



# A Tale of Two Cities During the COVID-19 Pandemic: Evaluating Food Insecurity in Chicago and New York City

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Received: 11 February 2022 / Revised: 17 June 2022 / Accepted: 21 June 2022  
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## Abstract

**Background** COVID-19 revealed and broadened existing disparities in large cities. This article interprets the early impacts of COVID-19 on food insecurity (FI) in the Chicago and New York City (NYC) metropolitan areas for Black, Indigenous, and People of Color (BIPOC) and provides a study using a Social Determinants of Health (SDOH) framework.

**Methods** A cross-sectional survey adapted from the National Food Access and COVID Research Team (NFACT) was deployed in Chicago ( $N=680$ ) and in NYC ( $N=525$ ) during summer 2020 and oversampled for race, ethnicity, and socio-economic status. Multivariate binary logistic regression generated adjusted odds ratios (aOR) and 95% CIs for FI and select SDOH variables, which was conducted on each dataset.

**Results** The prevalence of FI in NYC increased to 66.8% (from 57.8%) and in Chicago to 44.8% (from 41.0%). While higher income protected against FI before, protection was diminished or eliminated since COVID-19. FI declined for households with children in NYC while odds increased and became significant in Chicago. Respondents with chronic health conditions experienced increased odds of FI since COVID. In Chicago, this variable had the highest odds of FI. Respondents with depression or anxiety had increased odds of FI. In NYC, depression had the highest odds of FI. Females in NYC were protected against FI. Hispanics in NYC lost protection against FI from before to since COVID-19.

**Conclusions** Results support the observed rise of FI for BIPOC and its association with health status. The analysis has multifaceted, structural policy implications for reducing FI in urban centers.

**Keywords** Food insecurity · COVID-19 · Chicago · New York City · Racial/ethnic disparities · Social determinants of health

## Introduction

In public health, social inequities are examined across communities to understand the interlinkages between social structures and human well-being. Among diverse methods to better understand differential effects of the COVID-19 pandemic across communities, indices provide an assessment of household well-being useful in analyses [1]. Subsequent measures of health inequities during COVID-19 include access to quality healthcare, education, and food security [2–4]. In times of crisis such as the ongoing COVID-19 pandemic, pre-existing social inequalities lead to increased risks of infections, disease, disability, and mortality, especially among those of lower socioeconomic status. Even before COVID-19, historically marginalized communities experienced higher levels of unemployment, poor general health, poor nutritional status, and underlying chronic health conditions, such as diabetes mellitus and heart disease [5].

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During a public health crisis, addressing health inequities requires the application of a Social Determinants of Health (SDOH) framework, which includes five social-economic indicators: economic stability (income, employment, and access to quality education), access to quality healthcare, neighborhood and built environment, and social and community context [6]. Debates around measuring and tracking inequity include alternatives that draw on SDOH for measuring inequity outside of strictly income-based variables. Examining inequality beyond income paints a more accurate picture of social inequality and, conversely, well-being [7].

As such, food security is a core SDOH [6]. Food insecurity (FI) is defined as having limited or no access to sufficient, nutritious food for living an active, healthy life. FI disproportionately impacts low-income communities and Black, Indigenous, and People of Color (BIPOC) [8] and is associated with poor health outcomes [9]. The United States Department of Agriculture (USDA) Six-Item Household Food Security Module offers a validated index to measure FI that we used to test hypotheses about the impacts of COVID-19 on BIPOC households across multiple sites [10].

The COVID-19 pandemic has revealed and broadened fractures in social structures, widening disparities globally across spheres of food security, health, and income. Pandemics affect humanity along the “fault lines of society—exposing and often magnifying power inequities that shape population health even in [less uncertain] times” [11, 12]. COVID-19 has resulted in the worsening of FI, which exacerbates worry and distress about not being able to meet basic household needs [13]. This chasm became severe for BIPOC in the USA—those who were already experiencing greater FI before the pandemic [8] and were sicker and living shorter lives than Whites [14–17]. These disparities of COVID-19 morbidity and mortality are “unjust, avoidable and... preventable” [16, 18].

COVID-19 is associated with greater FI among BIPOC and worse mental health outcomes [19–21]. Moreover, the US Census Bureau’s Household Pulse Survey reported that, although economic activity resumed in the USA around May 2020, the pandemic and subsequent social distancing restrictions led to family hardship, particularly food scarcity [22]. As a result, many individuals turned to safety net programs in their localities for help early in the pandemic, including food pantries and social assistance programs (i.e., Supplemental Nutrition Assistance Program (SNAP), Medicaid, and Temporary Assistance for Needy Families (TANF)), the \$2.0 trillion Coronavirus Aid, Relief, and Economic Security (CARES) Act, and a more extensive relief package by the Trump administration [23].

While it is important to understand the breadth and depth of the impact of COVID-19 for building future resilience to public health crises [24, 25], few studies have reported empirical evidence about the impact of COVID-19 on FI in the USA [9, 26]. In addition to the inability to provide nutritious, affordable, available, and acceptable foods for

a household, FI is associated with multiple adverse health outcomes, such as diabetes mellitus, hypertension, cardiovascular disease, depression, and increased risk of mortality [26]. With the continued threat of the COVID-19 pandemic, worsening economic conditions and financial instability adversely impact FI households [27] and BIPOC [9, 28].

Large metropolitan areas have great variability in terms of policies that can influence FI and health outcomes for residents. Two of the largest cities in the USA—Chicago and New York City (NYC)—have different welfare-oriented policies in place that may influence differences in FI outcomes. For example, pre-COVID-19, NYC’s safety net structure was heavily reliant on human services nonprofit organizations that, since the pandemic, have experienced large budget decreases from a lack of government funding [29]. Meanwhile, Chicago’s pre-COVID-19 support is reliant on federal and state welfare programs, such as SNAP and the Healthy Hunger-Free Kids Act of 2010 (implemented in Chicago Public Schools [CPS]), all of which received continuous support during the pandemic. The city of Chicago also partnered with community nonprofit organizations for food distribution, and although resources were available, social distancing and business closures made it difficult to access [30].

Leveraging the SDOH framework [6] in combination with the safety net response to COVID-19, our study examines FI in Chicago and in NYC [23, 31–35]. The aims of this paper are to (1) report and interpret the impacts of COVID-19 on BIPOC FI households in the greater Chicago and NYC metropolitan areas and (2) discuss how these findings reflect differing urban contexts and safety net policies for the purpose of narrowing and eliminating disparities in FI.

## Methodology

### Study Design

Our exploratory study began early in the pandemic. We recognized the need to collect data quickly to identify the early impacts of COVID-19 on FI for BIPOC across geographies and populations. As such, our study contributes to the efforts of a larger national collaborative, known as the National Food Access and COVID Research Team (NFACT). This group developed a survey to evaluate the early and ongoing impacts of COVID-19 on food security. That survey relies on the USDA Six-Item Food Security Module to generate a comparable measure of FI [10]. As of August 2020, the NFACT survey was administered across 18 sites and 15 states, including a national poll [19].

