# Household Hardship and Stimulus Payments during the Pandemic: Differences Across Ethnic Minorities in the United States

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## Abstract

This study examines the impact of the American Rescue Plan Act (ARPA) Economic Impact Payments (EIP) on alleviating household hardship, primarily food insufficiency and expense difficulty, among ethnic groups in the United States during the COVID-19 pandemic. Using data from the Census Bureau's Household Pulse Survey (HPS) from 2020-2022, the study investigates who received the payments and how they used them. The study employs quasi-difference-in-difference models to address the issue of non-repetitive samples in the HPS dataset. The findings suggest that Black, Hispanic, and Other Races individuals reported consistently higher probabilities of food insufficiency and expense difficulty compared to Whites and Asians. The study further reveals that individuals across all ethnic groups reported less food insufficiency or expense difficulty after the distribution of the ARPA EIP in March 2021. In addition, individuals of all ethnic minority groups who used EIP for saving had a larger decrease in the probability of food insufficiency compared with the corresponding change for Whites. The study highlights the importance of targeted stimulus policies to address distinct problems faced by different ethnic minority groups.



Keywords: Food insufficiency, expense difficulty, American Rescue Plan Act, Economic Impact Payments, racial and ethnic inequalities

JEL: J15, I38, C54

## 1. Introduction

The COVID-19 pandemic disproportionately impacted ethnic minority groups, both from health and economic standpoints. Ethnic minority groups have higher rates of COVID-19 infection and hospitalization and more significant financial hardship, including food insufficiency and housing insecurity due to job loss or reduced income (Altman et al., 2022; Bowen et al., 2021; Chetty et al., 2020; Morales et al., 2021; Park, 2021; Parker et al., 2022). These adverse effects have further exacerbated pre-existing inequalities (Katikireddi et al., 2021; Tai et al., 2021; Wang, 2021).

In response to the pandemic, the federal government authorized three rounds of direct economic impact payments (EIP) under the Coronavirus Aid, Relief, and Economic Security (CARES) Act, the COVID-related Tax Relief Act, and the American Rescue Plan Act (ARPA). Although these stimulus payments potentially alleviated hardship faced by ethnic minority households, the policy effect for each ethnic group may differ due to cultural differences, inequitable access to resources, and disparate use patterns of the stimulus payments. Therefore, it is important to understand the differentiated impacts of the stimulus payments for each ethnic group. While some recent studies have investigated the effects of the EIP under the CARES Act (Asebedo et al., 2020, 2022; Baker et al., 2020; Chetty et al., 2020; Clark et al., 2023; Karger & Rajan, 2020), studies relevant to the EIP under the ARPA are still rare (Parker et al., 2022).

Focusing on the ARPA EIP, we investigate policy impacts on two types of household hardship, food insufficiency and expense difficulty, using Household Pulse Survey (HPS) data from the Census Bureau. The advantage of the HPS data lies in its persistent monitoring of food and expense conditions throughout the pandemic from 2020 to 2022, providing a valuable resource for studying these issues among different ethnic groups. The HPS also contains survey questions regarding the stimulus payments in some survey weeks, enabling us to see who received the payments and how they used them. However, the HPS has some critical problems limiting its ability to evaluate policy effects. One of the main challenges is that the HPS samples change over time, meaning that they are not panel data, which prevents us from estimating a difference-in-differences (DiD) model to tackle causal effects of the ARPA.

To address the issue of non-repetitive samples in the HPS dataset, we estimate quasi-difference-in-difference (quasi-DiD) models. Specifically, our baseline model is a probit regression using data from all HPS weeks. The model uses a dummy variable to indicate weeks before and after ARPA's implementation, which renders some resemblance to a DiD model. In the baseline model, the first difference is within ethnic groups, and the second difference is between the before-after ARPA periods. The quasi-DiD model is essentially a regression model with interaction terms, which we consider a viable alternative to a DiD model suitable for studying policy effects with non-repetitive samples. We estimate the baseline and alternative models to test the robustness of the results.

The ethnic groups we focus on in this study are based on the categories in the HPS dataset, including Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Asian, Hispanic, and Other Races (primarily consisting of Native Americans and Pacific Islanders). For simplicity, we will refer to them as White, Black, Asian, and Other Races throughout the study.[1] Another caveat is that we conduct all computations in this study at the individual level, although some key variables, such as food insufficiency, expense difficulty, EIP receipt and usage, and household size and income are at the household level. For example, we calculate the population percentage

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[1] Following the Chicago Manual of Style 17th edition, we capitalize White, Black, and other ethnic groups. Other Races are capitalized to specifically refer to Native Americans and Pacific Islanders.

of food insufficiency in the descriptive analysis using personal weights of the HPS, instead of household weights, which conforms with the practice in the Census Bureau's HPS data tables and the interactive tool. Therefore, we do not distinguish individuals and households in our writing unless their meaning is unclear.

Our findings suggest that individuals belonging to Black, Hispanic, and Other Races reported consistently higher probabilities of food insufficiency and expense difficulty when compared to Whites and Asians. After the ARPA EIP was distributed in March 2021, individuals across all ethnic groups reported less food insufficiency or expense difficulty. Such a reduction was more significant for ethnic minority individuals than Whites. Moreover, individuals who saved most of EIP funds upon receipt had a lower probability of food insufficiency and expense difficulty than those who spent most of the payments. Furthermore, paying off debts was associated with a higher probability of food insufficiency and expense difficulty. In addition, individuals belonging to ethnic minority groups who used EIP for savings had a greater decrease in the probability of food insufficiency than Whites.

