

The Impacts of Unemployment Benefits, Race and Ethnicity on Food Security, Health Access, and the Digital Divide during COVID-19

Don Mar, San Francisco State University, Economics Department, San Francisco, California, U.S.A.

Tom Larson, California State University Los Angeles, Department of Economics and Statistics, Los Angeles, California, U.S.A.

Paul Ong, UCLA Luskin School of Public Affairs, Los Angeles, California, U.S.A.

James Peoples, University of Wisconsin-Milwaukee, Department of Economics, Milwaukee, Wisconsin, U.S.A.,
ORCID 0000-0003-0674-8266.

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Abstract

The impact of COVID-19 on job displacement in the United States has been unevenly experienced by race, ethnicity, and the socioeconomically disadvantaged. Although unemployment benefits may mitigate the effects of job displacement, this social safety net is also unevenly distributed across workers. We begin by examining racial/ethnic differences in receiving unemployment benefits among workers displaced by the pandemic. We then turn to the impacts of not receiving UI benefits on food security, health access, and the digital divide during Covid. We use data from the US Census Household Pulse Survey (HPS), which is specifically designed to capture the near real time effects of the pandemic across a wide spectrum of social issues. (US Census, 2020) Unlike the Current Population Survey (CPS) data used in the monthly unemployment rate calculations, the HPS data allows us to identify workers directly displaced from their jobs by the pandemic. We analyze HPS interviews from the first year of the pandemic when the disruptions to the labor market were the most severe, covering the period from April 2020 to April 2021 and the following 2 years from April 2021 to May 2023. We contribute to the literature on the labor market effects of the pandemic in a number of ways. One, we identify workers who directly experienced job loss as a result of the disruptions created by COVID-19 and to determine who did not receive unemployment insurance. Two, we utilize multivariate analyses to examine the effects of receiving UI benefits on critical aspects of life during the pandemic. Three, we look at the racial and ethnic differences in food security, health access and digital access among non-Hispanic Whites, Hispanic, Blacks, Asians, and non-Hispanic Others across three years of the pandemic. We find that Black and Hispanic workers are more likely to be unemployed without Unemployment Insurance (UI). In addition, we find having UI had significant impacts on food insecurity, health insurance, and digital access.

Keywords: COVID-19; Unemployment; Racial Disparities; Unemployment Insurance

Introduction

The COVID-19 pandemic has had devastating economic and health impacts on the US population. According to the US Bureau of Economic Activity (US BEA, 2020), GDP declined at an annualized rate of 32.9% for the 2nd quarter of 2020, resulting in perhaps up to 20 million jobs. As of September 27, 2023, the Center for Disease Control reported 1.15 million deaths (CDC, 2023). Moreover, the morbidity, mortality, social, and employment effects of the pandemic and the subsequent recovery have not been evenly distributed across racial and ethnic groups.

Although the augmentation of Unemployment Insurance (UI)¹ benefits was an important policy tool to mitigate the pandemic's effects, UI benefits have also been unevenly distributed across the population during the pandemic's course. We utilize the US Census Bureau's Household Pulse Survey (HPS) to analyze racial and ethnic disparities in who receives UI benefits during the initial stage of the pandemic (US Census, 2020a). The HPS is a unique, experimental survey to specifically measure the effects of the pandemic across many aspects of society including employment and social welfare. The HPS data allow us to analyze racial/ethnic differences in the ability to collect UI directly caused by COVID-19 job losses. Previous studies of COVID unemployment using the Current Population Survey (CPS) unemployment data do not allow a distinction between non-COVID and COVID related unemployment

In a national response to the pandemic, the Coronavirus Aid, Relief, and Economic Stimulus (CARES) Act, signed into law in March 2020, provided a massive increase in unemployment insurance (UI) benefits starting early in the pandemic. Three major changes made UI benefits both larger and easier to obtain than in the past. The federal government provided a \$600 a week payment that was added to any state unemployment benefits workers received (later changed to \$300 as the program was extended). The government also extended the length of time that benefits could be received – initially by 13 weeks – finally by 53 weeks. Third, access to benefits was expanded by allowing part-time workers, the self-employed and gig economy workers' access. Those who stopped working because of COVID-19 exposure were allowed access. The usual rules on having to actively look for work and being required to accept work offers were effectively lifted. The number of people receiving UI benefits soared and for a while greatly exceeded the number of people officially unemployed.

The remainder of this study begins with a brief overview of prior studies of racial and ethnic differences in unemployment during recessions, the impact of COVID on minority and disadvantaged populations, and differences

in UI recipients by race and ethnicity. We then present a discussion of the data, methodology, simple share analyses, and finally the multivariate analyses of disparities by race/ethnicity in receiving UI during the period from 2020 to 2023.

Race/Ethnicity, Unemployment, and Unemployment Benefits under the Pandemic

Economists have a long history of studying the effects of recessions on minority and disadvantaged populations. Smith, Vanski, and Holt (1974) used CPS data from 1967 through 1973 to analyze employment, unemployment, and labor force participation over the course of the business cycle. They found that Black, women, and younger workers were likely to experience more unemployment than other groups during recessions. Couch and Fairlie (2010) linked monthly CPS data to create panel data from 1989 to 2004 to analyze men's labor market transitions during the business cycle. They found that Black men are not only more likely to lose their jobs during a downturn, but also to be more likely to leave the labor force when unemployed. Couch, Fairlie, and Xu (2016) later use a similar methodology to expand the study to include men and women and Hispanic workers just prior to and just after the Great Recession. Black and Hispanic workers are found to be more likely to be unemployed during recessions. In addition to Black workers, Hispanic workers were also more likely to leave the labor force after being unemployed during the Great Recession. More recently, Cajner et al. (2017) also used linked CPS data from 1976 to 2016 to examine the differential effects of recessions on racial groups. Like Couch et al., they also found that Blacks and Hispanics experience higher than average job loss rates. Black men and Latinas were again found to be more likely to leave the labor force after being unemployed.

A number of researchers have recently documented the general labor market impact of the current pandemic. For instance, Coibion, Gorodnichenko, and Weber (2020), used household level Nielsen Homescan data, to estimate that 20 million jobs were lost by early April 2020. They estimated that job losses were greater than the 16.5 million unemployment insurance claims by April 4, 2020. Forsythe et al. (2020) found that labor demand fell by over 40% by late April using job vacancy data from Burning Glass Technologies. Industry sector analysis by Cajner et al. (2020) used administrative data from a private human resources company (ADP) to analyze job losses from late April to late June of 2020. They found that in late April that employment in the Leisure and Hospitality industries fell by more than 45 percent; employment in Retail fell by almost 30 percent; and employment in "Other

Services” fell by 25 percent. Furthermore, Cajner et al. showed that these employment declines disproportionately fell on low wage workers, women, and workers at smaller firms.

Economists have also found ethnic and racial disparities in COVID-19’s labor-market impact. For instance, Montenegro et al. (2020) used CPS data to show greater employment losses and increases in unemployment for Hispanic workers, younger workers, and workers with less than college degrees for April 2020. In the subsequent months, re-employment of Black workers was slower than for other groups. They concluded that occupational segregation explains a substantial part of differences by race, ethnicity, and gender. Fairlie, Couch, and Xu (2020) provided an extensive analysis of racial and ethnic differences in unemployment using data from the CPS. They measured the impact of the pandemic on racial and ethnic unemployment rates using two methodologies. The first method measured unemployment using the standard Bureau of Labor Statistics (BLS) reporting methodology. Black and particularly Hispanic unemployment rates were higher than white unemployment rates for April 2020 using the BLS methodology. Their second method measured unemployment by counting workers who were absent from jobs and wanted jobs in an effort to adjust for BLS misclassification of workers. This second method found the April 2020 national rate to be 26.5% as opposed to the official BLS’ estimate of 14.7%. Furthermore, the Black and Hispanic unemployment rates were considerably higher at 31.8% and 31.4% respectively using the second method. Using an Oaxaca type decomposition method to control for differences in industry, occupation, education, and potential experience they found Hispanic workers to be the most impacted group of workers by ethnicity. Gezici and Ozay (2020) also used CPS data to examine racial and ethnic differences in pandemic unemployment with an additional focus on gender effects. After controlling for differences in individual characteristics, occupations and industry, they found that women and particularly non-white women were more likely to be unemployed in the early part of the pandemic. Anyamele, McFarland, and Fiakofi (2021) used the HPS data to examine racial, ethnic, and gender differences on the impact of COVID on household incomes. They also utilized an Oaxaca-Blinder type analysis and found that Hispanics, “Other” ethnics, and Blacks experienced much greater income losses compared to whites.