The Chicago and NYC studies adapted the NFACT survey to fit our respective contexts. The research team applied the SDOH Framework, with new measures on access to healthcare and mental health, among others [36–38], from a previously

validated survey [26]. Our adaptations included shortening the survey administration time by streamlining the language and eliminating most comment fields, and adding health measures such as access to health care, mental health status, physical health status, and high risk medical conditions for COVID-19.

Our analysis examined datasets for Chicago and NYC separately. Both were collected using a similar survey and methodology. We did not merge the data or attempt to draw statistical comparisons between the cities. The Chicago survey covered the Chicago Metropolitan Statistical Area (Cook, DeKalb, DuPage, Grundy, Kane, Kankakee, Kendall, Lake, McHenry, and Will Counties in Illinois; and Lake, Newton, and Porter Counties in Indiana). The NYC survey included NYC proper (Manhattan County [NYC], Kings County [Brooklyn], Queens County [Queens], Richmond County [Staten Island], and Bronx County [Bronx]) and surrounding Hudson and Westchester Counties in New York, Bergen County in New Jersey, and Fairfield County in Connecticut.

We used a nested quota sampling design to meet specific targets for race, ethnicity, income, and education. Estimating outcomes for BIPOC in public health research is crucial and oversampling is a way to deliver more accurate estimates than what can be obtained from comparisons to the general population [39]. We oversampled in both cities using a similar design to capture self-reported low-income populations (less than \$25,000 annual income before 2019 taxes) (50% Chicago, 50% NYC), Black (50% Chicago, 40% NYC), Native American (10% NYC), Hispanic (50% Chicago, 40% NYC), and those with a high school education or less (50% Chicago, 50% NYC). It is important to note that in our recently published NFACT multisite paper, three other studies also oversampled for BIPOC populations [19].

Both surveys used a cross-sectional design and were conducted independently at a single data collection time point during the summer of 2020. Respondents were asked about perceived differences in their state of living across two different time periods. Specifically, we asked participants to make a self-assessment of their state *before COVID-19* versus their current state in real time *since COVID-19*. All “before COVID-19” data were retrospective recalls by respondents at the same time they responded to items about “since COVID-19.” The start of the coronavirus outbreak was defined as March 2020. Responses to “before COVID-19” included the 12 months prior to March 2020, while “since COVID-19” included everything after the March 2020 onset of COVID-19 to the time of the survey.

Participants were recruited from a web-based consumer panel and screened based on age (18 and over), race, ethnicity, county of residence, income, and education levels [36]. Respondents were asked to provide information about their household which included all individuals who lived with them. Only one respondent per household participated. The consumer panel solicited participation from registered members and provided

compensation for participation. Subsample quotas were achieved by targeting solicitations to members who met the demographic and socioeconomic criteria. Final de-identified datasets were delivered to the research team.

## Variables

### Food Security

We utilized the United States Department of Agriculture (USDA) Six-Item validated Food Security Module to measure FI (outcome) before COVID-19 and since COVID-19. The Six-Item Short Form [10] was adapted to ask about the time period both “in the year before the coronavirus outbreak” and “since the coronavirus outbreak,” defined in the survey instrument as “before COVID-19” and “since COVID-19,” respectively (Appendix 17). Scoring and classification used established procedures from the USDA Food Security Module (Appendix 17). According to the USDA, for reporting purposes a raw score of 0–1 is described as “food secure,” and the two categories “low food security” (2–4) and “very low food security” (5–6) in combination are referred to as FI [10]. The measure was used without modifications in the univariate analysis and represented as three categories: “food secure” (0–1), “low food security” (2–4), and “very low food security” (5–6). In the bivariate and multivariate analyses, food security was re-coded as a binary categorical variable where 0 corresponds to “food secure” and 1 corresponds to “FI.”

### Household Determinants

This category has two variables: household income and household with children. Household income captures all income streams for the household to which the respondent belongs. Household income was categorized into seven sub-categories, where 0 corresponds to “Less than \$12,000 per year” and 6 corresponds to “\$125,000 or greater per year.”

Respondents were asked to report the number of persons less than 18 years old living in their households. This variable was re-coded into a binary categorical variable where 0 corresponds to “No children living in the household” and 1 corresponds to “Children are living in the household.”

### Individual Determinants

This category represents the respondent’s physical and mental health, in addition to their access to healthcare services. Respondents self-reported the presence of a health condition or multiple health conditions, including cancer, hypertension, diabetes, chronic respiratory disease, rheumatological disease, and cardiovascular disease. This variable was re-coded into a binary categorical variable, where 0 corresponds to “No health condition” and 1 corresponds to “Health condition present.” These specific chronic health conditions are a health burden, physically, mentally, and economically. These health

conditions place individuals at a greater risk for developing serious illness when contracting COVID-19 [40].

Anxiety and depression were measured using the GAD-2 [41] and PHQ-2 [42] scales, respectively. Both screening tests use a score scale from 0 to 6. If a respondent's score is higher than 3 (optimal cut point), the test is considered positive (positive GAD-2 and/or PHQ-2) and the respondent is at higher risk of having either anxiety or depression, respectively. Accordingly, these variables were coded as 0 which corresponds to "Negative" and 1 which corresponds to "Positive."

Health insurance status was categorized into three subcategories, where 0 corresponds to "Private health insurance," 1 corresponds to "Public health insurance," and 2 corresponds to "No health insurance."

This category of variables also represents the respondents' self-identified demographics and educational attainment. Participants' demographics consist of age, gender, race, and ethnicity. Age was categorized into three groups where 0 corresponds to ages "18 to 39," 1 corresponds to ages "40 to 55," and 2 corresponds to "56 years old and above."

Gender had five categories: "Female," "Male," "Non-binary," "Transgender," and "Other." The gender variable was re-coded to a binary categorical variable where 0 corresponds to "Male" and 1 corresponds to "Female" in the bivariate and multivariate analyses. Other subcategories of gender were omitted from these analyses due to very low statistical power.

Race and ethnicity were re-coded into two categories. The first category has two subcategories, where 0 corresponds to "Non-Hispanic White" and 1 corresponds to "Black, Indigenous, People Of Color (BIPOC)." The second category has two subcategories, where 0 corresponds to "non-Hispanic" and 1 corresponds to "Hispanic."

Respondents' education was re-coded into three categories based on the level of their educational attainment in the statistical analyses. Respondents who received education after bachelor's level were coded as 0. Those who attained education in a college (some college education, or associate degree) or a university degree (bachelor degree) were coded as 1. Finally, respondents who obtained education up to a high school level were coded as 2.

## Statistical Analysis

Descriptive analysis was conducted to explore the frequencies of the USDA Six-Item validated Food Security Module. The independent variables were treated as categorical variables (nominal or ordinal) and examined using frequencies. The mode was calculated as a measure of central tendency and dispersion. A McNemar's test was conducted to assess the statistically significant change in the proportions of food security status before COVID-19 and since COVID-19. Only respondents who answered all USDA Six-Item questions for before and since COVID-19 were included in the test (matched pairs pre-post test). Bivariate chi-square tests were conducted to examine the differences in FI

prevalence when stratified by the indicator variables. To consider the results of the McNemar's or chi-square tests to be statistically significant, the  $p$ -value must be less than 0.05.