## 2. Literature Review

Numerous studies have explored the impact of the COVID-19 pandemic on household hardship (Altman et al., 2022; Bowen et al., 2021; Chetty et al., 2020; Morales et al., 2021; Park, 2021; Parker et al., 2022). Studies found that the pandemic exacerbated food insufficiency in the United States (Drake et al., 2022; Kimani et al., 2021; Morales et al., 2021). According to the December 2021 Current Population Survey Food Security Supplement, approximately 10.2 percent of households in the United States experienced food insecurity at least once in 2021, with 3.8 percent of households facing severe food insecurity (Coleman-Jensen et al., 2021).

Racial and ethnic inequality has emerged as a crucial area of pandemic-related studies. Previous research indicates that Black, Hispanic, Indigenous, and other minority populations face higher food insecurity rates than their White counterparts (Berning et al., 2022; Dean & Sharkey, 2011; Gundersen, 2008). Using the data from HPS week 1, Morales, Morales, and Beltran (2021) showed that minority households did not necessarily experience higher rates of food insecurity than White households given their pre-pandemic food conditions, but still faced unique challenges such as affordability, lack of access to transportation, and fear of going out to purchase food. Minority households were also less confident about their food security for the near future. Using Amazon's Mechanical Turk platform, Lauren et al. (2021) conducted a survey of 1965 American adults and found that Respondents who identified as Black, Asian, or Hispanic/Latino, had an annual income of less than $100,000, or lived with children or others were more likely to be at a higher risk of experiencing food insecurity for the first time. In addition, the authors also found that experiencing anxiety or depression is often linked to being at risk for food insecurity.

This study also contributes to the expanding literature on evaluating the effect of EIP (Asebedo et al., 2020, 2022; Baker et al., 2020; Chetty et al., 2020; Karger & Rajan, 2020; Parker et al., 2022), most of which focused on EIP under the CARES Act. Chetty et al. (2020) tracked credit card transactions and found that following the CARES EIP disbursement, spending was more robust in zip code areas with low household income than those with high income. Baker et al. (2020) and Karger & Rajan (2020) estimated that the marginal propensity of consumption (MPC) out of the CARES EIP was around 25–46%. However, Parker et al. (2022) found a relatively low tendency for spending from the CARES EIP and even lower from the ARPA EIP. They attributed low spending to the fact that the EIP was broadly distributed to all eligible households rather than targeted towards those directly impacted by the pandemic. The authors also found that households with low income and limited liquidity spent the most. Conversely, high-income households tended to save more since the EIP was an addition to their preexisting, balanced financial resources, particularly during the ARPA's implementation when the economy was recovering.

Our study addresses the racial and ethnic disparities in the effects of stimulus policies, an area that has yet to be specifically studied. We use HPS survey weeks from 2020 to 2022 to examine the change in households' food insufficiency and expense difficulty during the pandemic, as compared to Morales, Morales, and Beltran (2021) who only used the HPS week-one data. Particularly, we focus on the change in household hardship before and after the ARPA EIP was distributed. While the EIPs were supposed to be disbursed non-randomly to all eligible households in a timely manner (Parker et al., 2022), due to such factors as banking account availability and citizenship, households of ethnic minority groups may have a delay or some difficulty in receiving the stimulus payments. Moreover, the difference in financial conditions, culture, and spending/saving habits among ethnic groups may lead to different use patterns of the EIP funds and thus different stimulus policy effects, which have not been fully addressed in the literature.

## 3. Data Description

### *Data sources*

The primary data source is the Household Pulse Survey (HPS), conducted by the Census Bureau throughout the pandemic. The HPS provides a real-time snapshot of the experiences and challenges faced by households during the pandemic. Our analysis focuses on two survey questions from the HPS data. The first question asked about the respondent's food situation: "*In* *the last 7 days, which of these statements best describes the food eaten in your household?" The selections are among "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, and 4) Often not enough to eat.*" We consider individuals who selected 3) or 4) as suffering from food insufficiency. The second question asked one's expense condition: "*In the last 7 days, how difficult has it been for your household to pay for usual household expenses, including but not limited to food, rent or mortgage, car payments, medical expenses, student loans, and so on?" The selections are among "1) Not at all difficult, 2) A little difficult, 3) Somewhat difficult, 4) Very difficult.*" We consider individuals who selected 2), 3), or 4) as having difficulty with expenses. The food insufficiency question is in all HPS survey weeks, while the expense difficulty question started from HPS week 13, beginning from August 19, 2020.

The HPS also asked whether households received EIP from the Federal Government and how they used it. These questions appeared in the questionnaires in only several HPS survey weeks. (See Table A3 in the appendix for a list of the HPS survey weeks when these questions appeared.) For example, Question 15 in HPS week 27 (March 17–29, 2021, the first week after the ARPA EIP was disbursed) asked, "*In the last 7 days, if you or anyone in your household received a 'stimulus payment,' that is a coronavirus related Economic Impact Payment from the Federal Government, did you: Select only one answer. 1) Mostly spend it, 2) mostly save it, 3) mostly used it to pay off debt, 4) Not applicable, I did not receive the stimulus payment.*"

It is important to note that the modifier "In the last 7 days" may underestimate the probability of households receiving EIP. This is because a respondent who received EIP two weeks before completing the survey might answer "Not applicable." As shown in Table A3, the percentage of individuals who reported receiving the ARPA EIP in HPS week 27 was 62% when weighted by population; however, the percentage dropped to 27% in the following week and continued to drop in the subsequent weeks. In contrast, the percentage for the first round of EIP disbursement under the CARES Act, where the "last-7-days" modifier did not appear, was more than 85% in all HPS weeks 7–12. Therefore, the "last-7-days" modifier makes it difficult to accurately estimate the probability of receiving the ARPA EIP using the data from any single survey week.