While Hispanics and Blacks are consistently found to suffer higher unemployment and greater income losses during recessions and during the pandemic, they are also less likely get relief from unemployment and income loss. Nichols and Simms (2012) used data from the Survey of Income and Program Participation (SIPP) to find that during the Great Recession, Black and Hispanic workers were less likely to receive UI benefits compared to whites

after controlling for individual characteristics. Kuka and Stuart (2021) used a larger sample of SIPP data from 1986 to 2014 to analyze Black-White differences in the receipt of UI benefits. After controlling for individual characteristics including region, education, pre-unemployment earnings, industry and gender, they found a large Black-white difference in UI receipt. Differences in the receipt of UI benefits have also been noted during the current pandemic. Grooms, Ortega, and Rubalcava (2020) found that amongst workers unemployed in March 2020, only 29% of Black unemployed workers had received unemployment benefits by mid to late March compared to 35% of white unemployed workers using the National Panel Study of COVID-19 data. Acks and Karpman (2020) used the Urban Institute’s Coronavirus Tracking survey to show that low-income families, particularly low income Hispanic families, suffered greater job and income losses during the early stage of the pandemic induced recession. Acks and Karpman also found that only 36% of unemployed workers said they received UI benefits within 30 days of job loss. A recent Department of Labor (2021) report using CPS data also noted that Black and Hispanic workers were less likely to receive UI benefits during the pandemic. In a previous study using the HPS data, we (Mar, et al, 2022) also find that Black and Hispanic workers, along with non-Hispanic “Other” workers were less likely to be receive UI during the first year of the pandemic.

In addition to providing a source of income and means of consumption during a recession, unemployment benefits have been shown to provide other social benefits. Kuka (2020) used SIPP data to find that workers receiving UI benefits reported better self-reported health as well as higher rates of health insurance and use of health services. Raifman, Bor, and Venkataramani (2021), using a national health survey of COVID’s effects, found that households receiving UI benefits experienced a large and significant reduction in food insecurity. Confining their study to households earning less than \$75,000 in 2020, their study found that having UI is associated with a 35% decline in the percentage of households reporting food insecurity. Berkowitz and Basu (2021) used HPS data from June and July 2020 to show that respondents receiving unemployment benefits were less likely to experience food insecurity, miss housing payments, and delay health and mental health care.

Clearly, receiving UI benefits helps mitigate the effects of the pandemic; however, minority and disadvantaged workers are also less likely to receive these benefits. While the current literature has documented the pandemic’s effects on earnings, employment, and unemployment, we examine the receipt of unemployment benefits as a direct result of COVID job displacement on health access, food security, and digital access over the course of the pandemic. Our use of the HPS data also allows us to directly link COVID job displacement to who receives UI

benefits and also to expand the literature to include Asians and “Other” workers – workers who do not identify as white, black, Hispanic, or Asian.

Data and Methodology

We analyze data from HPS interviews conducted by the U.S. Census from April, 2020 to May 9, 2023 to examine differences in UI reciprocity during the first stage of the pandemic. The data are publicly available from the US Census Bureau, <https://www.census.gov/data/experimental-data-products/household-pulse-survey.html>. Each period’s survey is commonly referred to as a “week” with consecutive numbering, even though there can be varying time gaps between surveys and differing lengths of survey duration. We use data from “weeks” 1 through 57. However, for most of the analyses we use data from after the first 6 weeks as these surveys did not contain questions regarding receipt of UI.

We begin by analyzing which workers are displaced by COVID and then turn to who received UI versus who did not receive UI. We then use logit regressions to analyze the determinants of displaced workers with and without unemployment insurance to with controls for individual characteristics, state of residence and time. Finally, we analyze the effects of receiving UI on displaced work on food security, health access, and digital access.

There are some limitations to the HPS data. One, the survey was administered online. As a result, the unweighted responses were more likely to be women, affluent, better educated, and from smaller sized households compared to the nation as a whole. Two, the questionnaire is available only in English and Spanish. This limitation means that limited-English-language Asians and other non-Hispanic immigrants are likely underrepresented in the sample. To overcome some of these limitations, responses were weighted by the Census to make the results representative of the nation. The Census bureau weighted responses by applying adjustments for non-response, estimates of occupied housing, and other demographic adjustments based on the 2018 American Community survey. (Fields et al, 2020, US Census, 2021) We used the Census bureau’s HPS developed weights to analyze the data. A third data limitation is that questions regarding industry of employment and occupation of respondents are asked only of employed workers, so no industry and occupational data are available for unemployed workers.

Our analyses focus on workers who were specifically job displaced by COVID-19 and whether they received unemployment benefits. We conservatively counted as displaced by the pandemic only respondents who answered “No” to the question, “In the last 7 days, did you do ANY work for either pay or profit?” and gave the following survey responses (US Census, 2020b) for not working:

- “I did not have work due to coronavirus pandemic related reduction in business (including furlough).”
- “I am/was laid off due to coronavirus pandemic.”
- “My employment closed temporarily due to the coronavirus pandemic.”
- “My employment went out of business due to the coronavirus pandemic.”

This method allows us to separate unemployment due directly to COVID from non-pandemic related unemployment, which is not possible with CPS data. As a result, workers unemployed for non-COVID related reasons are not included in the analysis.

We define *employed* workers as respondents who answered “Yes” to the question, “Now we are going to ask about your employment. In the last 7 days, did you do ANY work for either pay or profit?” Our previous research (Mar, Ong, Larson, Peoples, 2022) also added non-working respondents who answered “No” to the employment question in the last 7 days, but answered “Yes” when asked “Are you receiving pay for the time you are not working?” However, this employment question was not included in HPS surveys after week 21. In order to provide a consistent definition of COVID displaced workers, we define employed worker based solely on the any work question.

Using this definition, COVID only unemployed – defined as a percentage of COVID displaced and employed workers - is 15.3%. This figure is higher than the official BLS unemployment estimates which ranged from 14.8% in April 2020 to 6.7% by December 2020. These two statistics, however, are not directly comparable because of differences in HPS and CPS unemployment questions. However, the higher displacement numbers are more in keeping with the higher rates of unemployment found by Fairlie, Couch, and Xu (2020).

Our analyses of UI benefits focus on a the subsample of workers displaced by COVID. We use two methods to determine if a COVID displaced respondent was receiving UI payments. The first method uses the question, “Thinking about your experience in the last 7 days, which of the following did you use to meet your

spending needs?” Respondents who said “Yes” to using UI benefits as part of their spending were counted as receiving UI payments. The use of UI payments for spending was asked of respondents for weeks 7 through 57. The second method uses the question, “Since [reference date], did you receive Unemployment Insurance (UI) benefits?” Unfortunately, not all weeks asked about receiving UI. The question was not included in weeks 1 through 12 and in weeks 34 through 39. Surveys for weeks 13 through 27 used a reference date of March 13, 2020; for weeks 28 through 33 the reference date was January 1, 2021; for weeks 40 through 42 the reference date was June 1, 2021; for weeks 43 through 48 the reference date was January 1, 2022; and for weeks 49 through 57 the reference date was June 1, 2022. Given the different reference dates used in the surveys, we analyze data for two time periods. The first time period includes data from HPS weeks 7 through 27 which covers the period from June 11, 2020 to March 29, 2021, arguably when the effects of the first year of the pandemic were most severe in the labor market. The second time period is composed of HPS weeks 28 through 57 which represent the second and third year of the pandemic covering the period from April 14, 2021 through May 8, 2023. We combine these later HPS weeks as the interval between the HPS weeks increased, causing sample sizes to decrease for weeks 28 through 57 compared to the earlier weeks.

