Economics of Disasters and Climate Change (2022) 6:451–469
https://doi.org/10.1007/s41885-022-00115-9

ORIGINAL PAPER

Economic Impact Payments and Household Food Insufficiency during COVID-19: The Case of Late Recipients

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Received: 12 October 2021 / Accepted: 22 March 2022 / Published online: 30 May 2022
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Abstract
During the COVID-19 pandemic, the U.S. government distributed Economic Impact Payments (EIPs) to ease the economic hardships of American households. Using the Household Pulse Survey, we study the association of first-round EIPs with household-level food insufficiency in a sample of late recipients of EIPs. Studying the late recipients is important for two reasons, first, about 12 million eligible individuals did not automatically receive EIPs, and second, the late receipt of EIPs and the low-income status of late recipients allow us to tease out the relationship between EIPs and food insufficiency. We find that EIPs were associated with a 9.2 percentage points decrease in the likelihood of food insufficiency. However, households kept relying on free food acquisition to fight food hardship. Our results suggest that government efforts to provide more timely stimulus payments could be very impactful and significantly impact household food insufficiency.

Keywords Fiscal policy · Stimulus payments · COVID-19 · Food insufficiency

Introduction

In spring 2020, the United[1] States faced a rapid deterioration of economic conditions due to the coronavirus (COVID-19) pandemic. Most states ordered social distancing measures – leading to school and business closures – to avoid the spread of coronavirus (Courtemanche et al. 2020). The U.S. COVID-19 death toll exceeded 148,000 and infection rate reached 4.3 million by the end of July 2020 (Bauer et al. 2020). The growth rates of

[1] António Guterres, "COVID-19: We will come through this together," United Nations, March 13, 2020. https://www.un.org/en/coronavirus/covid-19-we-will-come-through-together

This article belongs to the Topical Collection: *Economics of COVID-19*

"COVID-19 is our common enemy. We must declare war on this virus. That means countries have a responsibility to gear up, step up and scale up". – António Guterres, Secretary-General of the United Nations

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unemployment and the Consumer Price Index (CPI) for all food surpassed those during the Great Recession, mainly affecting households with low-income, lower education, and households identifying as Black or Hispanic (Bitler et al. 2020; Gharehgozli et al. 2020).[2] Among non-senior adults, food insufficiency increased by threefold in July 2020 compared to 2019 (Ziliak 2021). The share of households with children who are food insecure went up by three percentage points compared to 2016/2017 (Ahn and Norwood 2021).[3] The number of food insecure Americans increased by a projected 17 million compared to the 2018 level, reaching a total of 54 million in 2020 (Gundersen et al. 2021).

In response to the pandemic, the U.S. government stepped up and enacted the Families First Coronavirus Response Act (2020) (FFCR) and the Coronavirus Aid (2020) (CARES), supporting American households through unemployment insurance (UI), Supplemental Nutrition Assistance Program (SNAP), Pandemic Electronic Benefit Transfer (P-EBT), and Economic Impact Payments (EIPs). The EIPs, which are also referred to as recovery rebates or stimulus payments, provided a refundable tax credit up to $1,200 for eligible single tax filers ($2,400 for eligible joint tax filers), plus $500 for each dependent child (Bitler et al. 2020).

Stimulus payments like EIPs are a significant fiscal expenditure of the U.S. government during recessions. For instance, the U.S. government distributed around $267 billion from early April to early June of 2020 (USDT 2020). It is imperative to investigate if EIPs were positively associated with the economic conditions of American households because that was an objective of EIPs. One particular and important manifestation of improving economic conditions is a decrease in food insufficiency among households. In this study, we particularly investigate the association of EIPs with household food insufficiency in a sample of late recipients of EIPs. We do this by exploiting the late receipt of first-round EIPs among food insufficient households. Studying food insufficiency of late recipients of EIPs is important because about 12 million eligible individuals did not automatically receive first-round EIPs, and these individuals were more likely to be low income and much in need of economic relief (Bitler et al. 2020). Additionally, the late receipt of EIPs was potentially anticipated by some households and may have led to consumption smoothing, so our study bears some evidence on the association between anticipated EIPs and food insufficiency. In other words, the anticipation of additional income can also be relevant for household food insufficiency.

In our analysis, we use the Census Bureau's Household Pulse Survey (HPS) for Weeks 7 – 12, which spans June 11, 2020 through July 21, 2020. Our analysis sample focuses on households that are late receivers of EIPs, i.e., households that did not automatically receive EIPs during early April to early June of 2020. The Internal Revenue Service could not automatically send EIPs to eligible households that did not have tax file information or benefit records. Given our analysis sample, the reader should interpret the results within the context of households that are late recipients of EIPs. The results do not apply to the overall population in the U.S.

[2] Black or Hispanic households could be multiracial or multiethnic.

[3] Food insufficiency and food insecurity are measures of food hardship, and both are related conceptually (USDA 2021). A household is defined to be in food hardship when it sometimes or often ran out of food, or worried about not having the means to secure food. More specifically, a household is food insufficient if it sometimes or often did not have enough to eat in the last 7 days. A household is food insecure if it was not able to secure adequate food for household member(s) due to lack of money or other resources in the last 12 months or 30 days.

Although the dependent variable of interest is household food insufficiency, we also study the association of EIPs with households' future food confidence and receipt of free food. We find that the receipt or expected receipt of EIPs is associated with a 9.2 percentage points decrease in the likelihood of household-level food insufficiency. And EIPs have no association with household-level future food confidence or receipt of free food. Although stimulus payments are aimed to boost aggregate demand during economic downturns, results from this study show that the first-round EIPs were also helpful in managing immediate food insufficiency at the household level during COVID-19. However, EIPs were not enough to fight food hardship because food insufficient households kept relying on other means of food assistance, for instance, receipt of free food. Because late-recipient households are more likely to be low-income, our work suggests that government efforts to deliver future stimulus payments more quickly to these households could have substantial benefits. Supporting low-income households on time will not only boost aggregate demand but also fight food hardship. A fiscal policy response during economic downturns certainly benefits from including consumption responsive households such as low-income households (Andreolli and Surico 2021).

