001***
	(0.00002)	(0.00003)

Male	-0.069***	-0.066***
	(0.010)	(0.006)
Married	0.001	0.002
	(0.012)	(0.014)
Hispanic	-0.063***	-0.073***
	(0.018)	(0.012)
Black	-0.137***	-0.165***
	(0.028)	(0.039)
Asian	-0.089***	-0.048**
	(0.018)	(0.019)
Other Race	-0.039**	-0.060**
	(0.017)	(0.024)
Bachelor degree/above	0.100***	0.156***
	(0.026)	(0.037)
Residential Mobility	0.006***	0.002
	(0.002)	(0.003)
Stay-at-home order	0.041***	0.014**
	(0.010)	(0.007)
Non-essential-business	-0.008	-0.002
	(0.014)	(0.014)
Time trend	-0.002*	-0.002
	(0.001)	(0.002)
Constant	0.392***	0.200**
	(0.065)	(0.085)
Observations	540,064	1,038,654

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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