In our analysis of racial and ethnic effects, we construct mutually exclusive racial and ethnic categories: non-Hispanic whites, Blacks, Asians, and Hispanics, and Other” (self-identified in the survey). The fifth category, “Other”, are non-Hispanics who did not self-identify as exclusively non-Hispanic white, Black, Asian, or Hispanic. We use this approach to both clearly define ethnic and racial groups and to specifically distinguish Hispanic workers from white workers.

To validate the results, we compare the final weighted frequency counts for the employed and unemployed receiving UI with the CPS estimates for comparable weeks. Weighted employment and workers with UI estimates from the HPS compared closely to the CPS employment and workers with continued UI claims numbers for the reference week in June 2020. The employment count from the HPS data for the week of 6/18/20 thru 6/23/20 was 146.8 million compared to the CPS estimate for the same June reference week of 142.8 million. The HPS count of 13.7 million workers receiving unemployment benefits for the same reference week also compared closely to the BLS continued UI claims of 16.3 million.

We measure food insecurity among the COVID displaced workers based on the following question: “In the *last 7 days*, which of these statements best describes the food eaten in your household?” Those classified as being food insecure includes respondents who answered with “Often not enough to eat” or “Sometimes not enough to eat” or “Enough, but not always the kinds of food (I/we) wanted to eat.” For those in the last category, we also included only those who stated that they “Couldn’t afford to buy more food” in the follow-up question.

We measure health care access among the COVID displaced workers in two ways based on questions on whether respondents had health insurance or delayed getting medical care. Respondents were asked to identify whether they had health insurance through an employer, privately enrolled market plan, Medicare, Medicaid, Military, Veterans, Indian Health Service. In our analyses, respondents who had any of these types of insurance were identified as having health insurance. Health care delayed was measure by the question, “At any time in the last 4 weeks, did you delay getting medical care because of the coronavirus pandemic?”

Computer availability and internet availability for educational purposes were based on the following questions for respondents with children. For computer availability issues: “How often is a computer or other digital device available to children for educational purposes?” Responses (3) “Sometimes available”, (4) “Rarely available” (5) “Never available” were coded as having computer access problems. For internet availability issues, we used the question, “How often is the internet available to children for educational purposes?” Responses: (3) “Sometimes available”, (4) “Rarely available” (5) “Never available” were seen as having internet availability problems.

We use logit regressions to control for the independent effects of individual worker characteristics and place of residence. Place of residence could have a significant impact on COVID related unemployment due to differences in shelter-in-place policies, UI programs across states, and industry mix differences. We also include survey week dummies to account for differences across time. We first estimate logit models of who is displaced by COVID for the two time periods:

$$(1) \text{ COVIDISPLACED} = f(\text{AGE, AGE_SQUARED, WOMEN, CHILDRENLT18, WOMEN_CHILDREN, HSGRAD, AADEGREE, BADEGREE, GRADDEGREE, MARRIED, HISPANIC, BLACK, ASIAN, NHISPANICOTHER, WEEK_DUMMIES, STATE_DUMMIES})$$

- COVIDISPLACED is a dummy variable equal to 1 if not working due to COVID.
- AGE is the respondent age calculated by subtracting year of birth from 2020.
- AGE_SQUARED is the square of age.
- WOMEN is a dummy variable equal to 1 for women respondents.
- CHILDRENLT18 if the respondent lives in a household with children under 18 years of age.
- WOMEN_CHILDREN is an interaction term equal to 1 if the respondent is a woman and lives in a household with children under 18 years of age; otherwise, equal to 0.
- HSGRAD is a dummy variable for high school graduates.
- AADEGREE is a dummy variable for workers with associate degrees.
- BADEGREE is a dummy variable for workers with BA or BS degrees.
- GRADDEGREE is a dummy variable for workers with a graduate degree.
- MARRIED is a dummy variable equal to 1 for married respondents.
- HISPANIC is a dummy variable for Hispanic workers.
- BLACK is a dummy variable for Black workers.
- ASIAN is a dummy variable for Asian workers.
- NHISPANICOTHER is a dummy variable for workers who do not self-identify as white, Hispanic, Black or Asian.
- WEEK_DUMMIES are dummy variables for the HPS survey week.
- STATE_DUMMIES are dummy variables for the state of residence.

For weeks 7 thru 27 the excluded week is week 7 in the logits using the unemployment benefit spending definition and for weeks 13 thru 27 using the receiving UI benefits definition, week 13 is excluded in the logits for the first year. The excluded state dummy is Alabama. For the second time period, the pooled HPS weeks for years 2 and 3, the excluded week is week 28. The excluded educational category is less than a high school education. The excluded racial/ethnic category is non-Hispanic whites.

We then examine who receives UI among the COVID displaced workers based on the 2 questions regarding receipt of UI based on the explicit question about receiving UI benefits and the question regarding UI spending question specified as:

- (2) $UIRECEIPT = f(AGE, AGE_SQUARED, WOMEN, CHILDRENLT18, WOMEN_CHILDREN, HSGRAD, AADEGREE, BADEGREE, GRADDEGREE, MARRIED, HISPANIC, BLACK, ASIAN, NHISPANICOTHER, WEEK_DUMMIES, STATE_DUMMIES)$
- (3) $UISPENDING = f(AGE, AGE_SQUARED, WOMEN, CHILDRENLT18, WOMEN_CHILDREN, HSGRAD, AADEGREE, BADEGREE, GRADDEGREE, MARRIED, HISPANIC, BLACK, ASIAN, NHISPANICOTHER, WEEK_DUMMIES, STATE_DUMMIES)$

where: UIRECEIPT is a dummy variable equal to 1 if the respondent received UI benefits during the reference period. UISPENDING is a dummy variable equal to 1 if the respondent spent UI benefits during the HPS week.

Finally, we analyze the effects of receiving UI on COVID displaced workers with logits specified as:

- (4) $FOODINSECURE \text{ or } HEALTHINS \text{ or } HEALTHDELAY \text{ or } COMPUTERUNAVAILABLE \text{ or } INTERNETUNAVAILABLE = f(UIRECEIPT \text{ or } UISPENDING, AGE, AGE_SQUARED, WOMEN, CHILDRENLT18, WOMEN_CHILDREN, HSGRAD, AADEGREE, BADEGREE, GRADDEGREE, MARRIED, HISPANIC, BLACK, ASIAN, NHISPANICOTHER, WEEK_DUMMIES, STATE_DUMMIES)$

where: FOODINSECURE is a dummy variable equal to 1 if the respondent is food insecure during the HPS week. HEALTHINS is a dummy variable equal to 1 if the respondent had health insurance during the HPS week. HEALTHDELAY is a dummy variable equal to 1 if the respondent delayed health services during the HPS week. COMPUTERUNAVAILABLE is a dummy variable equal to 1 if the respondent had computer availability issues during the HPS week. INTERNETUNAVAILABLE is a dummy variable equal to 1 if the respondent had internet availability issues during the HPS week.

Results

Figure 1 shows the estimates of COVID displacement, the percentages of COVID displaced workers with UI using the UI spending question, and percentages of displaced workers who received of UI using the explicit

question regarding receiving UI over the three-year period. COVID displaced workers as a percentage of employed and COVID displaced decreased during the 3 years but was above 10% in the first year (thru week 27). The percentage of COVID displaced workers estimated to be receiving UI using both the measures appears to drop off considerably by year 3, although there is an uptick towards the end of the third year using the UI receipt question. The uptick may be due to the small sample sizes of COVID displaced workers at the end of year 3. The decline after year 2 is likely due to the end of programs instituted at the onset of the pandemic such as the CARES Act. New pandemic UI claims ceased after September 6, 2021, but ongoing claims were still being paid for weeks after that. The UI receipt and UI spending questions are moderately correlated. In year 1, the correlation is 0.6334 and for years 2 and 3, the correlation is 0.6470.