Literature Review

The economic impact of recessions can vary across demographic groups. Since the late 1970s, the cyclical increase in unemployment has repeatedly occurred for the following demographic groups during economic recessions: men, Black or Hispanic workers, youth, and low-education workers (Hoynes et al. 2012). During COVID-19, disadvantaged demographic groups were at a high risk of food insecurity due to their vulnerability to unemployment and food price inflation (Bitler et al. 2020; Ziliak 2021). Although the economy may recover quickly after a recession, food insecurity can linger for many years. The Great Recession of 2007-09 led to an increase in food insecurity rate (from 11.1% to 14.9%), however, it was not until 2019 that the rate fell to 10.5% (Coleman-Jensen et al. 2020).

There are many determinants of food insecurity that could influence its prevalence, especially after an economic downturn. In a literature review of determinants and consequences of food insecurity, Gundersen and Ziliak (2018) highlight the importance of economic resources and family composition as determinants of food insecurity. Current income is another important determinant of food insecurity, but assets provide more protection against economic shocks (Gundersen and Ziliak 2018). Single-parent or female-headed households are more exposed to food insecurity, but so are households that are at risk of experiencing homelessness or with a disabled family member (Gundersen and Ziliak 2018; Ribar and Hamrick 2003).

In addition, the health consequences of food insecurity cannot be ignored from a public health perspective. The literature finds that food insecurity has a negative association with health. For instance, food insecurity is associated with birth defects, anemia, and various mental health problems (Gundersen and Ziliak 2015). One goal of food assistance programs is to avoid the negative health consequences of food insecurity.

Since social assistance programs are essential to households' well-being during economic downturns, this study adds to the literature that estimates the relationship of various social assistance programs with food insecurity. Among the various US social assistance programs, both SNAP and UI provide considerable relief during economic downturns. SNAP is a federally financed entitlement program and UI is a state financed entitlement

program (Moffitt and Ziliak 2020). SNAP benefits have been found to reduce food insecurity or increase food spending in SNAP-participating populations (Kim 2016; Van Hook and Balistreri 2006; Nord and Prell 2011). Meanwhile, UI benefits are also effective in reducing food insecurity. Two recent studies found that UI receipt is associated with a 1.9 and 4.3 percentage points decrease in food insecurity among American who lost jobs during COVID-19 (Karpman and Acs 2020; Raifman et al. 2021). During COVID-19, some families with school-age children lost access to school meals, so the FFCR Act of 2020 provided P-EBT payments to support the nutrition for affected families. The provision of P-EBT benefits reduced children's food hardship by about 11 percentage points during the first week of payments (Bauer et al. 2020). Our study contributes to the above line of research by focusing on the relationship between EIPs and household food insufficiency. We use the Household Pulse Survey (HPS), which to our knowledge is the most credible survey on measuring the social and economic impact of COVID-19 on American households. The HPS is conducted by the U.S. Census Bureau. While SNAP, UI, and school meal program (i.e., P-EBT during COVID-19) are social assistance programs that are managed on an ongoing basis, EIPs are one-time stimulus payments that are activated and distributed during economic recessions to alleviate economic hardship and to boost aggregate demand. During the COVID-19 pandemic, the federal government distributed three rounds of EIPs (more on this in the next section). Understanding the relationship between EIPs and household food insufficiency during recessions can inform whether EIPs were effective in alleviating household economic hardship among households that were food insufficient and late recipients of EIPs.

Finally, our research is relevant to the consumption smoothing literature, particularly the excess sensitivity of consumption spending when households anticipate future additional income from a stimulus, fund, or tax cuts (Hsieh 2003; Jappelli and Pistaferri 2010; Aladangady et al. 2018; Kueng 2018). A main prediction of the life-cycle and permanent income hypothesis is that consumption should not change as a result of anticipated income change. However, research shows that households increase consumption spending in response to anticipated income increase (Hsieh 2003; Aladangady et al. 2018; Kueng 2018). Research on social protection programs and EIPs further shows that without the government's support during COVID-19, household consumption and poverty would have fared poorly (Martin et al. 2020). In case of EIPs, about 12 million eligible individuals did not automatically receive first-round EIPs, and these individuals were more likely to be low income (Bitler et al. 2020). Since the receipt of EIPs was potentially anticipated by some of the late-recipient households, this may have led to consumption spending even before the actual receipt of EIPs.

Background on EIPs

After the signing of CARES Act into law on March 27, 2020, the Internal Revenue Service (IRS) started distributing the first round of EIPs to American households in early April 2020. The EIPs, which are also referred to as recovery rebates or stimulus payments, provided a refundable tax credit up to $1,200 for eligible single tax filers ($2,400 for eligible joint tax filers), including $500 for each dependent child (Bitler et al. 2020). The tax credit was designed to phase out at a rate of 5% of adjusted gross income beyond a threshold, which was $150,000 for joint filers, $112,500 for head of household, and $75,000 for single tax filers. The IRS sent first round of stimulus payments to the following groups of

eligible individuals: (a) individuals who filed taxes in 2018 and 2019, (b) individuals who did not have to file taxes in 2018 and 2019 but received Social Security benefits, Railroad Retirement benefits, Supplemental Security Income, and benefits from Veteran Affairs, and (c) eligible individuals without tax file information who submitted information through the IRS non-filers online tool (IRS 2021a).

The IRS managed the herculean task of processing 159 million stimulus payments (worth more than $267 billion) in two months, i.e., early April to early June of 2020 (USDT 2020). Overall, the IRS sent about 162 million first-round stimulus payments in calendar year 2020, worth more than $271 billion (IRS 2021b). Of all the first-round stimulus payments, 77% were sent by electronic fund transfers, 20.7% by paper check, and remaining 2.3% by EIP debit card.