Another problem of the HPS data is that its samples changed for each survey week. In other words, the HPS data is not panel data requiring the same sample set in each observed period. As a result, the non-repetitive nature of HPS samples limits our ability to evaluate the causal effect of the ARPA EIP on mitigating food insufficiency and expense difficulties. For example, we cannot estimate a difference-in-difference model as explained in the Regression Models section.

***Descriptive analysis***

Figure 1 shows the overall trends of food insufficiency and expense difficulty, calculated as the population-weighted percentage of individuals with these issues, along with the consumer price indices (CPI) from the Bureau of Labor Statistics (BLS). Before ARPA, peak food insufficiency occurred in December 2020, while expense difficulty was at its highest in February 2021. After ARPA, both measures declined, although the reduction in food insufficiency started in December 2020. However, as inflation increased, both variables rose again in late 2021. Expense difficulty exceeded its pre-ARPA peak in March 2022.

[Figure 1 around here]

Figure 2 presents a decomposition of the percentages of individuals with food insufficiency and expense difficulty with each ethnic group's trend line displayed. Throughout this period, these percentages for Whites and Asians are lower than other ethnic groups, while the trend lines for all ethnic groups dropped after the implementation of the ARPA and rose again in late 2022.

[Figure 2 around here]

To highlight these changes, we compared the percentages for food insufficiency and expense difficulty at three four-week intervals: HPS weeks 23-26 (January 20 to March 15, 2021), 27–30 (March 17 to May 24, 2021), and 48–51 (July 27 to November 14, 2022), and calculated the change from one period to the next as shown in Figure 3. Following the implementation of ARPA, Black individuals experienced the largest decrease in the percentages of both food insufficiency and expense difficulty, while individuals of Other Races had a significant reduction only in food insufficiency. However, in late 2022, individuals in these two ethnic groups had a higher increase in food insufficiency compared to other groups. Whites had the largest increase in expense difficulty in late 2022 compared to other ethnic groups.

[Figure 3 around here]

Figure 4 shows the percentages of individuals receiving EIP and how they used EIP among spending, saving, and paying debts. We compare these values for three rounds of EIP disbursement, using each round's data for the first HPS week (7, 22, and 27). The percentage for receiving EIP in the first round is higher than the other two rounds. As explained above, we attribute such a gap between the first and the other two rounds mainly to the change in the HPS question by adding the "last 7 days" time window.[2] Asians are slightly less likely to have received it, possibly due to their relatively high income (Peterson Foundation, 2022).

[Figure 4 around here]

The EIP use patterns changed noticeably from the first round to the subsequent rounds. In the first round, the largest category of EIP usage was spending, whereas in the second and third rounds, the biggest category became paying off debts. The timing of each round may be a factor for this change. The first round under the CARES Act was passed early in the pandemic, when people may have been more likely to use the stimulus payment for immediate needs like groceries or rent. However, the second and third rounds came after the shutdown orders and COVID-related restrictions were gradually lifted, and some debt relief policies ended, such as a pause on student loan payments and mortgage forbearance under the CARES Act.

The patterns of EIP usage varied across ethnic groups. Specifically, nearly 60% of Black, Hispanic, and Other Races individuals used most of their ARPA EIP to pay debts, compared with about 45% of Whites and Asians. In contrast, the latter two groups showed a higher saving or spending percentage than individuals from other ethnic groups. Many factors can contribute to disparate usage patterns, for example, differences in wealth and financial conditions across ethnic groups, the disproportionate impact of the pandemic on Black and Hispanic communities, and cultural differences in financial behaviors.

[2] It was also reported that some ineligible or deceased individuals received EIP (Special Inspector General for Pandemic Recovery, 2021) in the first round so that the decrease in the percentage for receiving EIP can also be due to the improved disbursement process.

The descriptive analysis reveals that: (1) Individuals of Black, Hispanic, and Other Races reported consistently higher percentages of food insufficiency or expense difficulty compared to Whites and Asians. (2) After the ARPA EIP was distributed in March 2021, individuals across all ethnic groups experienced a decrease in food insufficiency or expense difficulty. However, peak-level decline began one or three months before the ARPA implementation. (3) Food insufficiency and expense difficulty levels increased in late 2022 as inflation rose. (4) The probability of receiving the stimulus payments and the patterns of using the payments varied across ethnic groups.[3]

Tables A1 and A2 show the summary statistics of all variables used in this study. However, the problems with descriptive analysis are the lack of statistical significance tests and inability to account for confounding factors, such as individual characteristics, macroeconomic environment, local government policies, and other unobserved heterogeneity, all of which we address in the regression analysis.

## 4. Baseline Regression Model

Our research aims to examine if the ARPA EIP alleviated food insufficiency and expense difficulty for individuals and how the alleviation varied across ethnic groups. The HPS data is not panel data, with the sample changing in each survey week. Therefore, we cannot observe the same individuals across multiple periods, for example, the survey weeks before and after the

[3] Table A6 shows probit model results for receiving the ARPA EIP and for using EIP for saving, paying debts, and spending, using data of HPS week 27. The probability of receiving EIP was not significantly different across ethnic groups, ethnic minority individuals were less likely to use EIP for saving or spending but more likely to use it for paying debts than Non-Hispanic White individuals.