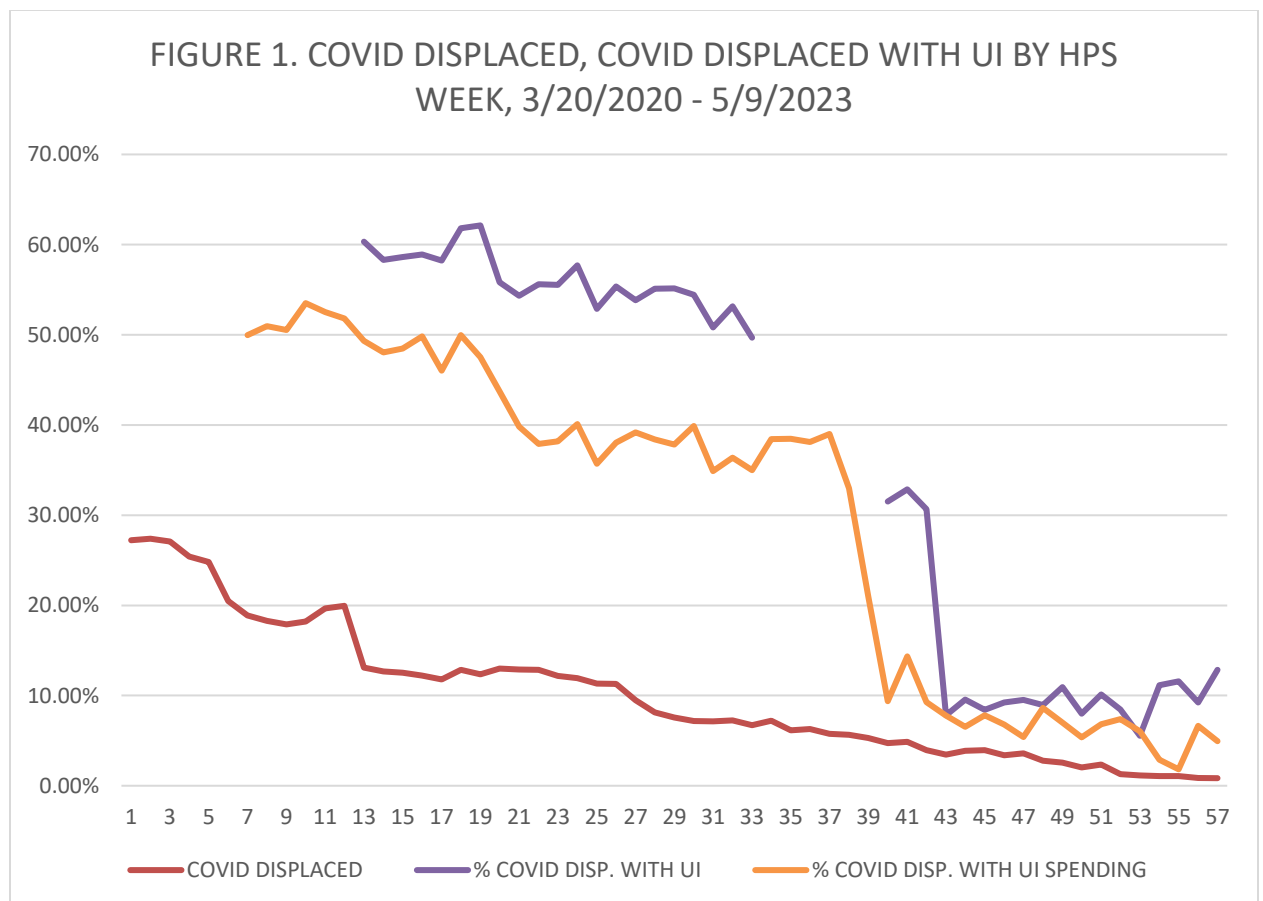
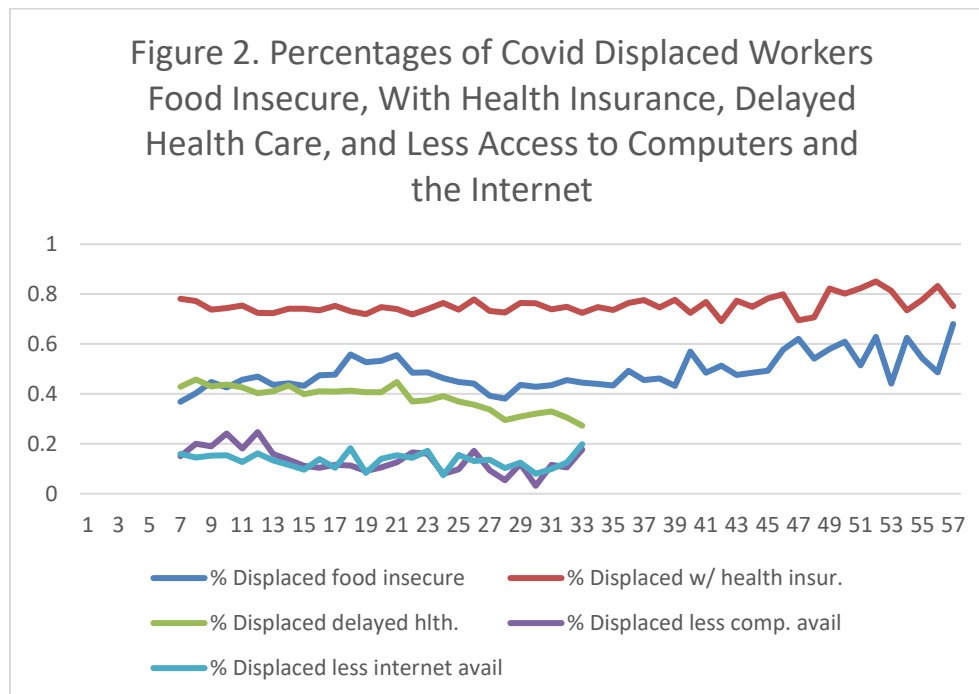


Figure 2 shows the dependent variables of COVID displaced workers on receiving UI, food insecurity, health insurance for the entire 3-year period and delayed health services, computer and internet availability problems for a 2-year period. The percentage of COVID displaced workers with health insurance varies between 70% to 80% for most the 3-year period until the last part of the third year. The percentages of displaced workers who delayed health services appears to decline from HPS week 21 until week 33. After week 33, the question concerning delaying health services was discontinued in the HPS. Food insecurity roughly increases throughout the first part of the first year of the pandemic, drops in the second part of the first year, then increases in years two and three. Computer and internet availability problems are also only shown for the year and a half when the questions concerning computer and internet availability were included in the survey. Availability of both a computer and the internet for respondents with children declined from week 12 but appears to have taken a sharp upturn in the last 2 weeks.



The logit results for who is displaced by COVID across the two time periods are shown in Table 1. The logit analyses include HPS weeks 7 through 27 in the first-year results. Briefly, the education dummies have all the correct signs and statistical significance in both time periods. The likelihood of being displaced by COVID decreased with higher levels of education. Married workers are less likely to be displaced by COVID whereas families with children under 18 are more likely to be displaced in years 2 and 3. The coefficients of ethnic and racial minorities are all statistically significant and positive. Black and Hispanic workers are more likely to be COVID displaced in both time periods. The coefficients for women are not significant. For clarity, the logit tables only show the coefficients of the individual characteristics and not the week and state dummies. The likelihood ratio tests of the significance of the state and week variables are shown instead. In addition to being statistically significant as a group, many of the state and time dummies are individually statistically significant. Future research will examine the state and time effects in greater detail.

Table1a. Logit Results for COVID DISPLACEMENT: YEARS 1 and 2 & 3

COVIDUNEMP		
Variables	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Years 2 and 3
AGE	-.0184144*** (.0033399)	.0254213*** (.0046747)
AGE_SQUARED	.0002714*** (.0000358)	-.0001115* (.0000489)
WOMEN	.017084 (.015024)	.0069551 (.023207)
HSGRAD	-.2596297*** (.0366328)	-.3702908*** (.051145)
AADEGREE	-.4924023*** (.0391848)	-.6733761*** (.0550697)
BADEGREE	-.8016912*** (.0375524)	-1.109383*** (.0524009)
GRADDEGREE	-1.33721*** (.0393503)	-1.496328*** (.0546166)
MARRIED	-.3782235*** (.0163761)	-.5184593*** (.0247388)
CHILDRENLT18	-.0182981 (.0168182)	.1427651*** (.0252605)
HISPANIC	.273972*** (.0229243)	.4186951*** (.0347345)
BLACK	.4337041*** (.0232063)	.5906814*** (.0342454)
ASIAN	.1616026*** (.0364804)	.3557628*** (.0476574)
NHISPANICOTHER	.2736222*** (.0365285)	.3912142*** (.0468673)
Fixed State Effects	7831.42 (50)***	2735.63 (50)***
LR Test χ^2 (df)		
Fixed Week Effects	9015.52 (20)***	16557.98 (29)***
LR Test χ^2 (df)		
Number of obs.	1168292	1167187
Log likelihood	-447941.82	-185498.75
Wald χ^2 (df)	9049.09(83)***	8232.85(92)***

Notes: Coefficients for individual State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

Table 2a shows the logit results for COVID displaced workers who received UI benefits based on the question “Are you receiving UI benefits?” using data from weeks 13 through 34 and weeks 40 through 57 while Table 2b shows who is receiving UI benefits based on the UI spending question to determine receipt of UI based on COVID unemployed workers reporting spending UI benefits for HPS weeks 7 - 57.