Since 2001, fiscal stimulus has been a crucial part of the U.S. economic policy response during recessions (Sahm et al. 2012). For instance, in 2001 and 2008, the federal government sent tax rebates and one-time stimulus payments to households via paper checks or electronic checks, respectively, to boost the economy. These stimulus payments can play an important role in supporting households' consumption expenditures during times of economic hardship. The first-round stimulus payments of 2020 were second to regular income in terms of their reported use to meet recipients' spending needs (Garner, Safir, Schild, 2020). Among individuals who received or expected to receive a first-round stimulus payment in 2020, majority mentioned using some part of it for food expenses (Garner et al. 2020).

Although the Treasury and IRS managed to send 159 million first-round stimulus payments in two months' time, two specific issues emerged that relate to stimulus payments' coverage and their late arrival. Regarding coverage, families were ineligible to receive a stimulus payment if they had an immigrant adult without a Social Security number, except families with a military member (Bitler et al. 2020). Regarding late arrival, eligible individuals without tax file information or benefit records had to apply for a stimulus payment through the IRS non-filers tool, so the non-filer population received payments later than those individuals who automatically received it. It is estimated that 12 million eligible individuals did not automatically receive first-round stimulus payments, and these individuals were more likely to be low income and much in need of economic relief (Bitler et al. 2020). Since some eligible individuals received or expected to receive stimulus payments later than usual, we focus on these "late recipients" to study the association between stimulus payments and household food insufficiency.

Methods

To study the association between EIPs and household-level food insufficiency, we use the Household Pulse Survey (HPS). In the data sub-section, we describe the HPS and the survey questions related to food insufficiency and EIPs.

Data

Starting in April 2020, the U.S. Census Bureau developed and fielded the HPS with five federal statistical agencies to collect information on the social and economic impacts of COVID-19 on American households. The five federal agencies include the Bureau of Labor Statistics, the National Center for Health Statistics, the United

States Department of Agriculture's Economic Research Service, the National Center for Education Statistics, and the Department of Housing and Urban Development. The HPS is a rapid household survey with a quick turnaround, thus enabling governmental and non-governmental organizations to measure the emerging impact of COVID-19 on American households.

The HPS data has been continuously collected and distributed since April 23, 2020 and is still being fielded as of writing on March 14, 2022. Each data release refers to a certain week, i.e., HPS Week 1, HPS Week 2, and so on. Using the Census Bureau's Master Address File (MAF), the HPS can provide weekly variable estimates at the national level, state level, and 15 Metropolitan Statistical Areas. The MAF serves as the sampling frame for sampled household units (HUs) for the HPS. The MAF contains about 144 million addresses, and about 80% of those addresses have cellphone, or email, or both types of contact information (USCB 2020). A new sample of HUs is drawn for each week of the survey, so the HPS is essentially a repeated cross-sectional survey. Household units are contacted via email, or text when email is not available. A respondent from a contacted household unit is eligible to take the survey if the respondent's age is 18 years or greater. When the Census Bureau receives a complete interview from a newly sampled household, the household stays in the sample for a maximum of two additional weeks of interviewing (these are called the "repeat households"). However, not all repeat households take the survey in each of the two weeks after their first survey. Although the HPS is a repeated cross-sectional survey, it is possible to create an unbalanced panel data with the subset of repeat households that take the survey in one or both of the subsequent two weeks. From a data perspective, a repeat household can have at least two observations and at most three observations in the HPS data. Two observations can happen if a household takes the survey in the second consecutive week after the first week's completed survey, but does not take the survey in the third consecutive week. The HPS has been conducted online through Qualtrics for rapid data collection purposes. The national level weighted response rates for Weeks 7 through 12 (our study period) range from 2.3% to 3.3% (USCB 2020).

In this study, we use HPS data for Weeks 7 through 12, which spans June 11, 2020 through July 21, 2020 (USCB 2021). Although the bulk of EIPs were processed and sent during the survey period of HPS Weeks 1 – 6 (early April to early June of 2020), the HPS only started asking about EIP from Week 7 through Week 12.[4]

Two HPS questions on EIPs and food insufficiency are of particular importance to our study. The HPS asks survey respondents the following question regarding EIP:

"Q15. If you, or anyone in your household, already received, or plan to receive a "stimulus payment," that is the coronavirus related Economic Impact Payment from the Federal Government, did or will you use it: Select only one answer".

1. Mostly to pay for expenses (food, clothing, shelter, etc.)
2. Mostly to pay off debt (car loans, student loans, credit cards)
3. Mostly to add to savings
4. Not applicable, I did not and do not expect to receive the stimulus payment

[4] Phase 1 of the HPS ran from April 23, 2020 through July 21, 2020 and covers twelve data releases (HPS Week 1 – 12). Phase 2 ran from August 19, 2020 through October 26, 2020 and covers five data releases (HPS Weeks 13 – 17). Phase 3 began on October 28, 2020 and is still being fielded as of writing on March 14, 2022. We use HPS Weeks 7 – 12.

If a household respondent selects any option from 1 to 3, it shows a receipt or an expectation to receive EIP. In this study's context, we consider a household "late recipient" of EIP if a household respondent selects option 4 in a survey week but then switches to any option from 1 to 3 in subsequent survey week(s). The Census Bureau keeps the repeat households in the HPS sample for a maximum of two additional weeks, so there can only be two more observations per repeat household at a maximum or one observation at a minimum. If a household has two more observations after switching from 4 to (1, or 2, or 3), we include the two observations in our "analysis sample", hence there will be three observations per household in total. If a household has one observation after switching from 4 to (1, or 2, or 3), we include the one observation in our analysis sample, hence there will be two observations per household in total. We describe our analysis sample after the next three paragraphs.