ARPA was implemented. As a result, we cannot estimate a DiD model that would allow us to control for individual fixed effects and time-varying unobserved heterogeneity. Instead, we use a quasi-DiD model that involves the creation of a dummy variable to indicate the timing of the disbursement of the stimulus payments.

The baseline model is a probit model with the following form,[4]

$$\Pr\,(y_{it} = 1) = \Phi(\alpha + \delta D_t + \boldsymbol{H}_{it}\boldsymbol{\beta} + D_t \cdot \boldsymbol{H}_{it}\boldsymbol{\gamma} + \boldsymbol{Z}'_{it}\boldsymbol{\theta} + s(t,\phi) + \eta_s) \qquad (1)$$

where the dependent variable is the probability of individual *i* reporting food insufficiency or expense difficulty in HPS survey week *t*. The main explanatory variables include the dummy variables of the before-after ARPA implementation ($D_t = 1$ for HPS weeks after March 17, 2021; otherwise, $D_t = 0$), the dummy variables for ethnic minority groups ($\boldsymbol{H}_{it} = \left[H_{it}^k = 1\right]_{k=1,\dots,5}$ if an individual belongs to an ethnic group *k*, and their interaction terms ($D_t \cdot \boldsymbol{H}_{it}$). Subscripts *i* and *t* indicate that the HPS samples changed over time. Control variables ($\boldsymbol{Z}_{it}$) include household and individual characteristics, such as household incomes, household size, gender, age, education, marital status, etc., as well as a cubic polynomial of time ($s(t,\phi)$) and dummy variables for states ($\eta_s$). The cubic polynomial of time accounts for macroeconomic conditions, especially for high inflation rates after mid-2021,[5] and the dummy variables for states account for all state-specific time-invariant factors.

Our main interest is in the parameters of $\delta$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$. For illustration, let $y^* = \Phi^{-1}(\Pr(y=1))$, i.e., the dependent variable transformed with a link function, so Equation (1)

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[4] The variables with a bold font face are vectors or matrices, others are scalars.

[5] We estimated alternative models with consumer price indices in place of the polynomial of time, which yielded similar results.

can be written as a linear model $y_{it}^{*} = \alpha + \delta D_t + \boldsymbol{H}_{it}\boldsymbol{\beta} + D_t \cdot \boldsymbol{H}_{it}\boldsymbol{\gamma} + \boldsymbol{Z}_{it}'\boldsymbol{\theta} + s(t, \phi) + \eta_s + \epsilon_{it}, \epsilon_{it} \sim N(0, \delta_{\epsilon}^{2})$. Then, we can interpret the parameters of interest as follows,

- $\delta = E\left(y_{i't'}^{*} \middle| D_{t'} = 1, \boldsymbol{H}_{i't'} = 0\right) - E(y_{it}^{*}|D_t = 0, \boldsymbol{H}_{it} = 0)$: the change in $y^*$ for Whites after the ARPA. We use subscripts $i'$ and $t'$ to emphasize that the HPS sample changed across survey weeks.
- $\boldsymbol{\beta} = E(y_{it}^{*}|D_t = 0, \boldsymbol{H}_{it} = 1) - E(y_{it}^{*}|D_t = 0, \boldsymbol{H}_{it} = 0)$: the difference in $y^*$ for individuals in ethnic minority groups compared with Whites.
- $\boldsymbol{\gamma} = \left[E\left(y_{i't'}^{*} \middle| D_{t'} = 1, \boldsymbol{H}_{i't'} = 1\right) - E(y_{it}^{*}|D_t = 0, \boldsymbol{H}_{it} = 1)\right] -$ $[E\left(y_{i't'}^{*} \middle| D_{t'} = 1, \boldsymbol{H}_{i't'} = 0\right) - E(y_{it}^{*}|D_t = 0, \boldsymbol{H}_{it} = 0)]$: the change in $y^*$ for individuals in ethnic minority groups after the ARPA implementation, relative to the corresponding change for Whites. As such, $\boldsymbol{\gamma}$ is in the form of a difference-in-difference (DiD) estimator. The first difference removes ethnic group specific time-invariant factors, and the second difference removes time specific factors that are common to all ethnic groups in the periods from $t$ to $t'$. However, as noted $\boldsymbol{\gamma}$ is not a true DiD estimator because the HPS samples are not repetitive, and we do not assign individuals into treatment and control groups based on whether they received the ARPA EIP or not. Therefore, we interpret $\boldsymbol{\gamma}$ as the quasi-DiD effect, although individual specific factors are not purged by quasi-DiD, we use $\boldsymbol{Z}_{it}$ to control these factors.

## 5. Regression Results

### *Results for the baseline estimation*

Table 1 displays results for equation (1) for food insufficiency and expense difficulty using data from all 51 HPS weeks. As most of the variables in our regression are categorical, we chose the reference category to be an individual who is White, male, single, childless, employed with an income exceeding $200,000, holding at least a bachelor's degree, and owning a house without paying a mortgage. We expect this reference case to have lower levels of food insufficiency or expense difficulty and to be ineligible for receiving the ARPA EIP. Therefore, we should observe no change in their food or expense condition before and after the ARPA implementation.