The education dummies generally have all the correct signs and statistical significance in both time periods and using both methods of determining receiving UI benefits. The coefficients of ethnic and racial minorities are all negative during all three years of the pandemic using both methods. In the first year using the UI receipt method, the Hispanic and Other coefficients are statistically significant. All the racial and ethnic coefficients are significant using the UI spending method in the first year. In the second and third years, Hispanic workers are also significantly less likely to receive UI based on the receiving UI question. The coefficients are also statistically significant for Hispanic and Other workers based on the UI spending question. The coefficients for women are positive and significant using both methods of UI determination.

The likelihood of receiving UI increased with education. The coefficients for married workers are mixed in terms of statistical significance across the time periods and method determining UI receipt. The married coefficients are positive in the first year and years 2 and 3 using the “Did you receive UI” question, but only significant in the later years. Using the UI spending question, the married coefficients are both negative and significant years 2 and 3. Workers in families with children under 18 were also less likely to be receive UI using both methods and for both time periods using the spending method. However, the coefficients are only significant in year 1 based on the UI receipt method and years 2 and 3 using the spending method.

Table2a. Logit Results for RECEIVING UI: YEARS 1, 2, and 3

UI RECEIPT		
Variable	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Years 2 and 3
AGE	.103086*** (.0069603)	.0704639*** (.013971)
AGE_SQUARED	-.0010934*** (.0000714)	-.0006595*** (.0001325)
WOMEN	.0827787* (.039835)	.1235035* (.0603294)
HSGRAD	.5936082*** (.0731232)	.3495447** (.1268733)
AADEGREE	.7443258*** (.0806623)	.3938721** (.1369705)
BADEGREE	.712742*** (.0750802)	.527961*** (.130318)
GRADDEGREE	.2631325** (.0784703)	.239244 (.1394083)
MARRIED	.0107161 (.0362397)	.1561993* (.0613552)
CHILDRENLT18	-.127577** (.0385213)	-.0450534 (.069432)
HISPANIC	-.4463659*** (.0504188)	-.2886117** (.0944057)
BLACK	-.1007887 (.0514882)	-.0326068 (.0900447)
ASIAN	-.1293994 (.0852216)	-.1116233 (.1292732)
NHISPANICOTHER	-.3238221*** (.0757301)	-.2223391 (.1273877)
Fixed State Effects	2203.25(50)***	710.08(50)***
LR Test χ^2 (df)		
Fixed Week Effects	208.61(14)***	5461.02(23)***
LR Test χ^2 (df)		
Number of obs.	72385	26775
Log likelihood	-47104.152	-14078.402
Wald χ^2 (df)	126.56(77)***	1358.04(86)***

Notes: Coefficients for individual State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

Table2b. Logit Results for UI Received based on Spending: YEARS 1, 2, and 3

UI SPENDING		
	Logit Coefficients with Robust Standard Errors in parentheses	
Variable		
	Covid Year 1	Covid Years 2 and 3
AGE	.1010972*** (.0059632)	.0634133*** (.0116012)
AGE_SQUARED	-.001073*** (.0000622)	-.00062*** (.0001162)
WOMEN	.0605108* (.0282339)	.1441399** (.0529565)
HSGRAD	.5249961*** (.0664847)	.4003483** (.1208476)
AADEGREE	.6740718*** (.0715239)	.4664402*** (.1278604)
BADEGREE	.6501274*** (.0685264)	.6613281*** (.1234737)
GRADDEGREE	.1957172** (.0724825)	.4059771** (.1309549)
MARRIED	-.0225859 (.0303564)	-.2002812*** (.0534999)
CHILDRENLT18	-.1004621** (.0311983)	-.1202638* (.0603549)
HISPANIC	-.4174077*** (.0426981)	-.2214934** (.0796719)
BLACK	-.1919882*** (.0426969)	-.0833344 (.0797514)
ASIAN	-.1329369* (.0673006)	-.1024396 (.1115528)
NHISPANICOTHER	-.2564697*** (.0688335)	-.3298965** (.1003934)
Fixed State Effects	2594.13(50)***	774.64(50)***
LR Test χ^2 (df)		
Fixed Week Effects	1533.29(20)***	4398.17(29)***
LR Test χ^2 (df)		
Number of obs.	123176	36272
Log likelihood	-81166.48	-18116.164
Wald χ^2 (df)	1606.7(83)***	1376.55(92)***

Notes: Coefficients for individual State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

We turn to assessing the impact of receiving UI on food insecurity, health access, and digital access. Tables 3a and 3b show the logit results of the effect of receiving UI benefits based on the question “Are you receiving UI benefits?” and spending UI on food insecurity.

Both methods of determining UI benefits show a large, statistically significant effect of receiving UI on reducing food insecurity for both time periods. Except for Asians, the coefficients of ethnic and racial minorities are all statistically significant and positive during the three years of the pandemic. The coefficients for women are also negative and significant using the two methods of determining UI benefits and for both time periods.

The education dummies generally have all the correct negative signs and statistical significance in both time periods and using both methods of determining receiving UI benefits. The likelihood of being food insecure decreased with increasing levels of education. The coefficients for married workers are negative and statistically significant across both time periods and methods of determining UI receipt. Displaced workers in families with children under 18 were also significantly less likely to be food insecure in years 2 and 3, but not in the first year of the pandemic.

Table3a. Logit Results for the Effects of Receiving UI on Who is Food Insecure: YEARS 1, 2, and 3

Food Insecure	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Years 2 and 3
UI RECEIPT	-.1999853*** (.0376647)	-.4027382*** (.0711021)
AGE	.0857082*** (.0098228)	.0847683*** (.0137886)
AGE_SQUARED	-.001018*** (.0001085)	-.0009904*** (.0001395)
WOMEN	-.1212574** (.0355531)	-.1360873* (.0582782)
HSGRAD	-.3381271*** (.084843)	-.2644878* (.1236708)
AADEGREE	-.387522*** (.0915087)	-.3257106* (.1330854)
BADEGREE	-.9091496*** (.0863706)	-.7355415*** (.1270533)
GRADDEGREE	-.9829754*** (.091175)	-.9035186*** (.1331981)
MARRIED	-.5051886*** (.0380516)	-.4321948*** (.0596347)
CHILDRENLT18	-.0287495 (.042293)	-.1629521* (.0652876)
HISPANIC	.3421204*** (.0531888)	.201368* (.0892532)
BLACK	.4181435*** (.0562391)	.2096992* (.0847792)
ASIAN	-.0935538 (.0837353)	-.252891* (.1203299)
NHISPANICOTHER	.4581989*** (.091409)	.3178888** (.1089105)
Fixed State Effects LR Test χ^2 (df)	284.75(50)***	240.73(50)***
Fixed Week Effects LR Test χ^2 (df)	604.2(14)***	250.94(23)***
Number of obs.	65070	23255
Log likelihood	-42203.191	-15041.105
Wald χ^2 (df)	1392.92(78)***	645.66(87)***

Notes: Coefficients for individual State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

Table3b. Logit Results for the Effects of UI based on Spending on Food Insecure: YEAR 1, 2, and 3