When households choose option 4 during their first survey appearance, it means that they had no expectation of receiving EIPs in earlier weeks. Otherwise, they would be selecting any option in 1 - 3 during their first survey appearance. When a household respondent switches from option 4 to any option in 1 – 3, it can only be that the household has either received EIP or has started expecting EIP. Although intended receipt of EIP is not the same as actual receipt of EIP, the anticipation of the EIP may lead to a food spending increase via consumption smoothing behaviors. The partially longitudinal nature of HPS in Weeks 7 – 12 is particularly helpful for the analysis in this study. Although, in HPS Weeks 22 – 24, there are questions about the second round of EIPs, the HPS has no repeat households during those survey weeks (hence, no partial longitudinal data structure exists all). Therefore, we do not use HPS Weeks 22 – 24 in this study.

Regarding measurement of household food insufficiency, we follow Ziliak (2021) and use the following HPS question:

"Q24. In the last 7 days, which of these statements best describes the food eaten in your household? Select only one answer".

1. Enough of the kinds of food (I/we) wanted to eat
2. Enough, but not always the kinds of food (I/we) wanted to eat
3. Sometimes not enough to eat
4. Often not enough to eat

Ziliak (2021) considers households to be food insufficient (or "food insufficient with reduced variety") when they select option 3 or 4 (2, 3, or 4). In this study, we focus on households that are food insufficient with reduced variety, i.e., households that responded with a 2, 3, or 4 to Question 24, and simply refer to them as food insufficient households. The food insufficiency question (Q24) in HPS aligns with the food insufficiency question (HESS1) in the Food Security Supplement (FSS) of the Current Population Survey (CPS), which is a monthly representative survey of about 60,000 U.S. households conducted by the United States Census Bureau for the Bureau of Labor Statistics (BLS) (Ziliak 2021). The FSS module is only included in the December CPS. The CPS makes it possible to compute the official estimates of food insecurity, i.e., it asks 18 questions (10 questions) about food hardship, targeted toward households with children under 18 years (households without children). In order for a household to be asked food insecurity questions in the CPS, it has to have income below 185% of Federal Poverty Line, or answer 2, 3, or 4 on food insufficiency (HESS1), or answer 1 (Yes) or -2 (Don't Know) on question (HES9), which asks a household if it ran out of money and had to struggle with food in the last 12

months? Given COVID-19 and the urgent need for data, the HPS was meant to be brief, so it was not meant to ask 18 or 10 questions about food insecurity. When the December 2021 CPS is released in 2022, it will have data about household food insecurity during 2021. We will not be comparing food insufficiency measure from the HPS with that of the CPS because (i) the CPS data was not available during our analysis stage, and (ii) the CPS does not identify late recipient of EIPs among survey households.

Regarding our analysis sample, we restrict the HPS data to households that meet two criteria: (i) the households are food insufficient before the receipt or expected receipt of EIPs, and (ii) they are late recipients of EIPs. The data structure of the analysis sample is such that households first appear as food insufficient and without an EIP in the HPS, but then receive or expect to receive an EIP in the later week(s) of the HPS. Such a data structure allows us to study the association of EIPs with food insufficiency. If we find that household food insufficiency is negatively associated with EIP receipt or anticipated receipt, this means that food consumption has increased ahead of EIP for a portion of our analysis-sample households. Although due to lack of information we cannot determine what portion of respondents have actually received EIP and what portion anticipates EIP arrival, our study bears some evidence on the association between anticipated EIPs and food insufficiency.

In the HPS Weeks 7 through 12, there are a total of 549,361 observations (the full sample), and only 1,388 observations make up the main analysis sample. A point to note regarding the full sample and the analysis sample is that each one is created by pooling data from survey Weeks 7 through 12. However, the full sample pools all survey respondents from Weeks 7 through 12 (hence, a repeated cross-section data); and the analysis sample only pools respondents that take the survey at least two times and at most three times in total, and fulfill the aforementioned two criteria (hence, an unbalanced panel data). We use household-level sampling weights from the HPS when generating descriptive statistics and regression estimates.

In Table 1, we provide summary statistics of dependent and independent variables by the full sample and the analysis sample. A brief look at Table 1 reveals that the households in the analysis sample are facing more food hardship and are disadvantaged when compared to the households in the full sample. Household food insufficiency stands at 83% versus 42% in the analysis and full samples, respectively. Household confidence in future affordability of food stands at 35% versus 66% in the analysis and full samples, respectively. When compared with the statistics in the full sample, the analysis sample has more male respondents, less married respondents, more Black respondents, fewer respondents with household income of $100,000 and above, more respondents with only high school degree, less employed respondents, more respondents with rental housing, and more respondents with poor or fair health. The difference in summary statistics between the full sample and the analysis sample is not surprising because we restrict the analysis sample to food insufficient households, and food insecurity literature shows that households from disadvantaged backgrounds are more likely to be food insecure (Gundersen and Ziliak 2018).

In Table 2, we provide summary statistics of socio-demographic variables by the analysis sample and the "on-time recipient" sample. As a reminder, each of the two samples is a sub-sample of the full sample. The two samples are similar in terms of food insufficiency, i.e., upon respondents' first interview in the HPS, they mention that their households are food insufficient. What really differentiates the two samples is that respondents in the analysis sample (on-time recipient sample) have not received and do not expect to receive EIPs (have received or expect to receive EIPs) at the time of interview. In other words, households in the on-time recipient sample are both food insufficient and receive EIPs on time

Table 1 Household summary statistics for socio-economic variables (full and analysis samples)