The multivariate binary logistic regression model was developed using the SDOH framework. Our model includes variables for four of the five social-economic indicator categories: (1) economic stability: household income range; (2) access to quality education: education level; (3) access to quality health-care: presence of a health condition, anxiety screen, depression screen, and health insurance status; and (4) social and community context: children in the household, age, gender, race, and ethnicity. We did not analyze variables for the neighborhood and built environment SDOH category [6]. The multivariate logistic regression model was applied to examine the associations between FI and all of the independent variables at the same time. The multivariate regression models' results were reported as adjusted odds ratios. The confidence intervals (CI) were set at 95% which corresponds to a  $p$ -value of 5%. To consider an association significant, the reported ratios must have had a  $p$ -value  $< 0.05$ . The area under the receiver operating characteristic (ROC) curve was calculated to evaluate how well the adjusted binary logistic regression models classify positive and negative food security status outcomes at all possible cutoff points. The analysis was performed with Stata/BE 17.0.

## Results

### Descriptives

The characteristics and demographics of individual respondents and households are shown in Table 1. The descriptives relevant to the sampling design include income, race, ethnicity, and education. A similar percentage of households reported an annual income of less than \$25,000 in Chicago and NYC (31.4% and 34.7%, respectively). Most respondents were 18 to 39 years old in Chicago and NYC (70%, 69.5%, respectively). The gender of respondents in Chicago was 46.2% female and 52.1% male, 0.9% non-binary, 0.7% transgender, and 0.1% other. In NYC, 52.6% of respondents were female, 45.5% male, 0.8% non-binary, 0.9% transgender, and 0.2% other. Most respondents in Chicago and NYC identified as BIPOC (74.4% and 92% respectively). Both Chicago and NYC had a similar percentage of respondents who identified as Hispanic (36.6% and 36.2% respectively). Respondents who have reported having up to a high school education in Chicago and NYC were 29.1% and 29.7% respectively.

Descriptives relevant to SDOH include the presence of children in the household, presence of a health condition, anxiety, depression, and health insurance status. In Chicago, 55.7% of respondents reported having children living in their household, and in NYC it was 60.4%. Respondents who reported a health condition were 32.9% in Chicago, and 51.2% in NYC. Most Chicago respondents screened positive

**Table 1** Descriptive characteristics

Indicator	Chicago ( <i>n</i> =680)	NYC ( <i>n</i> =525)
Household income range, 2019—no. (%)		
Less than \$12,999 per year	122 (17.9)	108 (20.6)
\$13,000–\$24,999 per year	92 (13.5)	74 (14.1)
\$25,000–\$49,999 per year	161 (23.7)	111 (21.1)
\$50,000–\$74,999 per year	134 (19.7)	85 (16.2)
\$75,000–\$99,999 per year	88 (12.9)	46 (8.8)
\$100,000–\$124,999 per year	45 (6.6)	36 (6.9)
\$125,000 or greater per year	38 (5.6)	65 (12.4)
Children in the household—no. (%)		
No	301 (44.3)	208 (39.6)
Yes	379 (55.7)	317 (60.4)
Health condition—no. (%)		
No	456 (67.1)	256 (48.8)
Yes	224 (32.9)	269 (51.2)
Anxiety screen—no. (%)		
Negative	199 (33.4)	326 (62.1)
Positive	397 (66.6)	199 (37.9)
Depression screen—no. (%)		
Negative	199 (33.3)	295 (56.2)
Positive	398 (66.7)	230 (43.8)
Health insurance—no. (%)		
Private insurance	285 (41.9)	196 (37.3)
Public insurance	298 (43.8)	259 (49.4)
No insurance	97 (14.3)	70 (13.3)
Age—no. (%)		
18–39	476 (70)	365 (69.5)
40–55	144 (21.2)	105 (20)
56+	60 (8.8)	55 (10.5)
Gender—no. (%)		
Male	354 (52.1)	239 (45.5)
Female	314 (46.2)	276 (52.6)
Transgender	5 (0.7)	5 (0.9)
Non-Binary	6 (0.9)	4 (0.8)
Other	1 (0.1)	1 (0.2)
Race/ethnicity—no. (%)		
Non-Hispanic White	174 (25.6)	42 (8)
BIPOC <sup>†</sup>	506 (74.4)	483 (92)
Non-Hispanic	431 (63.4)	335 (63.8)
Hispanic	249 (36.6)	190 (36.2)
Education—no. (%)		
Graduate and postgraduate	65 (9.6)	67 (12.8)
College	417 (62.3)	302 (57.5)
Up to high school	198 (29.1)	156 (29.7)

<sup>†</sup>Black, Indigenous, and People Of Color and reference is non-Hispanic White

for anxiety and depression (66.6% and 66.7%, respectively), while positive screens for anxiety and depression in NYC were 37.9% and 43.8%, respectively. A similar percentage of respondents reported having a type of health insurance in Chicago and NYC (85.7% and 86.7% respectively).

Food security assessments before and since COVID-19 in Chicago and NYC are shown in Table 2. Since COVID-19, the percentage of households classified as food secure (score 0–1) declined and FI households (score 2–6) increased in both cities. In Chicago, 44.8% of households were FI since

COVID-19, compared to 41% before. In NYC, the percentage of FI households since COVID-19 was 66.8%, compared to 57.8% before. A greater percentage of households in Chicago and NYC reported very low food security since COVID-19 (20.6% and 28.7%, respectively) compared to before (14.6% and 22.7%, respectively).

## Bivariate Analyses

Table 3 shows the food security status (food secure vs FI) of matched-pairs (before COVID-19 and since COVID-19) respondents in Chicago and NYC. We classified FI households that completed all Food Security Index questions for before and since COVID-19 into consistently FI (CFI) and newly FI (NFI) categories. Households that were FI before and since COVID-19 were categorized as CFI. Households were categorized as NFI when they were food secure before and FI since COVID-19 [26]. NFI is significant because it demonstrates the loss of food security since COVID-19. In Chicago, the number of CFI households was 200 (80%) and that of NFI households was 50 (20%). Similarly, in NYC, the number of CFI households was 272 (79.5%) and that of NFI households was 70 (20.5%).

Table 4 shows the FI status of respondents (matched-pairs) in Chicago and NYC before and since COVID-19. In Chicago, the difference in proportions of FI was 3.99% higher ( $p < 0.05$ , 95% CI: 0.01–0.07) since COVID-19 compared to before COVID-19. Likewise in NYC, the difference in proportions of FI was higher ( $p < 0.001$ , 95% CI: 0.05–0.13) since COVID-19 when compared with before COVID-19.