[Table 1 around here]

Before the ARPA implementation, ethnic minority groups had higher probabilities of reporting food insufficiency and expense difficulty than Whites, except for Asians whose probability of food insufficiency was only slightly lower than that of Whites. After the ARPA, food and expense conditions improved for all ethnic groups, as evidenced by the quasi-DID coefficients and the coefficient on the *After ARPA* variable. Compared to Whites, Asians and Blacks experienced greater improvements in both food and expense conditions, and Hispanics reported significantly less expense difficulty. However, food insufficiency worsened significantly after the ARPA compared to the before-ARPA period for individuals of Other Races, and their expense difficulty improved only slightly.

The coefficients for control variables conform to expectations. First, more household incomes and higher education levels were associated with decreasing probabilities of food insufficiency and expense difficulty, as suggested by the decreasing coefficients for income groups and educational attainment variables. Older individuals were also less likely to experience food insufficiency or expense difficulty. Secondly, households with large sizes, unemployed members, children under 18, or widowed, divorced, or separated couples had worse food and expense conditions. Mortgage debt and rental housing were also detrimental to food and expense conditions. Thirdly, females and married couples were less likely to suffer from food insufficiency but more often from expense difficulties. These results are robust when each ethnic minority variable is entered into the model separately.

***Results for the robustness estimation with the four-week data***

The baseline estimation uses data of all 51 HPS weeks, a coarse time window that encompasses all peaks during the pandemic in 2020 and the troughs in the mid-2021 as well as the rise in late 2022. To check the robustness of the baseline results, we limit the estimation to smaller time windows. We use the data for the HPS weeks 23–26 as the reference point, and each four-week window since then is compared to it. In other words, we estimate equation (1) separately for each four-week period after ARPA, while holding the weeks 23–26 as the reference. Using this method, we preserve the quasi-DiD specification in equation (1) and are able to examine changes in the impact of the ARPA on food insufficiency and expense difficulty over time. Any changes we observe closer to the ARPA implementation could be attributed more to the ARPA's impact than other factors, whereas changes further away should be explained more by a diminished ARPA effect and a confluence of other factors, such as high inflation. Therefore, we must be more cautious in drawing conclusions for the effects observed in later periods.

Figure 5 shows the results for the quasi-DiD effects with the four-week-data estimation, and more detailed results are shown in Tables A4 and A5. The results are consistent with the results of the baseline estimation. Tables A4 and A5 show that, for most periods from March 2021 to June 2023, Whites (seeing the coefficients on the *After ARPA* variable) had lower probabilities of reporting food insufficiency and expense difficulty than in the January–March 2021 period before ARPA's implementation. However, there was an exception: from May to August 2021, Whites had a higher probability of food insufficiency than before the ARPA, and in the last period (June-November 2022), they had significantly higher probabilities of food insufficiency and expense difficulty than in the before-ARPA period.

As for the quasi-DiD effects, we find that individuals in ethnic minority groups, except for Other Races, had greater improvements in food insufficiency and expense difficulty than Whites. In the first period after ARPA, the reduction in food insufficiency and expense difficulty was statistically significantly larger for Blacks and Hispanics than for Whites and individuals in other ethnic minority groups. In the subsequent periods, expense difficulty for Black, Hispanic, and Asian individuals continued to decline. However, Other Races had higher probabilities of food insufficiency and expense difficulty than Whites in some periods from May 2021 to February 2022, but their conditions got better after March 2022.

[Figure 5 around here]

***Results for the robustness estimation by state***

We re-estimate the baseline model with all HPS weeks for each state separately to examine whether the results hold and how they vary across states. The probit model is the same as Equation (1) except for the state dummy variables. Figures 6 shows the estimated quasi-DiD coefficients for food insufficiency and expense difficulty. The coefficients are divided by their standard errors, i.e., t-statistics, to allow clearer presentation in the maps. The darker colors, either blue or red, indicate a higher level of statistical significance. These maps show that individuals of Other Races in 40 states had a higher probability of food insufficiency after ARPA's implementation than before, and in 24 states they had a higher probability for expense difficulty, relative to Non-Hispanic White individuals. This finding to some extent echoes the study of Wang (2021) who documented that Native Americans, living in the Navajo Nation, were hit hard by the pandemic. He attributed to the Navajo's slow response to the COVID-19 pandemic to four factors: "*prevalence of underlying chronic health conditions, lack of institutional resilience, the relationship between the federal government and tribal governments, and lack of social trust*."

[Insert Figure 6 around here]

## 6. Impacts of receiving and using the ARPA EIP on food insufficiency and expense difficulty

### *Receiving the ARPA EIP*

Thus far all estimations use a before-after-ARPA dummy variable, not the variable that indicates whether individuals received the ARPA EIP and how they utilized them. While the HPS does include relevant survey questions, these questions have the issue of an "in-the-last-7-day" issue, leading to an underestimated probability of receiving EIP. Despite this limitation, for our next robustness analysis we focus exclusively on HPS Week 27 data (March 17–29, 2021), when 62 percent of respondents, weighted by population, reported receiving stimulus payments within the last seven days. On the one hand, this means that many eligible individuals could have not received their EIP payments by March 29, 2021.[6] On the other hand, these individuals who did

[6] Using HPS week 27 data, we calculated that a roughly 78 percent of individuals, weighted by population, were likely eligible for the ARPA EIP. We computed this weighted percentages for individuals who were in single-membered or divorced households with income below $75,000 or married or widowed households with income below $150,000.

not receive EIP can serve as a control group in comparison with a treatment group for individuals who did receive it. This 7-day-window issue motivates us to estimate a slightly modified probit model as follows,

$$\Pr(y_i = 1) = \Phi(\alpha + \delta D_i + \boldsymbol{H}_i\boldsymbol{\beta} + D_i \cdot \boldsymbol{H}_i\boldsymbol{\gamma} + \boldsymbol{Z}_i'\boldsymbol{\theta} + \eta_s) \tag{2}$$

in which $D_i = 1$ when individual *i* received EIP, and the time subscript and the polynomial of time are dropped because we have single-week data. All other explanatory and control variables in equation (1) remain, including household income, size, and children, the key variables for EIP eligibility. However, we still cannot claim a DiD effect for equation (2) because we cannot observe a change before and after receiving EIP.