	Full Sample Mean (St. dev.)	Analysis Sample Mean (St. dev.)
Dependent Variables (each one is binary)		
Food Insufficient (n = 538,277; n = 1,388)	0.42	0.83
Confident to Afford Food (n = 512,845; n = 1,321)	0.66	0.35
Received Free Food (n = 536,386; n = 1,374)	0.09	0.14
Independent Variables		
Number of Adults (n = 549,361; n = 1,388)	2.19 (1.16)	2.24 (0.85)
Number of Kids (n = 549,361; n = 1,388)	0.69 (1.09)	0.65 (0.73)
Age (n = 549,361; n = 1,388)	48.7 (17.21)	46.83 (10.97)
EIP (n = 544,368; n = 1,387)		
Received or Expect to Receive (binary)	0.86	0.8
Gender (n = 549,361; n = 1,388)		
Male (binary)	0.48	0.54
Marital Status (n = 545,345; n = 1,382)		
Married (binary)	0.50	0.33
Race (n = 549,361; n = 1,388)		
White (base cat.)	0.76	0.66
Black	0.13	0.21
Asian	0.05	0.06
Other	0.06	0.07
Origin (n = 549,361; n = 1,388)		
Hispanic (binary)	0.15	0.22
Income (n = 479,117; n = 1,226)		
$50,000 to $74,999 (binary)	0.18	0.16
$75,000 to $99,999 (binary)	0.12	0.08
$100,000 to $149,999 (binary)	0.13	0.06
$150,000 and above (binary)	0.12	0.07
Education (n = 549,361; n = 1,388)		
High School Graduate (binary)	0.30	0.37
Some College (binary)	0.21	0.21
Associate's Degree (binary)	0.09	0.09
Bachelor's Degree and Above (binary)	0.32	0.20
Employment (n = 546,584; n = 1,387)		
Employed Last 7 Days (binary)	0.52	0.34
Tenant (n = 496,786; n = 1,268)		
Housing Rented (binary)	0.34	0.47
Health (n = 505,675; n = 1,296)		
Fair or Poor (binary)	0.20	0.38

Summary statistics for variables used in regression analysis. Source of the data is the Household Pulse Survey, Weeks 7 – 12. Summary statistics are generated using household-level sampling weights that come with the HPS. Each category of income and education is a binary variable

Table 2 Household summary statistics for socio-economic variables (on-time recipient and analysis samples)

	On-Time Recipient Sample	Analysis Sample
	Mean (St. dev.)	Mean (St. dev.)
Dependent Variables (each one is binary)		
Food Insufficient (n = 160,848; n = 1,388)	0.92	0.83
Confident to Afford Food (n = 151,930; n = 1,321)	0.40	0.35
Received Free Food (n = 158,654; n = 1,374)	0.13	0.14
Independent Variables		
Number of Adults (n = 161,350; n = 1,388)	2.24 (1.08)	2.24 (0.85)
Number of Kids (n = 161,350; n = 1,388)	0.85 (1.07)	0.65 (0.73)
Age (n = 161,350; n = 1,388)	46.09 (14.45)	46.83 (10.97)
EIP (n = 161,172; n = 1,387)		
Received or Expect to Receive (binary)	1	0.8
Gender (n = 161,350; n = 1,388)		
Male (binary)	0.45	0.54
Marital Status (n = 160,606; n = 1,382)		
Married (binary)	0.43	0.33
Race (n = 161,350; n = 1,388)		
White (base cat.)	0.71	0.66
Black	0.18	0.21
Asian	0.04	0.06
Other	0.07	0.07
Origin (n = 161,350; n = 1,388)		
Hispanic (binary)	0.18	0.22
Income (n = 142,482; n = 1,226)		
$50,000 to $74,999 (binary)	0.18	0.16
$75,000 to $99,999 (binary)	0.10	0.08
$100,000 to $149,999 (binary)	0.08	0.06
$150,000 and above (binary)	0.03	0.07
Education (n = 161,350; n = 1,388)		
High School Graduate (binary)	0.35	0.37
Some College (binary)	0.24	0.21
Associate's Degree (binary)	0.10	0.09
Bachelor's Degree and Above (binary)	0.19	0.20
Employment (n = 161,095; n = 1,387)		
Employed Last 7 Days (binary)	0.48	0.34
Tenant (n = 146,956; n = 1,268)		
Housing Rented (binary)	0.45	0.47
Health (n = 149,671; n = 1,296)		
Fair or Poor (binary)	0.31	0.38

Summary statistics for variables used in regression analysis. Source of the data is the Household Pulse Survey, Weeks 7 – 12. The on-time recipients sample include households that are both food insufficient and on-time recipients of EIPs during their first interview in HPS (i.e., they selected any option 1 to 3 on Q15). Each category of income and education is a binary variable. Summary statistics are generated using household-level sampling weights that come with the HPS

during their first interview in HPS (i.e., households selected any option 1 to 3 on Q15). Table 2 is helpful in that we can check if respondents in the analysis sample are particularly different in terms of socio-demographic characteristics against the early-recipient sample.

Although household food insufficiency is 9 percentage points lower in the analysis sample when compared to the early-recipient sample, household confidence in future affordability of food is also lower by 5 percentage points in the analysis sample (see Table 2). In comparison to the early recipient sample, the analysis sample is mainly characterized by more male respondents, less married respondents, more Black or Asian respondents, more Hispanic-origin respondents, fewer respondents with a household income in the range of $50,000 to $149,999 but more respondents with an income of $150,000 and above, more respondents with only high school degree and less respondents with some college education, less employed respondents, more respondents with rental housing, and more respondents with poor or fair health. Since the analysis-sample respondents are more vulnerable based on socio-demographics when compared to the early-recipient and full sample respondents, studying the association of EIPs with household food insufficiency is particularly important in the analysis sample.