Chi-square analyses were conducted to test if there were differences in prevalence of FI when stratified by the indicators before and since COVID-19 in Chicago and NYC. There was a significant difference in the prevalence of FI between the subcategories of household income, anxiety and depression screens, health insurance, age, race, and education in Chicago before COVID-19 (Appendix 6). After COVID-19, FI prevalence remained significantly different across the previous variables in addition to children in a household and ethnicity (Appendix 7). In NYC, there was a

**Table 3** Food security status for respondents before and since COVID-19 in Chicago and NYC

Chicago	Since COVID-19		Total
	Food secure	FI	
Before COVID-19			
Food secure	300 (91.7)	50 (20)	350
Food insecure	27 (8.3)	200 (80)	227
Total	327	250	577
McNemar's $\chi^2(1) = 6.8$ , exact McNemar $p < 0.05$ , difference in proportions = 0.0399 (95% CI = 0.01–0.07)			
NYC	Since COVID-19		Total
	Food secure	FI	
Before COVID-19			
Food secure	146 (85.9)	70 (20.5)	216
Food insecure	24 (14.1)	272 (79.5)	296
Total	170	342	512
McNemar's $\chi^2(1) = 22.5$ , exact McNemar $p < 0.001$ , difference in proportions = 0.0898 (95% CI = 0.05–0.13)			

significant difference in the prevalence of FI across children in a household, health condition, anxiety, depression, health insurance, age, gender, race, and ethnicity before COVID-19 (Appendix 8). Since COVID-19, FI prevalence remained significant for the previous variables except for age, race, and ethnicity (Appendix 9).

## Multivariate Logistic Regression

### Before COVID-19

Table 5 shows the multivariate binary logistic regression analyses before and since COVID-19 in Chicago and NYC. In Chicago, the adjusted model showed that the association of income was significant across almost all subcategories. When controlling for all covariates, the higher the income subcategory, the lower the odds to have reported FI. As such, income subcategory \$125,000 or above had the least odds of reported FI (aOR = 0.11, 95% CI: 0.03–0.41). In NYC, all income subcategories except one (\$100,000–\$124,999) were significantly associated with FI after adjustment for covariates.

**Table 2** Food security scores in Chicago and NYC before and since COVID-19

Chicago	Before COVID-19	Since COVID-19
	Food security score	
0–1: Food secure—no. (%)	356 (59)	335 (55.2)
2–4: Low food security—no. (%)	159 (26.4)	147 (24.2)
5–6: Very low food security—no. (%)	88 (14.6)	125 (20.6)
Total—no. (%)	603 (100)	607 (100)
NYC	Before COVID-19	Since COVID-19
	Food security score	
0–1: Food secure—no. (%)	216 (42.2)	170 (33.2)
2–4: Low food security—no. (%)	180 (35.1)	195 (38.1)
5–6: Very low food security—no. (%)	116 (22.7)	147 (28.7)
Total—no. (%)	512 (100)	512 (100)

**Table 4** Before and since COVID-19 FI of matched pairs in Chicago and NYC

FI	Before COVID-19	Since COVID-19	<i>N</i>	Difference in proportions	95% CI
Chicago—no. (%)	227 (39.34%)	250 (43.33%)	577	3.99% *	0.01–0.07
NYC—no. (%)	296 (57.81%)	342 (66.79%)	512	8.98% ***	0.05–0.13

\*Exact McNemar  $p < 0.05$ , \*\*exact McNemar  $p < 0.01$ , \*\*\*exact McNemar  $p < 0.001$

In NYC, households with children had more than two times the odds to have reported FI when compared to households without children (aOR=2.62, 95% CI: 1.68–4.1). Respondents with health conditions had higher odds to have reported FI in Chicago and NYC (aOR=1.76, 95% CI: 1.08–2.85, aOR=1.95, 95% CI: 1.28–2.97, respectively). People with self-reported depression had greater odds to have reported FI in Chicago and NYC (aOR=1.9, 95% CI: 1.08–3.34, aOR=2.37, 95% CI: 1.45–3.87, respectively). Chicago respondents who had public health insurance had lower odds to have reported FI compared to respondents who had private health insurance (aOR=0.56, 95% CI: 0.34–0.93). In NYC, the respondent's type of health insurance had no significant association with FI. Respondents in Chicago over 56 years of age had fewer odds to have reported FI compared to those 18 to 39 years old (aOR=0.34, 95% CI: 0.15–0.8). Females in NYC had lower odds to have reported FI (aOR=0.59, 95% CI: 0.38–0.91) compared to males. Respondents in NYC who identified as Hispanic had fewer odds to have reported FI compared to non-Hispanic respondents (aOR=0.44, 95% CI: 0.29–0.68). Educational attainment showed no association with FI in Chicago or NYC.

### Since COVID-19

As shown in Table 5, income subcategories either lost their significant association with FI or had their association significance reduced in Chicago and NYC. Most respondents of different income subcategories had their reported FI adjusted odds reduced since COVID compared to before. Income subcategories ranging from \$50,000 to \$124,999 per year lost their significant association among NYC respondents and remained significant among Chicago respondents. In general, income subcategories remained significantly associated with lower adjusted odds of FI with various degrees in Chicago and NYC.

Households with children had higher odds to have reported FI in Chicago and NYC (aOR=1.78, 95% CI: 1.15–2.76, aOR=2.35, 95% CI: 1.48–3.72, respectively). Among respondents who reported living with chronic health conditions, there was an increase in the odds of reported FI since COVID-19. Respondents living with health conditions had higher odds to have reported FI in Chicago and NYC (aOR=1.97, 95% CI: 1.23–3.15, aOR=2.2, 95% CI: 1.43–3.39, respectively). Chicago respondents with a positive anxiety screen had higher odds to have reported FI (aOR=1.97, 95% CI: 1.23–3.15). Respondents with a positive depression screen in NYC had more than two times the odds to have reported FI (aOR=2.52, 95% CI:

1.52–4.18). Compared to respondents with private health insurance, NYC respondents with public health insurance or no health insurance were at increased odds to have reported FI (aOR=2, 95% CI: 1.26–3.18, aOR=2.22, 95% CI: 1.05–4.73, respectively). Having health insurance and the type of health insurance were significantly associated with FI in NYC since COVID-19 compared to before COVID-19. In Chicago, this factor lost its significant association with FI since COVID-19. Since COVID-19, respondents in Chicago over 56 years of age had fewer odds to have reported FI compared to those 18 to 39 years old (aOR=0.39, 95% CI: 0.17–0.9). Females in NYC had lower odds to have reported FI (aOR=0.6, 95% CI: 0.38–0.93). Being female in Chicago was not significantly associated with FI. NYC respondents who identified as Hispanic no longer had a significant association with lower odds of reported FI since COVID-19 compared to before COVID-19. Educational attainment was not significantly associated with FI in either city since COVID-19.

### Discussion

Overall, the results of the analyses for Chicago and NYC returned similar trends and associations. In both cities, FI increased since COVID-19, with minor deviations for unique scenarios in either Chicago or NYC. Increases in FI for NYC and Chicago have been reported elsewhere [43–45]. This is unsurprising considering the intensity with which the COVID-19 pandemic affected U.S. urban areas [46]. Chicago and NYC are two of the three largest metropolitan areas in the USA and urban research has confirmed the vulnerability of large cities to pandemics and infectious diseases [47]. However, our findings are higher compared to other sources, likely because we oversampled populations previously known to experience higher rates of FI [8, 16, 17].