Table 2 presents our main findings from estimating equation (2). Receiving ARPA EIP significantly reduced the probability of reporting food insufficiency and expense difficulty for Whites compared to their White peers who did not receive the stimulus payments, while controlling for all relevant variables affecting EIP eligibility. For ethnic minority groups, receiving EIP further reduced food insufficiency, but the effect was not significantly different from that for Whites. However, Blacks and Asians who received EIP had a higher probability of reporting expense difficulty than their counterparts who did not, relative to the difference between Whites who did and did not receive the payments. This suggests that Blacks and Asians may have additional expenditures that are not accounted for with our control variables.

[Table 2 around here]

***Using the ARPA EIP***

The final analysis examines the associations among spending, saving, and paying off debt with ARPA EIP, food insufficiency, and expense difficulty. The descriptive analysis indicates that more Whites and Asians chose to spend or save most of the ARPA EIP while fewer chose to pay debts, and that their food and expense conditions were better than those of individuals in the other three ethnic groups. Therefore, we expect saving to be negatively associated with food insufficiency and expense difficulty, while paying debts to be positively associated. Again, we cannot claim the causal effect of using EIP for saving or paying debts because such a causal effect would be more pertinent to examining the intertemporal effect of saving or paying debts in one period on food and expense conditions in the next period, an analysis we cannot perform due to the non-repetitive sample of the HPS.

Here we still use the data from HPS week 27 but confine samples to respondents who reported receiving the ARPA EIP, which cause a sample selection problem. Individuals who received EIP were in low- or middle-income households which were more likely to have food or expense problems than high-income households which were ineligible to receive EIP. To address this problem, we revise the probit model of Equation (2) by including the inverse Mill's ratio ($\rho$) as follows,

$$\Pr\,(y_i = 1) = \Phi(\alpha + \boldsymbol{D}_i\boldsymbol{\delta} + \boldsymbol{H}_i\,\boldsymbol{\beta} + \boldsymbol{D}_i\boldsymbol{H}_i\boldsymbol{\gamma} + \widetilde{\boldsymbol{Z}}_i'\boldsymbol{\theta} + \hat{\rho}_i\phi + \eta_s) \tag{3}$$

in which $\boldsymbol{D}_i$ is a vector of two dummy variables for saving and paying debts. $\widetilde{\boldsymbol{Z}}_i$ includes all control variables as in equation (2) except for household incomes that are used in computing $\hat{\rho}_i = \phi(\widetilde{\boldsymbol{X}}_i'\hat{\boldsymbol{\vartheta}})/\Phi(\widetilde{\boldsymbol{X}}_i'\hat{\boldsymbol{\vartheta}})$. $\hat{\rho}_i$ is derived from a probit model in which the main independent variables ($\widetilde{\boldsymbol{X}}_i$) are household incomes, household sizes, and children under 18, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density and cumulative functions of the standard normal distribution.

Table (3) shows the main results for equation (3). First, for Whites, compared with their counterparts who spent most of the ARPA EIP, saving more was associated with reduced probabilities of reporting food insufficiency and expense difficulty, while paying debts was associated with an increase in these probabilities. Second, individuals from ethnic minority groups who saved most of their EIP had a significantly larger reduction in the probabilities of reporting food insufficiency and expense difficulty than their counterparts who spent most, relative to such a difference for Whites. Additionally, ethnic minority individuals who paid debts out of EIP also had lower probabilities of reporting food insufficiency and expense difficulty than their peers who spent most of the payments. These findings are somewhat counterintuitive but suggest that financial decisions have disparate implications for food and expense conditions across ethnic groups. One possible explanation is that paying off debts might provide individuals with more financial stability, which could lead to fewer difficulties in meeting basic needs. However, further research is needed to explore this relationship and understand the underlying mechanisms.

[Table 3 around here]

## 7. Conclusion

Our study demonstrates that ethnic minority groups, primarily Blacks, Hispanics, and Other Races, faced consistently higher levels of food insufficiency or expense difficulty when compared to Whites and Asians during the pandemic. Nevertheless, while individuals from all ethnic groups experienced a reduction in food insufficiency or expense difficulty after receiving the ARPA EIP, the reduction in food insufficiency and expense difficulty was more significant for individuals belonging to any ethnic minority group. However, individuals of Other Races were more likely to suffer from food insufficiency and expense difficulty problems than other ethnic groups after the ARPA implementation.

We also found that Whites who received the ARPA EIP and saved most of the payments had lower probabilities of food insufficiency and expense difficulty than those who did not receive or spend most of EIP. This suggests that these households were not facing severe income limitations in the first place. In contrast, individuals using EIP to pay off debt were also likely to have higher probabilities of food insufficiency and expense difficulty. Moreover, compared with those who spent most of EIP, ethnic minority individuals who saved EIP had a further decrease in food insufficiency rates, and those who used EIP to pay debts had a smaller increase in expense difficulty.