Statistical Model

To find the association of EIPs with household food insufficiency, food confidence, or receipt of free food, we estimate the following logistic regression model,

$$ln\left(\frac{P(Y_{ist}=1)}{1-P(Y_{ist}=1)}\right)=\alpha+EIP_{ist}\gamma+X_{ist}\beta+\delta_s+\rho_t, \quad (1)$$

where ln is the natural logarithm; P is the probability that the event Y_{ist} occurs ($Y_{ist}=1$); $ln\left(\frac{P(.)}{1-P(.)}\right)$ is the log odds ratio or logit; and Y_{ist} is household i's food insufficiency, food confidence, or receipt of free food in state s during week t. Household food insufficiency is a binary variable (=1 if a household is sometimes or often without enough to eat, or has enough to eat but with reduced variety).[5] Household food confidence is a binary variable (=1 if a household can afford needed foods in the next 4 weeks). Household free food is a binary variable (=1 if someone in the household received free food or grocery in the last 7 days). *EIP* is a binary variable that indicates whether a household i in state s has received or expects to receive EIP (=1) in a given week t. In other words, *EIP* (=1) if a household chooses any option in 1 - 3 from the EIP question (Q15). *EIP* variable has the same definition in the full sample and in the analysis sample.[6] Following Ziliak (2021) and Restrepo et al. (2021), vector X includes the following socio-demographic variables: number of adults, number of kids, age, gender (=1 if male respondent), marital status (=1 if married

[5] If we restrict food insufficiency definition to households that are sometimes or often without enough to eat (i.e., options 3 or 4 in the food insufficiency question), it leaves us with a couple hundred observations that renders maximum likelihood estimation impractical.

[6] Remember that the analysis sample is restricted to households that are food insufficient and who have not received EIP, but then receive or expect to receive EIP in subsequent week(s). The full sample is made of the analysis-sample households and every other surveyed household that does not fit the definition of the analysis-sample households, for instance, households that are food sufficient and without EIP but receive or expect to receive EIP in later survey week(s), or households that did not receive and do not expect to receive EIP during all survey week(s), or households that expressed a receipt or an expectation to receive EIP during all survey week(s), etc.

respondent), race (white is the base category), ethnicity (=1 if Hispanic respondent), binary variable for each category of income and education as in Table 1, employment status (=1 if respondent is employed in the last 7 days), tenant (=1 if respondent's housing is rented), and health status (=1 if respondent has poor or fair health). Variables income, tenant, and health have missing values in them. Following Ziliak (2021), instead of dropping observations due to missing values, we keep them by introducing binary variables for the missing values of each income, tenant, and health variables. For instance, "Missing Income" is a binary variable (=1 if a household respondent has a missing value for the income question). Similarly, "Missing Tenant" is a binary variable (=1 if a household respondent has a missing value for the tenant question). Finally, "Missing Health" is a binary variable (=1 if a household respondent has a missing value for the health question).[7] Each δ and ρ represent controls for state fixed-effects and survey week fixed-effects, respectively. We cluster the standard errors of coefficients at the state level. Since logistic regression is a non-linear transformation of a linear regression, we estimate equation (1) via maximum likelihood. Instead of reporting the odds ratios, we provide the marginal effects of each explanatory variable while holding all other variables at their average values. For the purpose of this study, we are interested in the marginal effect of EIP variable which measures the association of receipt or expected receipt of EIP with household food insufficiency, food confidence, or receipt of free food. In addition, we briefly discuss socio-demographic variables that have a significant association with household food insufficiency.

Since we restrict our analysis sample to households that are food insufficient before the receipt of EIP, this raises concern regarding selection on the outcome variable. A possible remedy is to include socio-demographic variables from last year, i.e., 2019. Although HPS does not ask questions about household socio-demographics in 2019, the income question is specifically about household income in 2019. Furthermore, variables on gender, race, and ethnicity are fixed characteristics that should not change with year. Regarding other variables, i.e., number of kids, number of adults, marital status, education, and tenant, we assume that such socio-demographic characteristics have remained the same from 2019 until June 2020. So, we think selection on outcome variable should not be a serious concern here.

Regarding confounding variables, we are potentially missing two confounders from our analysis that may affect the coefficient estimates on EIP variable. The two confounding factors are following: (i) households that are EIP ineligible due to having an immigrant adult in the household who does not have a social security number, and (ii) whether the Treasury (IRS) has tax records for a household's members. A household that has an immigrant adult without a social security number, or a household without tax records, is likely to be low income (Bitler et al. 2020), which can lead to food insufficiency. Having information about the two confounding factors would have improved our analysis and understanding. We think the presence of income variable may help remedy the effect of these two confounders on EIP coefficient.

Finally, we also estimate equation (1) using the full sample. The full sample includes every surveyed household in the HPS. Although the analysis sample is our sample of interest in this study, some readers may like to see regression results for the full sample, which is a representative sample of all U.S. households. In the analysis sample, which is made

[7] The "missing" variables are important for two reasons: (i) we avoid losing observations, and (ii) the variables are informative, for instance, whether households that have missing values for income are food insufficient as well?

of households that are food insufficient before the receipt or expected receipt of EIPs, we expect that EIPs will be associated with a decrease in household food insufficiency. However, the full sample includes households that are not food insufficient, or households who received EIPs before Week 7, so the association of EIPs with household food insufficiency is ambiguous in the full sample.

Results

Using the analysis sample, Table 3 presents marginal effects from the logit regressions of food insufficiency, food confidence, or receipt of free food. Column (1) shows that the receipt or expected receipt of EIPs is associated with a 9.2 percentage points decrease in the likelihood of household-level food insufficiency. However, Columns (2) and (3) show that the receipt or expected receipt of EIPs has no association with household-level future food confidence or receipt of free food, at least during the survey weeks in June and July 2020. The main take-away is that the first-round EIPs of 2020 helped in managing household-level food insufficiency, but the EIPs were not enough to improve the likelihood of food confidence or reduce the likelihood of receipt of free food.