Our study reports that, before COVID-19, income was significantly associated across nearly all subcategories across both cities, with higher income as a protective factor against FI in Chicago. Here, we used income as an indicator variable for economic stability in the Healthy People 2030 goals, as is common in the SDOH framework [48]. In the examined time period since COVID-19, high income subcategories did not appear to be protective against FI in NYC. Findings also reveal income's relevance to FI as low-income populations saw higher odds of FI and, since COVID-19, the protective effects of income were reduced or eliminated in both cities [49].

**Table 5** Multivariate binary logistic regression

Indicators	FI before COVID-19 aOR (95% CI)		FI since COVID-19 aOR (95% CI)	
	Chicago ( <i>n</i> = 489)	NYC ( <i>n</i> = 502)	Chicago ( <i>n</i> = 497)	NYC ( <i>n</i> = 502)
Household's income range, 2019				
Less than \$12,999 per year	-	-	-	-
\$13,000–\$24,999 per year	0.58 (0.28–1.23)	0.44 (0.21–0.91) *	0.97 (0.46–2.05)	0.75 (0.35–1.6)
\$25,000–\$49,999 per year	0.33 (0.17–0.65) **	0.33 (0.17–0.63) **	0.54 (0.28–1.06)	0.43 (0.22–0.84) *
\$50,000–\$74,999 per year	0.24 (0.11–0.49) ***	0.41 (0.2–0.86) *	0.43 (0.21–0.88) *	0.68 (0.32–1.43)
\$75,000–\$99,999 per year	0.34 (0.16–0.74) **	0.31 (0.13–0.75) **	0.4 (0.18–0.88) *	0.55 (0.22–1.37)
\$100,000–\$124,999 per year	0.23 (0.08–0.63) **	0.47 (0.17–1.29)	0.28 (0.1–0.74) *	0.46 (0.16–1.27)
\$125,000 or greater per year	0.11 (0.03–0.41) **	0.25 (0.11–0.61) **	0.18 (0.05–0.63) **	0.3 (0.12–0.71) **
Children in the household				
No	-	-	-	-
Yes	1.22 (0.78–1.93)	2.62 (1.68–4.1) ***	1.78 (1.15–2.76) **	2.35 (1.48–3.72) ***
Health condition				
No	-	-	-	-
Yes	1.76 (1.08–2.85) *	1.95 (1.28–2.97) **	1.97 (1.23–3.15) **	2.2 (1.43–3.39) ***
Anxiety screen				
Negative	-	-	-	-
Positive	1.58 (0.9–2.76)	1.11 (0.67–1.84)	1.97 (1.15–3.38) *	1.27 (0.76–2.14)
Depression screen				
Negative	-	-	-	-
Positive	1.9 (1.08–3.34) *	2.37 (1.45–3.87) **	1.62 (0.94–2.78)	2.52 (1.52–4.18) ***
Health insurance				
Private health insurance	-	-	-	-
Public health insurance	0.56 (0.34–0.93) *	1.24 (0.79–1.95)	0.76 (0.46–1.24)	2 (1.26–3.18) **
No health insurance	1.09 (0.59–2.04)	1.56 (0.76–3.2)	1.27 (0.68–2.37)	2.22 (1.05–4.73) *
Age				
18–39	-	-	-	-
40–55	0.6 (0.34–1.05)	0.65 (0.38–1.11)	0.63 (0.37–1.07)	0.74 (0.43–1.28)
56+	0.34 (0.15–0.8) *	0.56 (0.27–1.16)	0.39 (0.17–0.9) *	0.76 (0.37–1.58)
Gender				
Male	-	-	-	-
Female	1.16 (0.75–1.78)	0.59 (0.38–0.91) *	1.15 (0.75–1.74)	0.6 (0.38–0.93) *
Race/ethnicity				
Non-Hispanic White	-	-	-	-
BIPOC <sup>†</sup>	1.28 (0.7–2.31)	0.54 (0.22–1.37)	1.67 (0.93–2.98)	0.87 (0.36–2.06)
Non-Hispanic	-	-	-	-
Hispanic	0.82 (0.5–1.35)	0.44 (0.29–0.68) ***	0.97 (0.6–1.56)	1.05 (0.67–1.64)
Education				
Graduate and postgraduate	-	-	-	-
College	1.48 (0.51–2.61)	1.11 (0.56–2.23)	0.86 (0.41–1.79)	0.87 (0.43–2.17)
Up to high school	1.5 (0.62–3.64)	1.1 (0.5–2.42)	0.88 (0.39–1.99)	0.97 (0.43–2.17)
Area Under ROC curve	0.7634	0.7685	0.7568	0.7548

aOR adjusted odds ratio. \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ . <sup>†</sup>Black, Indigenous, and People Of Color

Our results reported households with children under 18 years of age had higher odds of being FI in both Chicago and NYC. These results support other research that finds households with children experienced higher odds of FI than those without children [50]. A possible common explanation across the two cities

could be the sudden loss of free school meals with school district closures. With schools closed, families would be expected to experience an increase in spending on food to account for any meals provided by the school, across each school-aged child in the household. For instance, there are 337,664 children attending



642 K-12 public schools in Chicago and 1.1 million children attending 1866 K-12 public schools in NYC [51]. In NYC public schools, 73 percent of 1.1 million students experience poverty and therefore qualify for free or reduced lunches [52].

Similarly, respondents living with chronic health conditions had higher odds of being FI in Chicago and NYC. Our findings corroborate with the literature indicating that people who live in FI households often face difficulties in managing diet-related chronic conditions, including being on a limited budget and restricted healthcare access [53]. These conditions also place them at a higher risk of COVID-19 infections and death, such as obesity, diabetes mellitus, hypertension, and heart disease [40]. Again, respondents living with chronic health conditions had higher odds of being FI since COVID-19 began, understandably, given the sudden and drastic decline in access to health care due to the immediate infrastructural and institutional shutdowns [2].

Since COVID-19, FI has been identified as a major predictor of depression, anxiety, and high stress among low-income Americans [20, 21]. Even prior to the pandemic, FI has been a well-known predictor for mental health factors, including major depression and anxiety [54]. However, it should be noted that there is a bidirectionality to the relationship between FI and mental health, and therefore, we cannot infer causality [55]. Depression had two times greater odds to be associated with FI in NYC and was associated with higher FI in Chicago. Research shows that financial insecurity and FI create feelings of sadness, hopelessness, shame, guilt, and anxiety [56]. It is possible that social isolation since COVID-19 exacerbated these feelings and increased depression and/or depression symptoms in individuals [2].

Furthermore, Chicago respondents who had public health insurance had fewer odds to be FI, while in NYC, the type of health insurance a respondent had showed no significant association with FI. This could be due to differences between access and affordability of health insurance in both cities, including public health insurance. Our findings differ from other studies, in particular research that shows Medicare enrollees to have higher odds to experience FI [57].

Age was inversely associated with the odds of being FI before COVID-19 in both cities, but age was only significant in Chicago since the onset of COVID-19. It is important to note that the study is limited in evaluating the relationship between age and FI, since age was measured as a categorical variable with three categories, and age of the participants is not representative of the population. Overall, our results confirm that age is a significant predictor for FI in Chicago, but there was no significance in NYC.