Food Insecure	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Years 2 and 3
UI SPENDING	-.2259341*** (.0309103)	-.251294*** (.0605467)
AGE	.0870871*** (.0078463)	.071531*** (.011841)
AGE_SQUARED	-.001053*** (.0000865)	-.0008706*** (.0001216)
WOMEN	-.1210736*** (.0301403)	-.1978759*** (.0496879)
HSGRAD	-.3287953*** (.0680587)	-.342914** (.106745)
AADEGREE	-.4154766*** (.0734128)	-.3997606*** (.1145535)
BADEGREE	-.8659998*** (.0703208)	-.816898*** (.1096898)
GRADDEGREE	-.8553879*** (.0760388)	-.8555427*** (.1150946)
MARRIED	-.4698155*** (.0321262)	-.4634402*** (.0511913)
CHILDRENLT18	-.0480685 (.0346045)	-.1977758*** (.0564265)
HISPANIC	.3469008*** (.0443174)	.2545739** (.0745958)
BLACK	.3787508*** (.0456779)	.2250103** (.072327)
ASIAN	-.0981045 (.0744167)	-.159712 (.1062007)
NHISPANICOTHER	.3325417*** (.076617)	.3335533** (.0965548)
Fixed State Effects LR Test χ^2 (df)	604.81(50)***	300.33(50)***
Fixed Week Effects LR Test χ^2 (df)	1074.06(20)***	321.52(29)***
Number of obs.	114653	32017
Log likelihood	-74179.264	-20806.079
Wald χ^2 (df)	1732.20(84)***	755.11(93)***

Notes: Coefficients for individual State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

We assess health care access among COVID displaced workers with two measures. The first measure is whether a displaced worker had health insurance. The second measure is whether a displaced worker delayed seeking health care services during the pandemic. Tables 4a and 4b shows the logit results of the effect of UI benefits on whether a displaced worker had health insurance using both methods of determining UI receipt. Tables 5a and 5b shows the logit results of the effect of UI benefits on whether a displaced worker delayed seeking health care during the pandemic years.

The UI receipt question method of determining UI benefits shows a positive effect but marginally significant effect ($p < .053$) on having health insurance in the first year of the pandemic and a positive, but non-statistically significant effect for years two and three. Using, the UI spending question method, the UI benefits coefficients are also positive but not statistically significant for both time periods. Hispanic displaced workers were statistically significant less likely to have health insurance during the three years of the pandemic using both methods of determining UI status. The coefficients for Black workers are negative, but only significant using the spending method during the first year of the pandemic. The coefficients for women are positive and significant using the UI receipt and UI spending questions for both time periods.

The education dummies generally have positive signs and statistical significance coefficients in both time periods and using both methods of determining receiving UI benefits. The coefficients for married workers and workers in families with children under 18 are both positive and statistically significant across both time periods and methods of determining UI receipt.

Table4a. Logit Results for the Effects of Receiving UI on Who has Health Insurance: YEARS 1, 2, and 3

Health Insured	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Years 2 and 3
UI RECEIPT	.0925488 (.0478513)	.1264257 (.0971455)
AGE	-.1172357*** (.0159155)	-.1347122*** (.0213054)
AGE_SQUARED	.0015936*** (.0001858)	.0018572*** (.00023)
WOMEN	.6036107*** (.045127)	.689681*** (.0769781)
HSGRAD	.476283*** (.0912401)	.2614113 (.1374368)
AADEGREE	.785107*** (.1008587)	.453947** (.1602274)
BADEGREE	.9248143*** (.0949377)	.6511597*** (.1458539)
GRADDEGREE	1.070239*** (.1038855)	.745103*** (.1549859)
MARRIED	.5238027*** (.0496432)	.5414827*** (.0828821)
CHILDRENLT18	.181279** (.0533479)	.2749959** (.0882745)
HISPANIC	-.5440129*** (.0635849)	-.6608221*** (.1070828)
BLACK	-.1075319 (.069067)	-.11554 (.1068804)
ASIAN	.1259471 (.1051133)	-.0052995 (.1515874)
NHISPANICOTHER	.0607011 (.1035241)	.1835127 (.1679289)
Fixed State Effects LR Test χ^2 (df)	2298.77(50)***	633.58(50)***
Fixed Week Effects LR Test χ^2 (df)	101.44(14)***	186.59(23)***
Number of obs.	60079	21630
Log likelihood	-29995.135	-10372.086
Wald χ^2 (df)	1360.66(78)***	629.21(87)***

Notes: Coefficients for individual State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

Table4b. Logit Results for the Effects of UI based on Spending on Who has Health Insurance: YEARS 1, 2, and 3

Health Insured	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Years 2 and 3
UI SPENDING	.0662879 (.0393336)	.088404 (.0799042)
AGE	-.115295*** (.0119442)	-.1290999*** (.0198956)
AGE_SQUARED	.0016163*** (.0001373)	.001784*** (.0002203)
WOMEN	.5572287*** (.0386359)	.7380114*** (.0653959)
HSGRAD	.4683777*** (.073259)	.2745298* (.116464)
AADEGREE	.6559613*** (.0811701)	.5493695*** (.1344683)
BADEGREE	.8903768*** (.0778445)	.7183425*** (.1244109)
GRADDEGREE	.98114*** (.0910158)	.8727716*** (.131765)
MARRIED	.556069*** (.0418557)	.4783408*** (.0704894)
CHILDRENLT18	.150329** (.0444336)	.199559** (.0751923)
HISPANIC	-.5584046*** (.0522516)	-.5811307*** (.0891253)
BLACK	-.1887505** (.0563515)	-.0954912 (.0946044)
ASIAN	-.0553221 (.0977124)	.0283687 (.1304774)
NHISPANICOTHER	.0606547 (.0815129)	.1881186 (.14294)
Fixed State Effects LR Test χ^2 (df)	3617.79(50)***	1029.36(50)***
Fixed Week Effects LR Test χ^2 (df)	176.22(20)***	189.16(29)***
Number of obs.	106331	29923
Log likelihood	-52907.321	-14317.596
Wald χ^2 (df)	1873.46(84)***	790.10(93)

Notes: Coefficients for individual State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

The question on delayed health services ended with HPS week 33 (June 23, 2021). As a result, the logit analyses are only for partial year 2 of the pandemic. Having UI does decrease the likelihood of delaying health service based on the UI receipt question method of determining UI benefits. The coefficients using the UI receipt question are statistically significant and negative in determining delaying health services. Using, the UI spending question method, the UI benefits coefficients are still negative but not statistically significant for both time periods.

The racial and ethnic coefficients are quite mixed and somewhat unexpected. Surprisingly, the coefficients of Hispanic, Black, and Asian displaced workers are statistically significant and negative in delaying health services during the first year of the pandemic using both methods of determining UI status. Conversely, the coefficients for Non-Hispanic Other workers are positive in year 1 for both the receiving UI and spending UI. The coefficients for Black workers remain negative and significant using both methods and for the partial year 2 of the pandemic. Displaced women are more likely to delay health service as the coefficients for women are positive and significant using the UI receipt and UI spending questions for the first year.

The education coefficients are mostly statistically significant and positive in the first year, but generally not significant in the second year. Apart from first year using the UI spending question, the coefficients for married workers are negative and significant. The coefficients for individuals in families with children under 18 are not statistically significant across both time periods and methods of determining UI receipt.

Table 5a. Logit Results for the Effects of Receiving UI on Delaying Health Care: YEARS 1 and 2

Delay Health Care	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Year 2
UI RECEIPT	-.1006287** (.0385704)	-.247526* (.0873639)
AGE	.0327554*** (.0089884)	.05195** (.0194748)
AGE_SQUARED	-.0003237** (.0000955)	-.0006307** (.000194)
WOMEN	.173175*** (.036289)	.1351063 (.0841853)
HSGRAD	.1071101 (.0873992)	.24488 (.1824523)
AADEGREE	.3046876** (.0933792)	.3799117 (.1963672)
BADEGREE	.3807543*** (.0883795)	.2040312 (.1868418)
GRADDEGREE	.5249134*** (.0924137)	.3584636 (.1956589)
MARRIED	-.115063** (.0375905)	-.1890299* (.0921185)
CHILDRENLT18	.0429551 (.0423472)	-.0226489 (.093889)
HISPANIC	-.1490976** (.0554423)	-.01415507 (.1240911)
BLACK	-.2748313*** (.0590302)	-.4133329** (.1435856)
ASIAN	-.2691399** (.0851315)	-.1738278 (.1658924)
NHISPANICOTHER	.311349** (.0901886)	.1794537 (.1631927)
Fixed State Effects LR Test χ^2 (df)	222.07(50)***	74.48(50)*
Fixed Week Effects LR Test χ^2 (df)	183.88(14)***	15.98(5)**
Number of obs.	59293	11198
Log likelihood	-39248.992	-6757.9749
Wald χ^2 (df)	358.5(78)***	104.95(69)**