Column (1) of Table 3 further shows that households with married respondents are 5 percentage points less likely to be food insufficient compared to households where respondents are not currently married (i.e., widowed, divorced, separated, and never married altogether). Households of Asian respondents are 22 percentage points more likely to have lower food insufficiency than white respondents' households. Households with employed respondents are 5.4 percentage points less likely to be food insufficient compared to households with unemployed respondents. Households with respondents of poor or fair health are 6.1 percentage points more likely to be food insufficient compared to households with respondents of excellent, very good, and good health.

Using the full sample, Table 4 presents marginal effects from the logit regressions of food insufficiency, food confidence, or receipt of free food. In Column (1) of Table 3, we find that the household receipt or expected receipt of EIPs is associated with an 8.1 percentage points increase in the likelihood of household-level food insufficiency. In regards to future food confidence and receipt of free food, Columns (2) and (3) of Table 4 show that receipt or expected receipt of EIPs is associated with a 5.8% decrease (0.8% increase) in the likelihood of future food confidence (receipt of free food). These results are counterintuitive but not surprising because the base group (EIP non-receivers) is mainly composed of respondents with relatively higher household income, i.e., $75,000 and above. It appears that food insufficiency prevailed among the households even after the receipt or expected receipt of EIPs during June and July 2020. This contrasts with the result from Column (1) in Table 3, i.e., household receipt or expected receipt of EIPs is associated with a 9.2 percentage points decrease in the likelihood of household-level food insufficiency. The reader should note that in the full sample, a household that received or expects to receive an EIP is not necessarily food insufficient beforehand. However, in the analysis sample in Table 3, households are food insufficient before the receipt or expected receipt of EIPs. So, conditional on households' pre-EIP food insufficiency, EIPs have a negative association with the likelihood of food insufficiency. Karpman and Acs (2020) also find that receipt of EIPs is associated with a decrease in the likelihood of food insecurity. We remind the reader that our results represent statistical associations rather than causation. Furthermore, the reader should interpret our results

Table 3 Marginal Effects from Logit Regression (Analysis Sample)

	(1) Food insufficient	(2) Food confident	(3) Free food received
EIP Received	-0.0928***	-0.00518	0.000878
	(0.0107)	(0.0635)	(0.00128)
Number of Kids	-0.00830	-0.0584*	0.00190**
	(0.00840)	(0.0272)	(0.000720)
Number of Adults	0.00470	-0.0166	0.000155
	(0.00853)	(0.0183)	(0.000406)
Age	-0.000368	0.00188	0.0000911**
	(0.000571)	(0.00218)	(0.0000351)
Male	-0.000318	0.0250	-0.00676***
	(0.0183)	(0.0520)	(0.00162)
Married	-0.0505*	0.116	-0.000261
	(0.0217)	(0.0665)	(0.00242)
Black	0.0292	-0.115	0.00152
	(0.0193)	(0.0642)	(0.00247)
Asian	-0.220*	-0.0955	-0.000425
	(0.110)	(0.0619)	(0.00372)
Other Race	0.00215	-0.000875	-0.00253
	(0.0522)	(0.101)	(0.00151)
Hispanic	0.0166	0.115	0.00391
	(0.0224)	(0.0988)	(0.00281)
$50K-$74,999	-0.0254	0.0576	-0.00177
	(0.0358)	(0.0923)	(0.00185)
$75K-$99,999	-0.149	-0.180**	-0.000806
	(0.0760)	(0.0649)	(0.00212)
$100K-$149,999	-0.106	0.0904	-0.00401**
	(0.0679)	(0.101)	(0.00147)
≥$150K	-0.0872	0.241	-0.00416***
	(0.0840)	(0.163)	(0.00111)
Income Missing	-0.00181	0.00616	0.0152
	(0.0477)	(0.198)	(0.0134)
High School Grad.	-0.00239	0.0632	-0.00376
	(0.0370)	(0.121)	(0.00203)
Some College	-0.00163	0.205*	-0.00392*
	(0.0424)	(0.100)	(0.00186)
Associate's Degree	0.0143	0.132	-0.00443**
	(0.0368)	(0.149)	(0.00136)
≥Bachelor Degree	0.0104	0.273*	-0.00584***
	(0.0343)	(0.106)	(0.00125)
Employed	-0.0541*	0.128*	-0.000480
	(0.0247)	(0.0620)	(0.00138)
Housing Rented	0.0274	0.0261	-0.000311
	(0.0234)	(0.0557)	(0.00258)
Housing Missing	-0.0623	0.429	-0.00597***

Table 3 (continued)

	(1) Food insufficient	(2) Food confident	(3) Free food received
	(0.163)	(0.226)	(0.00146)
Health Poor or Fair	0.0610**	-0.112	-0.00438
	(0.0189)	(0.0626)	(0.00264)
Health Missing	0.00195	-0.127	0.0261
	(0.0597)	(0.194)	(0.0262)
Observations	1,382	1,315	1,368

Author's calculations using the Household Pulse Survey (HPS), Weeks 7 – 12. Analysis Sample refers to EIP late recipients as defined in the Data section. Regression coefficients are marginal effects from logit regression. Each regression is weighted using HPS household-level sampling weights. Each regression controls for state and survey week fixed-effects. Standard errors clustered at the state level appear in parentheses

within the context of households that are late receivers of EIPs. The results do not apply to the overall population in the U.S.

Policy Implications

From an economic policy perspective, stimulus payments like the EIPs are aimed to increase consumer spending and boost aggregate demand during economic downturns. Direct stimulus payments can also act as a financial cushion when households are short on funds or safety net programs have not yet kicked in. Tying stimulus payments to households' economic condition and deploying them in an automatic fashion can play the dual role of (i) stimulating the economy, and (ii) saving households from economic hardships and food insufficiency. In this study, we find that the receipt or expected receipt of EIPs is associated with a 9.2 percentage points decrease in the likelihood of household-level food insufficiency during June and July 2020. Since some of the households in the analysis sample are potentially anticipating the receipt of EIPs, the decrease in household-level food insufficiency is partially due to an anticipatory increase in food consumption by households.[8] About 75% of household respondents in our analysis sample mention that they spent or will spend EIPs on "food (groceries, eating out, take out)". The magnitude of our result (i.e., 9.2 percentage points) seems plausible when comparing to studies that look at the effect of SNAP on food insecurity. Using a nationally representative survey, Nord and Prell (2011) find that the temporary increase in SNAP benefits due to the American Recovery and Reinvestment Act (2009) reduced food insecurity by 2.2 percentage points from 2008 to 2009. Accounting for self-selection into SNAP and participation misreporting, Kreider et al. (2012) find the impact of SNAP on reducing food insecurity to range from 2.7 to 12.8 percentage points.