One limitation of this study is the inability to estimate a reliable DiD model due to the non-repetitive HPS samples. However, our findings emphasize the significance of recognizing the diverse results of policy interventions across various ethnic groups, and draw attention to the potential for targeted policies to address food insufficiency and financial stress faced by ethnic minority groups. It is worth noting that the disadvantaged position of Other Races, which mainly includes Native Americans and Pacific Islanders, should prompt policy makers to provide more support to these communities.

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## Tables

Table 1. Estimated coefficients in probit models using all HPS weeks

| | Food insufficiency | Expense difficulty |
|---|---|---|
| Intercept | -2.425*** | -1.430*** |
| | (0.016) | (0.011) |
| Non-Hispanic Black | 0.290*** | 0.300*** |
| | (0.005) | (0.006) |
| Hispanic | 0.151*** | 0.220*** |
| | (0.005) | (0.006) |
| Asian, alone | -0.001 | 0.110*** |
| | (0.009) | (0.007) |
| Other races, alone | 0.256*** | 0.261*** |
| | (0.007) | (0.008) |
| After ARPA | -0.180*** | -0.234*** |
| | (0.008) | (0.005) |
| After ARPA * Hispanic | 0.001 | -0.039*** |
| | (0.008) | (0.007) |
| After ARPA * Non-Hispanic Black | -0.018* | -0.049*** |
| | (0.008) | (0.008) |
| After ARPA * Asian | -0.080*** | -0.071*** |
| | (0.015) | (0.009) |
| After ARPA * Other races | 0.046*** | -0.006 |
| | (0.012) | (0.010) |
| Income: Less than $25,000 | 1.487*** | 1.893*** |
| | (0.011) | (0.005) |
| Income: $25,000 - $34,999 | 1.241*** | 1.657*** |
| | (0.011) | (0.005) |
| Income: $35,000 - $49,999 | 1.064*** | 1.436*** |
| | (0.011) | (0.005) |
| Income: $50,000 - $74,999 | 0.827*** | 1.172*** |
| | (0.011) | (0.004) |
| Income: $75,000 - $99,999 | 0.585*** | 0.921*** |
| | (0.011) | (0.004) |
| Income: $100,000 - $149,999 | 0.340*** | 0.643*** |
| | (0.011) | (0.004) |
| Income: $150,000 - $199,999 | 0.144*** | 0.384*** |
| | (0.013) | (0.005) |
| Female | -0.069*** | 0.036*** |
| | (0.003) | (0.002) |
| Age | -0.013*** | -0.011*** |
| | (0.000) | (0.000) |
| Household size | 0.075*** | 0.132*** |
| | (0.001) | (0.001) |
| Child under 18 | 0.043*** | 0.020*** |
| | (0.004) | (0.003) |
| Less than high school | 0.544*** | 0.328*** |
| | (0.007) | (0.008) |
| High school diploma or GED | 0.360*** | 0.215*** |
| | (0.004) | (0.003) |
| Some college/associate degree | 0.293*** | 0.255*** |

| | Food insufficiency | Expense difficulty |
|---|---|---|
| | (0.003) | (0.002) |
| Renting | 0.330*** | 0.446*** |
| | (0.004) | (0.003) |
| Owning with mortgage | 0.107*** | 0.339*** |
| | (0.004) | (0.002) |
| Unemployed | 0.248*** | 0.104*** |
| | (0.003) | (0.002) |
| Married | -0.017*** | 0.067*** |
| | (0.004) | (0.003) |
| Widowed, divorced, or separated | 0.212*** | 0.187*** |
| | (0.004) | (0.003) |
| Num.Obs. | 3084836 | 2150490 |
| AIC | 1104426 | 2358653 |
| RMSE | 0.224 | 0.429 |

Notes: (1) The estimation used data from all 51 HPS weeks from April 23, 2020 to November 14, 2022. (2) The cubic polynoial of time and state dummy variables were included. (3) Significance levels: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 2. Estimated coefficients in probit models for the effects of receiving EIP on food insufficiency and expense difficulty

| | Food insufficiency | Expense difficulty |
|---|---|---|
| Intercept | -2.466*** | -1.665*** |
| | (0.128) | (0.067) |
| Non-Hispanic Black | 0.294*** | 0.284*** |
| | (0.057) | (0.038) |
| Hispanic | 0.302*** | 0.244*** |
| | (0.051) | (0.035) |
| Asian, alone | 0.028 | -0.011 |
| | (0.093) | (0.043) |
| Other races, alone | 0.384*** | 0.282*** |
| | (0.075) | (0.053) |
| Received EIP | -0.107*** | -0.073*** |
| | (0.028) | (0.014) |
| Receiving EIP * Non-Hispanic Black | -0.013 | 0.108* |
| | (0.069) | (0.048) |
| Receiving EIP * Hispanic | -0.119+ | 0.030 |
| | (0.062) | (0.043) |
| Receiving EIP * Asian, alone | 0.072 | 0.355*** |
| | (0.113) | (0.056) |
| Receiving EIP * Other races, alone | -0.145 | -0.026 |
| | (0.094) | (0.066) |
| All controls | Yes | Yes |
| Num.Obs. | 57927 | 57878 |
| AIC | 17425 | 64317 |
| Log.Lik. | -8634 | -32079 |
| RMSE | 0.200 | 0.432 |