FI is most prevalent among females in a household with children [54]. Females had greater odds of being FI before COVID-19 began in NYC potentially due to the high cost of living, if women are assumed to earn lower incomes and bear greater care responsibilities [58, 59]. Female caregivers with children may also have gained access to school meal programs and other related programs before, but not early during, the COVID-19 pandemic. At the start of the pandemic, all Chicago Public School (CPS) students were eligible

to receive meals. CPS increased food accessibility for children and families by providing “grab and go” family food packages that contained up to 3 days’ worth of food for breakfast and dinner [60]. In addition, CPS students received up to \$450 distributed through a P-EBT card to meet food needs, increasing food accessibility [61]. The confluence of NYC’s higher population density, higher cost of living, greater relative poverty, and the public’s higher dependence on public transportation and therefore inability to avoid crowds may help explain some of the greater disparate effects across gender, caused by the early first wave of the pandemic when NYC was the epicenter [62]. However, further studies are needed with a larger sample size, to make such assessments.

Findings of earlier studies in Chicago support our findings that, pre-COVID, BIPOC households in Chicago had higher odds of experiencing FI [26, 63]. Notably, a larger proportion of BIPOC households, not Hispanic households, in NYC appeared to be better protected from FI since COVID-19 than before the pandemic. This pattern was not observed among BIPOC in Chicago. Because BIPOC households in NYC had differing results than the Hispanic population in NYC, as well as both BIPOC and Hispanic households in Chicago, the data suggests that we need a closer look at the local policies and programs in place as well as other potential factors influencing FI protections for historically marginalized communities in both cities [64]. Using slightly different nested quotas in the sampling designs for NYC and Chicago, as well as the different proportion of White respondents in the two cities, could have contributed to different outcomes for BIPOC and Hispanic respondents. It should be noted that our study was not powered to detect differences across specific race or ethnicity groups, except for Hispanic, despite our intention to oversample households affected by FI.

Finally, educational attainment served as a proxy variable for quality access to education in the SDOH framework [6]. While not unimportant to conversations about economic instability, our findings showed that educational attainment had no significant association with self-reported FI status, when comparing the periods before COVID-19 and since the onset of COVID-19 in March 2020.

## Conclusion

Our study found that FI increased since COVID-19 in both Chicago and NYC for BIPOC populations known to be vulnerable to FI. While FI increased since COVID-19 in both Chicago and NYC, SDOH factors across the two cities did not show substantially different effects on FI since COVID-19, aside from specific cases such as females and Hispanics in NYC. Our study was exploratory in nature, conducted in the early months of the COVID-19 pandemic, cross-sectional in design, and oversampled for BIPOC.

These urban centers are densely populated and often experience “staggering income inequalities” among a

heterogeneous population with a mix of diverse races, cultures, and backgrounds [62, 65]. Population density in NYC (26,403 people per square mile) is over 2.2 times greater than Chicago (11,783 people per square mile). Manhattan alone, the borough with the highest population density at more than 66,000 people per square mile, is 5.6 times greater than Chicago [66]. In turn, the dense social composition of NYC impacted people across all income brackets, helping to explain that in our study, high income was not a protective factor in NYC. Beyond general population density, overcrowding has been linked to COVID-19 risks of exposure, regardless of geography [67].

Moreover, there may be wider social and economic disparities in NYC, as evidenced by higher costs of living and greater relative poverty. In fact, NYC has continued to be reported as being the most expensive city in the USA, compared to other large American cities such as San Francisco, Boston, Chicago, and Los Angeles [68]. In NYC, higher costs of living (i.e., out-of-pocket rent expenses) are often associated with not only lower levels of economic achievement, but also worse self-reported health conditions and a higher likelihood of postponing medical services for financial reasons [69]. In NYC, the cost of living index data is 1.6 times higher than Chicago: based on a Composite Index of 100%, 116.9% for Chicago, and 185.8% for NYC (combined average of Manhattan [216.7%], Brooklyn [181.7%], and Queens [159%]) [70]. Despite these differences, we did not find substantial differences in FI before and since COVID-19 for the two cities.

Income inequality was associated with FI before COVID-19 in both cities. However, since COVID-19, increasing annual income was either lost or diminished in its association with FI. Aside from income, employment and access to quality education are components of economic instability within the SDOH framework. Ultimately, employment was not included in this study as income and education have been sufficient proxy variables across COVID-19 FI studies [44, 45, 71]. However, we believe there is a complex relationship surrounding the type and nature of employment that needs future exploration. Access to quality education, through the educational attainment variable, was not significant in our study.

This study shows that beyond income, other structural, social, and health inequities had a greater impact on predicting FI since COVID-19 in both cities. When accounted for, such factors diminished the protective effect of increasing annual income against FI. We recognize the limitations of using income as an indicator of economic standing. Future studies will expand beyond income to discuss variables such as educational attainment, employment status, and types of employment as additional indicators of economic well-being.

Age is a characteristic often linked to or dependent on other factors such as gender, race and ethnicity, and social class, building on what Estes [72] calls an interlocking system of oppression that is interactional in nature. Similar to the conclusions drawn from our BIPOC results, future studies need to be larger

to capture the nature of age, which may have adverse effects on young populations (i.e., teenagers), in addition to any elderly-related results. In order to truly understand the impact of an emergency or crisis on FI, we need to further study the intersectionality of race, ethnicity, gender, and low-income populations.

Our study is useful for understanding how SDOH influence COVID-19's impacts on FI among BIPOC populations in general. While we oversampled for specific race and ethnicity groups, the study was not sufficiently powered to detect differences among groups. Since our study design is cross-sectional, findings indicate associations and cannot determine causality or temporality. Despite the limitations of our study, higher rates of FI were reported for our sample population across both sites. Additionally, similar studies confirm not only the continuation of FI since COVID-19, but also suggest amplified outcomes on households with children as well as widening dietary inequities across low-income and BIPOC households [43–45]. These results underscore the early impact of the pandemic on existing socioeconomic inequities affecting BIPOC populations, as well as the higher prevalence of FI among these communities before the pandemic [26]. Similarly, our transgender, non-binary, and other gender categories did not have sufficient statistical power to be tested as their own category.

As the world rapidly urbanizes, studying urban centers can ultimately unlock the key to future public health solutions [73]. Despite observed differences between Chicago and NYC, the magnitude of the results does not change the overall rise of FI reported in all US cities studied by NFACT publications. Singularly testing each variable for its predictive capacity on FI may have overlooked interlocking influences, also referred to as syndemics theory [74]. As we do more research at the intersection of income, food, and health security, we can discover more commonalities across insecure communities and account for emerging insecure groups.

Future studies should address the intersectionality of demographic characteristics on outcomes like FI instead of relying on the predictive power of any single factor. Further evidence on the drivers of FI, and how we can predict and combat further increases in FI, can enable us to better alleviate the issue via policy solutions. From a policy perspective, Chicago continues to increase accessibility through the new "Food Equity Agenda," a multi-year project to transform the food system in Chicago. The goals of the agenda are to eliminate barriers for food pantry expansions, eliminate barriers to urban farming, market nutrition programs and benefits, support local BIPOC food business, and increase funding for BIPOC food producers and businesses [75].