Notes: State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

Table5b. Logit Results for the Effects of UI based on Spending on Delaying Health Care: YEARS 1 and 2

Delay Health Care	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Year 2
UI SPENDING	-.0076949 (.0312226)	-.1392073 (.0845247)
AGE	.038951*** (.0072425)	.0502175* (.019473)
AGE_SQUARED	-.0003758*** (.0000775)	-.0006163** (.0001941)
WOMEN	.1566209*** (.0303961)	.1357004 (.0843132)
HSGRAD	.1646419* (.0733824)	.2449308 (.1836575)
AADEGREE	.3542527*** (.0778791)	.379548 (.1970468)
BADEGREE	.4065545*** (.0749982)	.200615 (.1879931)
GRADDEGREE	.5949679*** (.0796338)	.3687152 (.19665)
MARRIED	-.051199 (.0317781)	-.1844357* (.0921822)
CHILDRENLT18	.0221059 (.0348426)	-.0258284 (.0936258)
HISPANIC	-.2223327*** (.0467753)	-.131474 (.1239267)
BLACK	-.3424271*** (.0472418)	-.4085153** (.1447615)
ASIAN	-.335533*** (.076459)	-.1667821 (.1658384)
NHISPANICOTHER	.1591353* (.0753014)	.1842883 (.1660047)
Fixed State Effects	296.33(50)***	72.7(50)*
LR Test χ^2 (df)		
Fixed Week Effects	330.83(20)***	15.76(5)**
LR Test χ^2 (df)		
Number of obs.	105267	11198
Log likelihood	-701116.934	-6766.254
Wald χ^2 (df)	505.61(84)***	98.51(69)**

Notes: State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

We also assess digital access with two measures. The first measure is the availability of computer access. The second measure is the availability of internet access. Tables 6a and 6b shows the logit results of the effect of receiving UI benefits on the *unavailability* of computer access. Tables 7a and 7b shows the logit results of the effect of receiving UI benefits on the *unavailability* of internet access. As with the question on delayed health services, questions regarding both computer and internet access were discontinued with HPS week 33 (June 23, 2021). As a result, year 2 is only a partial year for both measures.

Having UI does decrease the likelihood of having limited computer availability based on the UI receipt question method determining UI benefits during the first and second year of the pandemic. The coefficients using the UI receipt question are statistically significant and negative in terms of less computer access in both years. In the logits using the UI spending question method and the UI receipt coefficients are still negative but only statistically significant for the first year.

The racial and ethnic coefficients are generally positive but mixed with respect to statistically significant. The coefficients for Other displaced workers are significant and positive for the first year using both methods of determining UI status. The coefficient for Black workers is positive and significant in the first year using the UI spending method, but the Black coefficient is significantly *negative* in year 2 based on the UI receipt question. This result may be due to a small number of Black respondents in the partial year 2. None of the coefficients for women are significant using the UI receipt and UI spending questions for both years.

The education coefficients are generally statistically significant and negative in the first year, but less significant in year 2. The coefficients for married workers are negative and significant in both UI logits in both years except year 2 using the UI spending method. The coefficients for workers in families with children under 18 are negative and statistically significant for methods of determining UI receipt for year 2.

Table 6a. Logit Results for the Effects of Receiving UI on *Less* Computer Availability, Years 1 and 2

Computer Availability Problems	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Year 2
UI RECEIPT	-.3413508** (.1233233)	-.223228** (.0881093)
AGE	-.0864604** (.0255451)	.0517435** (.0195535)
AGE_SQUARED	.00105*** (.0002837)	-.0006286** (.0001946)
WOMEN	-.0193752 (.1238335)	.138954 (.084526)
HSGRAD	-.2168844 (.2048337)	.2435817 (.1836109)
AADEGREE	-.4909425* (.226001)	.379171 (.1976938)
BADEGREE	-.8704579*** (.223037)	.2087391 (.1885322)
GRADDEGREE	-.6251137** (.2547574)	.3530286 (.1965635)
MARRIED	-.2861693* (.1294485)	-.1878757* (.092274)
CHILDRENLT18	.5390805 (.5709307)	-.0233197 (.095056)
HISPANIC	.1049883 (.1633332)	-.1415799 (.1246671)
BLACK	.1049883 (.1633332)	-.4099287** (.1442434)
ASIAN	.0086482 (.279099)	-.1689251 (.1665667)
NHISPANICOTHER	.9909533*** (.2099599)	.1811524 (.1650142)
Fixed State Effects	286.49(50) ***	149.85(44) ***
LR Test χ^2 (df)		
Fixed Week Effects	109.65(14) ***	41.75(5) **
LR Test χ^2 (df)		
Number of obs.	14519	2211
Log likelihood	-4933.6304	-579.31821
Wald χ^2 (df)	257.07(78) ***	137.18(63) ***

Notes: State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$; degrees of freedom smaller due to respondents reporting the same responses in Washington DC, Hawaii, Iowa, North and South Dakota, and Vermont.

Table6b. Logit Results for the Effects of Receiving UI based on Spending on *Less* Computer Availability, Years 1 and 2

Computer Availability Problems	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Year 2
UI SPENDING	-.2462333** (.0897883)	-.5172608 (.2947784)
AGE	-.0431525 (.0242969)	.0778369 (.068801)
AGE_SQUARED	.0004891 (.0002903)	-.0007625 (.0007726)
WOMEN	.0359895 (.0909747)	-.4566957 (.2821509)
HSGRAD	-.3798223* (.1473186)	-.6551165 (.4287521)
AADEGREE	-.6535137*** (.1636821)	-1.162223* (.4917508)
BADEGREE	-1.015961*** (.1605149)	-1.17186* (.4844217)
GRADDEGREE	-.8134563*** (.1859284)	-1.338577* (.6325348)
MARRIED	-.2399116* (.0948292)	-.5239113 (.3037892)
CHILDRENLT18	.2182403 (.3417578)	-4.212901*** (1.091852)
HISPANIC	.1815235 (.1138086)	-.7084997 (.4055339)
BLACK	.2887236* (.1194639)	.3065818 (.4950182)
ASIAN	-.0997526 (.2355616)	-.626356 (.5457551)
NHISPANICOTHER	.7797235*** (.1767406)	.5040396 (.5099279)
Fixed State Effects	375.89(50)***	149.83(44)***
LR Test χ^2 (df)		
Fixed Week Effects	541.28(20)***	37.30(5)***
LR Test χ^2 (df)		
Number of obs.	27530	2211
Log likelihood	-11177.442	-577.0148
Wald χ^2 (df)	387.88(84)***	139.85(63)***

Notes: State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

The results for access to the internet are similar to computer access. As with computer access, having UI does decrease the likelihood of having limited access to the internet based on both the UI receipt question method and UI spending methods of determining UI benefits during the first and second year of the pandemic. The coefficients using the UI receipt and the UI spending questions are statistically significant and negative in determining problems accessing the internet in both years.

During the first year, the racial and ethnic coefficients are generally positive, with the exception of Asian displaced workers. In the first year, the non-Hispanic Other coefficient is significant using the UI receipt question. The Other coefficients are also positive and significant in the first and second years based on UI spending. In the second year, only the coefficients of Other displaced workers are statistically significant in both years for both methods of determining UI status. The Black coefficient is significant and positive using the UI spending method in the first year. The Asian coefficients are all negative across years and UI methods, but significant only in year 1 using the UI receipt method. None of the coefficients for women are significant using the UI receipt and UI spending questions for both years.

The education coefficients are generally statistically significant and negative in both years. The coefficients for married workers are also negative and significant in all the UI logits. The coefficients for individuals in families with children under 18 are negative and statistically significant for methods of determining UI receipt for year 2, but not for year 1.