[8] However, a research study that cleanly identifies the effect of anticipated stimulus payment on food insufficiency would be an interesting and important contribution to the consumption smoothing and food insecurity literature.

Table 4 Marginal effects from logit regression (Full Sample)

	(1) Food Insufficient	(2) Food Confident	(3) Free Food Received
EIP Received	0.0815***	-0.0589***	0.00881**
	(0.00420)	(0.00630)	(0.00273)
Number of Kids	0.0395***	-0.0322***	0.0230***
	(0.00249)	(0.00170)	(0.000758)
Number of Adults	0.0188***	-0.0110***	0.00322***
	(0.00210)	(0.00190)	(0.000636)
Age	-0.00369***	0.00305***	-0.0000109
	(0.000191)	(0.000221)	(0.0000597)
Male	0.000383	0.00580	-0.00848**
	(0.00353)	(0.00334)	(0.00263)
Married	-0.00635	-0.00196	-0.00182
	(0.00340)	(0.00366)	(0.00220)
Black	0.0698***	-0.131***	0.0210***
	(0.00609)	(0.00767)	(0.00487)
Asian	0.0309***	-0.0784***	0.00199
	(0.00774)	(0.00869)	(0.00422)
Other Race	0.0763***	-0.0691***	0.0171***
	(0.00986)	(0.00766)	(0.00428)
Hispanic	0.0603***	-0.0910***	0.0431***
	(0.00752)	(0.00807)	(0.00284)
$50K-$74,999	-0.0887***	0.0848***	-0.0284***
	(0.00460)	(0.00319)	(0.00134)
$75K-$99,999	-0.157***	0.136***	-0.0344***
	(0.00505)	(0.00588)	(0.00262)
$100K-$149,999	-0.199***	0.185***	-0.0474***
	(0.00589)	(0.00515)	(0.00153)
≥$150K	-0.283***	0.259***	-0.0623***
	(0.00494)	(0.00332)	(0.00115)
Income Missing	-0.150***	0.120***	-0.0246***
High School Grad.	-0.0533***	0.0482***	-0.0112**
	(0.0126)	(0.0124)	(0.00404)
Some College	-0.0367**	0.0703***	-0.0160***
	(0.0124)	(0.0117)	(0.00315)
Associate's Degree	-0.0356*	0.0646***	-0.0146***
	(0.0144)	(0.0149)	(0.00372)
≥Bachelor Degree	-0.137***	0.164***	-0.0259***
	(0.0150)	(0.0136)	(0.00412)
Employed	-0.0649***	0.0638***	-0.00652**
	(0.00427)	(0.00598)	(0.00239)
Housing Rented	0.0683***	-0.0776***	0.00860**
	(0.00814)	(0.00593)	(0.00302)
Housing Missing	0.0429*	-0.0973***	0.00864
	(0.0182)	(0.0164)	(0.00637)

Table 4 (continued)

	(1) Food Insufficient	(2) Food Confident	(3) Free Food Received
Health Poor or Fair	0.233***	-0.200***	0.0162***
	(0.00448)	(0.00650)	(0.00296)
Health Missing	0.114***	-0.0249	0.00135
	(0.0155)	(0.0182)	(0.00713)
Observations	536,187	510,883	534,276

Author's calculations using the Household Pulse Survey (HPS), Weeks 7 – 12. Regression coefficients are marginal effects from logit regression. Each regression is weighted using HPS household-level sampling weights. Each regression controls for state and survey week fixed-effects. Standard errors clustered at the state level appear in parentheses

Beside SNAP, school meal programs, and P-EBT, which form the foundation of food assistance programs, the role of stimulus payments should not be discounted during economic downturns. However, it is important to design future stimulus payments such that they reach all eligible households on time, so that the food insufficient households may tackle their food hardship from early on. When the first round of EIPs were distributed during COVID-19, an estimated 12 million eligible individuals did not automatically receive the payments, and these individuals were more likely to be low income and in actual need of economic support (Bitler et al. 2020). In table 1, we also saw that the late recipients of first-round EIPs had a lower share of households (21%) with income $75,000 and above, compared to the full sample households (37%). Households that are low-income, with unemployed respondents, or liquidity constrained during economic downturns are more likely to spend EIPs for meeting household needs. For instance, during June 11–June 16, 2020, more than 70% of households with gross income below $25,000 chose to use EIPs for expenses; however, less than 40% of households with gross income $150,000–$199,999 chose to do so Garner et al. (2020).

Conclusion

We use the Household Pulse Survey, Weeks 7 – 12 (June 11 – July 21, 2020) to study the association of first-round EIPs with household-level food insufficiency. We restrict the analysis to households that are late recipients of EIPs and who are already food insufficient before the receipt or expected receipt of EIPs. We find that the receipt or expected receipt of EIPs is associated with a 9.2 percentage points decrease in household-level food insufficiency. However, EIPs have no association with future food confidence or receipt of free food. These results only apply to households that are late recipients of EIPs. Our results suggest that government efforts to provide more timely stimulus payments could be very impactful and significantly impact household food insufficiency.

Data Availability Statement The HPS data analysed during the current study are available through the Household Pulse Survey Public Use Files, [https://www.census.gov/programs-surveys/household-pulse-survey/datasets.html#phase1].

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