The results have multifaceted, structural policy implications insofar as income does not necessarily indicate food security,

which could question the means-tested approach of social policies in the USA. For example, along with demographic and employment information, applications for programs such as SNAP require disclosure of income. As applications for benefits become more user-friendly, accounting for categories like chronic health conditions or health insurance status can better address issues of FI. This study corroborates other recent publications that call for a paradigmatic shift in our policies by

taking a human rights framework to address upstream social and economic determinants of health that create health disparities to eliminate FI [26]. Moreover, further studies that include food security as a SDOH are necessary to inform targeted improvements in social protection policies and programs.

## Appendix 1 USDA Six-Item Food Security Questionnaire and Scoring and Classification

### Six-Item Food Security Module [10]

	Before COVID-19				Before COVID-19			
	Often true	Sometimes true	Never true	Don't know	Often true	Sometimes true	Never true	Don't know
The food that my household bought just didn't last, and I/we didn't have money to get more								
I/we couldn't afford to eat balanced meals								
Did you or others in your household ever CUT the size of meals or SKIP meals because there wasn't enough money for food?*								
Did you ever eat less than you felt you should because there wasn't enough money for food?								
Were you ever hungry but didn't eat because there wasn't enough money for food?								

\*If "Often True" is selected on "Did you or others in your household ever CUT the size of meals or SKIP meals because there wasn't enough money for food?"

	Before COVID-19				Since COVID-19			
	Almost every month	Some months but not every month	In only 1 or 2 months	Don't know	Almost every month	Some months but not every month	In only 1 or 2 months	Don't know
How often did this happen?								

## Scoring and Classification [10]

Each response of “often true,” “sometimes true,” “almost every month,” and “some months but not every month” is coded as affirmative (yes). The sum of affirmative responses to the six questions in the module is the household’s raw score on the scale.

Household food security status is assigned as follows:

Raw score 0–1—“Food Secure”: High or marginal food security (raw score 1 may be considered marginal food security, but a large proportion of households that would be

measured as having marginal food security using the household or adult scale will have raw score zero on the six-item scale)

Raw score 2–4—Low food security

Raw score 5–6—Very low food security

For some reporting purposes, the food security status of households with raw score 0–1 is described as food secure and the two categories “low food security” and “very low food security” in combination are referred to as FI.

## Appendix 2

**Table 6** Chi-square analysis of food security status in Chicago before COVID-19

Indicator	Food secure	FI	$\chi^2$	<i>p</i> -value
Household income range, 2019—no. (%)			69.03	0.000
Less than \$12,999 per year	30 (29.4)	72 (70.6)		
\$13,000–\$24,999 per year	34 (45.9)	40 (54.1)		
\$25,000–\$49,999 per year	86 (60.6)	56 (39.4)		
\$50,000–\$74,999 per year	83 (69.2)	37 (30.8)		
\$75,000–\$99,999 per year	59 (67.8)	28 (32.2)		
\$100,000–\$124,999 per year	30 (75)	10 (25)		
\$125,000 or greater per year	34 (89.5)	4 (10.5)		
Children in the household—no. (%)			2.25	0.13
No	169 (62.4)	102 (37.6)		
Yes	187 (56.3)	145 (43.7)		
Health condition—no. (%)			0.53	0.818
No	241 (59.4)	165 (40.6)		
Yes	115 (58.4)	82 (41.6)		
Anxiety screen—no. (%)			19.77	0.000
Negative	135 (74.6)	46 (25.4)		
Positive	190 (54.8)	157 (45.2)		
Depression screen—no. (%)			24.99	0.000
Negative	138 (76.7)	42 (23.3)		
Positive	191 (54.4)	160 (45.6)		
Health insurance—no. (%)			41.77	0.000
Private insurance	119 (47.6)	131 (52.4)		
Public insurance	197 (73.5)	71 (26.5)		
No insurance	40 (47.1)	45 (52.9)		
Age—no. (%)			15.97	0.000
18–39	221 (53.6)	191 (46.4)		
40–55	93 (69.4)	41 (30.6)		
56+	42 (73.7)	15 (26.3)		
Gender—no. (%)			1.49	0.222
Male	193 (61.3)	122 (38.7)		
Female	156 (56.3)	121 (43.7)		
Race/ethnicity—no. (%)				
Non-Hispanic White	114 (72.2)	44 (27.8)	15.23	0.000
BIPOC <sup>†</sup>	242 (54.4)	203 (45.6)		
Non-Hispanic	237 (61.2)	150 (38.8)	2.17	0.141
Hispanic	119 (55.1)	97 (44.9)		
Education—no. (%)			10.85	0.004
Graduate and postgraduate	44 (74.6)	15 (25.4)		
College	225 (60.3)	148 (39.7)		
Up to high school	87 (50.9)	84 (49.1)		

<sup>†</sup>Black, Indigenous, and People Of Color and reference is non-Hispanic White

## Appendix 3

**Table 7** Chi-square analysis of food security status in Chicago since COVID-19

Indicator	Food secure	FI	$\chi^2$	<i>p</i> -value
Household income range, 2019—no. (%)			54.66	0.000
Less than \$12,999 per year	33 (33.3)	66 (66.7)		
\$13,000–\$24,999 per year	29 (38.7)	46 (61.3)		
\$25,000–\$49,999 per year	79 (54.1)	67 (45.9)		
\$50,000–\$74,999 per year	73 (59.8)	49 (40.2)		
\$75,000–\$99,999 per year	57 (67.1)	28 (32.9)		
\$100,000–\$124,999 per year	31 (73.8)	11 (26.2)		
\$125,000 or greater per year	33 (86.8)	5 (13.2)		
Children in the household—no. (%)			10.31	0.001
No	168 (62.5)	101 (37.6)		
Yes	167 (49.4)	171 (50.6)		
Health condition—no. (%)			1.03	0.311
No	231 (56.6)	177 (43.4)		
Yes	104 (52.3)	95 (47.7)		
Anxiety screen—no. (%)			30.52	0.000
Negative	133 (74.3)	46 (25.7)		
Positive	176 (49.3)	181 (50.7)		
Depression screen—no. (%)			30.45	0.000
Negative	135 (75.4)	44 (24.6)		
Positive	181 (50.6)	177 (49.4)		
Health insurance—no. (%)			25.36	0.000
Private insurance	118 (46.8)	134 (53.2)		
Public insurance	179 (66.5)	90 (33.5)		
No insurance	38 (44.2)	48 (55.8)		
Age—no. (%)			21.14	0.000
18–39	205 (49)	213 (51)		
40–55	89 (66.9)	44 (33.1)		
56+	41 (73.2)	15 (26.8)		
Gender— no. (%)			1.13	0.288
Male	179 (57)	135 (43)		
Female	148 (52.7)	133 (47.3)		
Race/ethnicity—no. (%)				
Non-Hispanic White	114 (70.8)	47 (29.2)	21.61	0.000
BIPOC <sup>†</sup>	221 (49.5)	225 (50.5)		
Non-Hispanic	235 (60.1)	156 (39.9)	10.72	0.001
Hispanic	100 (46.3)	116 (53.7)		
Education—no. (%)			9.29	0.01
Graduate and postgraduate	43 (68.3)	20 (31.7)		
College	210 (56.8)	160 (43.2)		
Up to high school	82 (47.1)	92 (44.8)		