Table 7a. Logit Results for the Effects of Receiving UI on *Less* Internet Availability, Years 1 and 2

Internet Availability Problems	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Year 2
UI RECEIPT	-.324753** (.1392569)	-.976052* (.2380305)
AGE	-.0682023* (.0264106)	-.0345851 (.0509781)
AGE_SQUARED	.0007439* (.0002965)	.0004731 (.0005686)
WOMEN	.0419819 (.1296276)	-.2002233 (.2410193)
HSGRAD	-.5029102* (.2101389)	-.8527334* (.3503111)
AADEGREE	-.702639** (.23114)	-1.423976** (.4429442)
BADEGREE	-1.185721*** (.2275079)	-1.530515** (.4433147)
GRADDEGREE	-.6571425** (.2469189)	-1.535914** (.5857121)
MARRIED	-.4277296** (.1349388)	-.6451367** (.2453857)
CHILDRENLT18	-.5378705 (.5486527)	-4.134214*** (1.128948)
HISPANIC	.2426144 (.1747738)	-.3696256 (.3918557)
BLACK	.2171701 (.1747738)	.4297432 (.3309444)
ASIAN	-.5372892* (.2710126)	-.4443073 (.6323915)
NHISPANICOTHER	1.182626*** (.2023944)	1.209517** (.4150266)
Fixed State Effects LR Test χ^2 (df)	237.65(50)***	157.38(47)***
Fixed Week Effects LR Test χ^2 (df)	137.84(14)***	6.65(5)
Number of obs.	14403	2292
Log likelihood	-5038.6501	-679.47728
Wald χ^2 (df)	299.70(78)***	160.6(66)***

Notes: State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$; degrees of freedom smaller due to respondents reporting the same responses in Montana, South Dakota, and Vermont.

Table7b. Logit Results for the Effects of Receiving UI based on Spending on *Less* Internet Availability, Years 1 and 2

Internet Availability Problems	Logit Coefficients with Robust Standard Errors in parentheses	
	Covid Year 1	Covid Year 2
UI SPENDING	-.2502087** (.09424284)	-.6231729* (.2425631)
AGE	-.0440954 (.0247015)	-.0309244 (.0491796)
AGE_SQUARED	.0004508 (.0002931)	.0004248 (.0005399)
WOMEN	.0715464 (.0973599)	-.2111755 (.2428696)
HSGRAD	-.4547803** (.1520888)	-.8109462* (.3430077)
AADEGREE	-.6265182*** (.1760229)	-1.35901** (.4350274)
BADEGREE	-1.139104*** (.1762561)	-1.472602** (.4278335)
GRADDEGREE	-.7230668*** (.1930924)	-1.447922* (.5752505)
MARRIED	-.2488939* (.1038779)	-.6734816** (.2432254)
CHILDRENLT18	-.4340192 (.3712117)	-4.254634*** (1.144881)
HISPANIC	.1253125 (.1219439)	-.3558597 (.3902589)
BLACK	.3498429** (.1269632)	.4187475 (.3376796)
ASIAN	-.4601992 (.3065669)	-.4562092 (.6250084)
NHISPANICOTHER	.7706977*** (.1747977)	1.123387** (.4060235)
Fixed State Effects LR Test χ^2 (df)	427.46(50)***	155.31(47)***
Fixed Week Effects LR Test χ^2 (df)	168.80(20)***	5.90(5)
Number of obs.	27307	2292
Log likelihood	-10287.557	-676.47772
Wald χ^2 (df)	388.06(84)***	160.53(66)***

Notes: State and HPS week dummies not reported for clarity; *** = $p < .001$, ** = $p < .01$, * = $p < .05$

Conclusion and Policy

We have attempted to document the effects of receiving unemployment benefits on workers displaced by COVID during the early and later stages of the pandemic. Clearly, COVID displaced workers who received UI benefits experienced less food insecurity, were more likely to delay health care, and less likely to suffer from the digital divide. At the same time, we show that the pandemic had significant racial and ethnic differences in who was displaced by the pandemic as well as who collects unemployment relief during both stages of the pandemic as well as in determining who is food insecure and less likely to receive health insurance. Black, Hispanic, Asian, and “Other” workers were more likely to have been displaced by the pandemic. The logit results, controlling for individual characteristics and state of residence, also show that Hispanic, Black, and “non-Hispanic Others” are less likely to receive unemployment insurance. Unemployment benefits provide not just a source of income and consumption for recipients, but also have effects on food insecurity, health, and digital access. These differences in who receives UI benefits by race are part of the increasing racial dimension of economic inequality in the US. The HPS data allows us to contribute to the growing literature on the labor market effects of the pandemic by identifying workers directly displaced by COVID and linking these workers to whether they received UI benefits. We are also able to expand this literature with the inclusion of Asians and “non-Hispanic Other” workers who do not self-identify with a single race or ethnicity. Finally, we directly examine the effects of receiving UI on other social indicators over three years of the pandemic.

These results have an impact on public policy. Although the CARES Act did increase benefits, eligibility, and the duration of UI benefits, this expansion still did not remove racial and ethnic disparities. In addition to augmenting UI benefits, policies should include better community outreach to minority and low-income communities as well as language and assistance programs to better explain UI eligibility and enrollment. Past studies have shown that younger workers, Black workers, and Hispanic workers are more likely to leave the labor force when unemployed during a recession. UI policies to keep these workers in the labor force would help to mitigate economic inequities in incomes and employment by race and ethnicity in the aftermath of the pandemic. In the short-run, policies include extended benefit duration, increased family assistance payments, and job search

assistance. Over the longer run, programs could be developed to preserve jobs and small businesses, provide job skill development, and expand social services for lower-income and minority workers who have been heavily impacted but underserved by traditional social welfare programs. Although there is currently a debate over the labor market effects of expanded UI benefits during the pandemic (Altonji et al, 2020 and Coombs et al, 2022), these studies show that racial economic inequalities have been exacerbated by the pandemic.

This study contributes to the knowledge of how the pandemic has had a differential impact on the labor market by specifically examining the direct effects of COVID job displacement and who received unemployment benefits. Along with previous studies, we find that Blacks, Hispanics and “non-Hispanics Other” workers in particular face a greater labor market impact as a result of the pandemic. Use of the HPS data allows us to identify workers directly unemployed by COVID and to control for individual characteristic. Using the HPS data does have some limitations. We are unable to analyze the effects of industry and occupation as the HPS data does not include this information for unemployed workers. Industries employing a large percentage of Black and Hispanic workers – hospitality and leisure, personal services, and retail industries – were hard hit by the pandemic. It is likely that omitting the industry and occupational effects would lower the magnitude of the racial and ethnic effects on unemployed workers without UI. However, studies of the pandemic labor market effects on unemployment and earnings still find significant racial and ethnic effects even with industry and occupation controls. On the other hand, the online survey collection method has likely underrepresented disadvantaged households in the data which may increase the magnitude of racial/ethnic disparities. Finally, the HPS data also does not allow analysis of the critical question of why workers do not receive UI. Reasons include difficulty in accessing UI applications, knowledge of the UI program, linguistic problems, immigration status, differences in local administration of UI, and discrimination. In order to develop appropriate policies as the pandemic continues, future research is necessary to determine specific reasons different ethnic/racial groups have accessing UI.

Some directions of future research suggested by this study includes a closer examination of changes in UI over time as a result of policy changes. For example, the end of the CARES Act in 2021 likely decreased UI benefits after 2021. In addition, states had much different implementation of social programs during the pandemic. The logit results show significant state and time effects that need further investigation. Future research should also investigate the “scaring ” effects on labor market outcomes as past studies have shown significant negative effects on wages and future unemployment due to recessions.

Conflict of Interest Statement

On behalf of all authors, the corresponding author states that none of the authors have a financial or personal relationship with a third party whose interests could be positively or negatively influenced by the article's content.

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

These datasets were derived from the following public domain resources:

<https://www.census.gov/data/experimental-data-products/household-pulse-survey.html>

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Endnotes

¹ In the United States, unemployment insurance is a federal program administered by state agencies. Employers fund the program with an unemployment insurance tax. Cash payments are normally made to eligible recipients for up to 26 weeks. Eligibility and level of benefits are normally based on earnings during a period before job loss. Eligibility is also based on a job loss due to an involuntary separation. During the pandemic, the 2020 Coronavirus Aid, Relief, and Economic Security (CARES) Act expanded both eligibility, duration, and benefits.