<sup>†</sup>Black, Indigenous, and People Of Color and reference is non-Hispanic White

## Appendix 4

**Table 8** Chi-square analysis of food security status in NYC before COVID-19

Indicator	Food secure	FI	$\chi^2$	<i>p</i> -value
Household income range, 2019—no. (%)			9.51	0.147
Less than \$12,999 per year	33 (32)	70 (68)		
\$13,000–\$24,999 per year	31 (44.3)	39 (55.7)		
\$25,000–\$49,999 per year	53 (48.6)	56 (51.4)		
\$50,000–\$74,999 per year	37 (43.5)	48 (56.5)		
\$75,000–\$99,999 per year	20 (44.4)	25 (55.6)		
\$100,000–\$124,999 per year	11 (30.6)	25 (69.4)		
\$125,000 or greater per year	31 (4)	33 (51.6)		
Children in the household—no. (%)			31.98	0.000
No	117 (57.4)	87 (42.6)		
Yes	99 (32.1)	209 (67.9)		
Health condition—no. (%)			10.16	0.001
No	122 (49.4)	125 (50.6)		
Yes	94 (35.5)	171 (64.5)		
Anxiety screen—no. (%)			11.33	0.001
Negative	152 (47.9)	165 (52.1)		
Positive	64 (32.8)	131 (67.2)		
Depression screen—no. (%)			29.12	0.000
Negative	151 (52.6)	136 (47.4)		
Positive	65 (28.9)	160 (71.1)		
Health insurance—no. (%)			6.6	0.037
Private insurance	92 (47.7)	101 (52.3)		
Public insurance	105 (41.2)	150 (58.8)		
No insurance	19 (29.7)	45 (70.3)		
Age—no. (%)			8.96	0.011
18–39	136 (38.1)	221 (61.9)		
40–55	51 (49)	53 (51)		
56+	29 (56.9)	22 (43.1)		
Gender—no. (%)			7.878	0.005
Male	82 (35.2)	151 (64.8)		
Female	128 (47.6)	141 (52.4)		
Race/ethnicity				
Non-Hispanic White	8 (19.1)	34 (80.9)	10.04	0.002
BIPOC <sup>†</sup>	208 (44.3)	262 (55.7)		
Non-Hispanic	113 (34.8)	212 (65.2)	20.08	0.000
Hispanic	103 (55.1)	84 (44.9)		
Education			1.37	0.504
Graduate and postgraduate	26 (40.6)	38 (59.4)		
College	132 (44.3)	166 (55.7)		
Up to high school	58 (38.7)	92 (61.3)		

<sup>†</sup>Black, Indigenous, People Of Color and reference is non-Hispanic White

## Appendix 5

**Table 9** Chi-square analysis of food security status in NYC since COVID-19

Indicator	Food secure	FI	$\chi^2$	<i>p</i> -value
Household income range, 2019—no. (%)			9.73	0.137
Less than \$12,999 per year	26 (25.2)	77 (74.8)		
\$13,000–\$24,999 per year	20 (28.6)	50 (71.4)		
\$25,000–\$49,999 per year	42 (38.5)	67 (61.5)		
\$50,000–\$74,999 per year	28 (32.9)	57 (67.1)		
\$75,000–\$99,999 per year	15 (33.3)	30 (66.7)		
\$100,000–\$124,999 per year	10 (27.8)	26 (72.2)		
\$125,000 or greater per year	29 (45.3)	35 (54.7)		
Children in the household—no. (%)			19.89	0.000
No	91 (44.6)	113 (55.4)		
Yes	79 (25.7)	229 (74.4)		
Health condition—no. (%)			15.54	0.000
No	103 (41.7)	144 (58.3)		
Yes	67 (25.3)	198 (74.7)		
Anxiety screen—no. (%)			14.56	0.000
Negative	125 (39.4)	192 (60.6)		
Positive	45 (23.1)	150 (76.9)		
Depression screen—no. (%)			31.55	0.000
Negative	125 (43.6)	162 (56.4)		
Positive	45 (20)	180 (80)		
Health insurance—no. (%)			13.22	0.001
Private insurance	82 (42.5)	111 (57.5)		
Public insurance	74 (29)	181 (71)		
No insurance	14 (21.9)	50 (78.1)		
Age—no. (%)			5.76	0.056
18–39	107 (30)	250 (70)		
40–55	41 (39.4)	63 (60.6)		
56+	22 (43.1)	29 (56.9)		
Gender—no. (%)			4.33	0.037
Male	67 (28.8)	166 (71.2)		
Female	101 (37.6)	168 (62.4)		
Race/ethnicity				
Non-Hispanic White	10 (23.8)	32 (76.2)	1.82	0.177
BIPOC <sup>†</sup>	160 (34)	310 (66)		
Non-Hispanic	105 (32.3)	220 (67.7)	0.32	0.571
Hispanic	65 (34.8)	122 (65.2)		
Education			2.62	0.269
Graduate and postgraduate	22 (34.4)	42 (65.6)		
College	106 (35.6)	192 (64.4)		
Up to high school	42 (28)	108 (72)		

<sup>†</sup>Black, Indigenous, and People Of Color and reference is non-Hispanic White

**Acknowledgements** This research is conducted as part of the National Food Access and COVID Research Team (NFACT). NFACT is a national collaboration of researchers across 18 sites who are committed to rigorous and timely food access research during the time of COVID-19. To learn more, visit: [www.nfactresearch.org](http://www.nfactresearch.org). We would like to acknowledge Victoria Rivkina for her assistance with project management for the Chicago study. We would like to acknowledge the sponsorship by the Vincentian Institute for Social Action at St. John's University, Queens, for the New York City study.

**Author Contribution** J.M. contributed to the design of the study, collected and interpreted the data, and contributed to the production of the final manuscript. Z.Q. analyzed and interpreted the data and contributed to the production of the final manuscript. P.G. contributed to the design of the study, collected and interpreted the data, and contributed to the production of the final manuscript. T.F. interpreted the data and contributed to the production of the final manuscript. B.B. contributed to the design of the study, collected and interpreted the data, and contributed to the production of the final manuscript. A.S. analyzed and interpreted the data and contributed to the production of the final manuscript. A.T. contributed to the production of the final manuscript.

**Funding** This work was supported by DePaul University, University Research Council, Competitive Research Grant, Project Number 602101, and DePaul University, College of Liberal Arts and Social Sciences, Undergraduate Research Assistantship Program.

This study was approved by the IRBs of DePaul University & St. John's University. Informed consent was obtained from all participants for being included in this study.

## Declarations

**Conflict of Interest** The authors declare no competing interests.

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