Notes: (1) This table shows the estimation results of equation (2) The estimation only used the data of HPS week 27. (3) Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3. Estimated coefficients in probit models for the effects of using EIP on food insufficiency and expense difficulty

| | Food insufficiency | Expense difficulty |
|---|---|---|
| Intercept | -1.515*** | -0.090 |
| | (0.153) | (0.089) |
| Non-Hispanic Black | 0.568*** | 0.561*** |
| | (0.095) | (0.072) |
| Hispanic | 0.247* | 0.414*** |
| | (0.096) | (0.060) |
| Asian, alone | 0.162 | 0.500*** |
| | (0.136) | (0.072) |
| Other races, alone | 0.372** | 0.279** |
| | (0.142) | (0.091) |
| Saving EIP | -0.364*** | -0.412*** |
| | (0.054) | (0.024) |
| Paying debt with EIP | 0.287*** | 0.600*** |
| | (0.043) | (0.023) |
| Saving EIP * Non-Hispanic Black | -0.255+ | -0.252** |
| | (0.147) | (0.093) |
| Saving EIP * Hispanic | -0.108 | -0.172* |
| | (0.139) | (0.077) |
| Saving EIP * Asian, alone | 0.043 | -0.279** |
| | (0.201) | (0.097) |
| Saving EIP * Other races, alone | -0.083 | -0.039 |
| | (0.201) | (0.119) |
| Paying debt with EIP * Non-Hispanic Black | -0.368*** | -0.329*** |
| | (0.107) | (0.082) |
| Paying debt with EIP * Hispanic | -0.041 | -0.194** |
| | (0.105) | (0.070) |
| Paying debt with EIP * Asian, alone | -0.047 | -0.102 |
| | (0.159) | (0.093) |
| Paying debt with EIP * Other races, alone | -0.169 | -0.090 |
| | (0.158) | (0.107) |
| Inverse Mill's ratio | -0.206** | -0.659*** |
| | (0.077) | (0.038) |
| Income groups | No | No |
| Other controls | Yes | Yes |
| Num.Obs. | 32387 | 32351 |
| AIC | 10979 | 36702 |
| Log.Lik. | -5411 | -18273 |
| RMSE | 0.211 | 0.437 |

Notes: (1) This table shows the estimation results of equation (2) The estimation only used the data of HPS week 27. (3) The inverse Mill's ratios were computed from a probit model that only includes the regressors for household incomes, sizes, and children under 18. (4) Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

## Figures

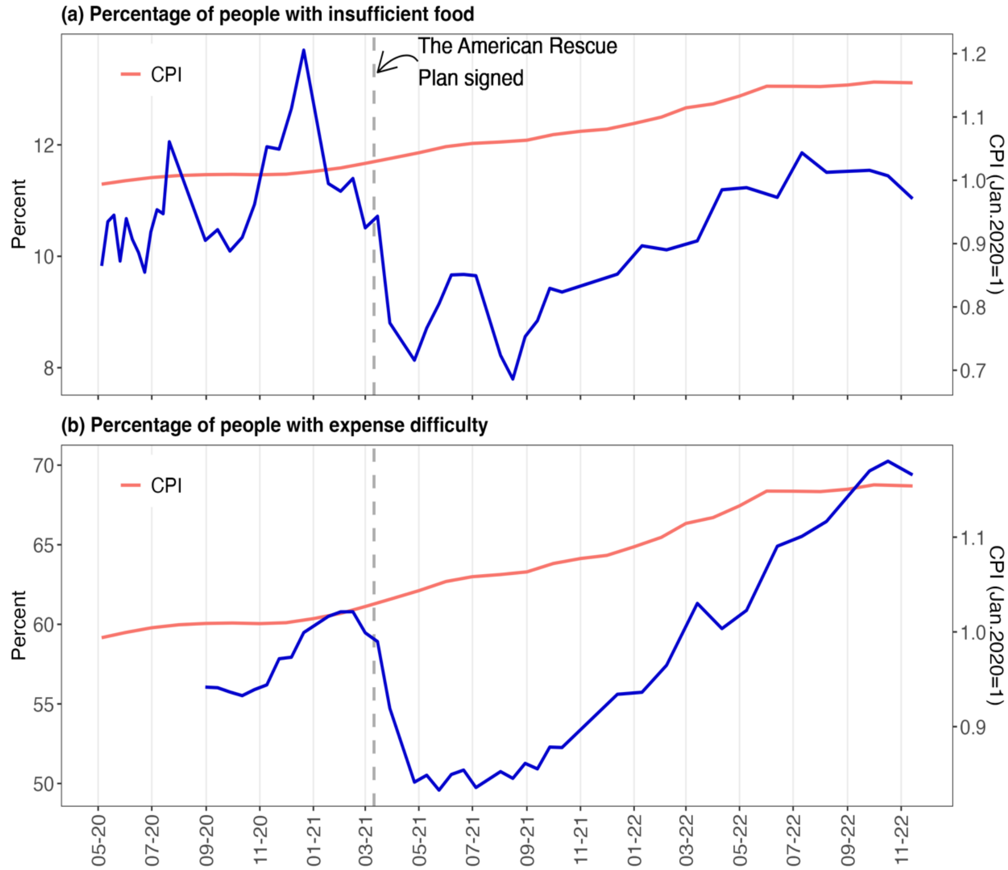


Figure 1. Trends of food insufficiency, expense difficulty, and CPI. Blue lines represent the population-weighted percentage of individuals with food insufficiency and expense difficulty (left y-axis). Red lines represent the consumer price indices (right y-axis). Source: HPS, BLS, and authors' calculation.

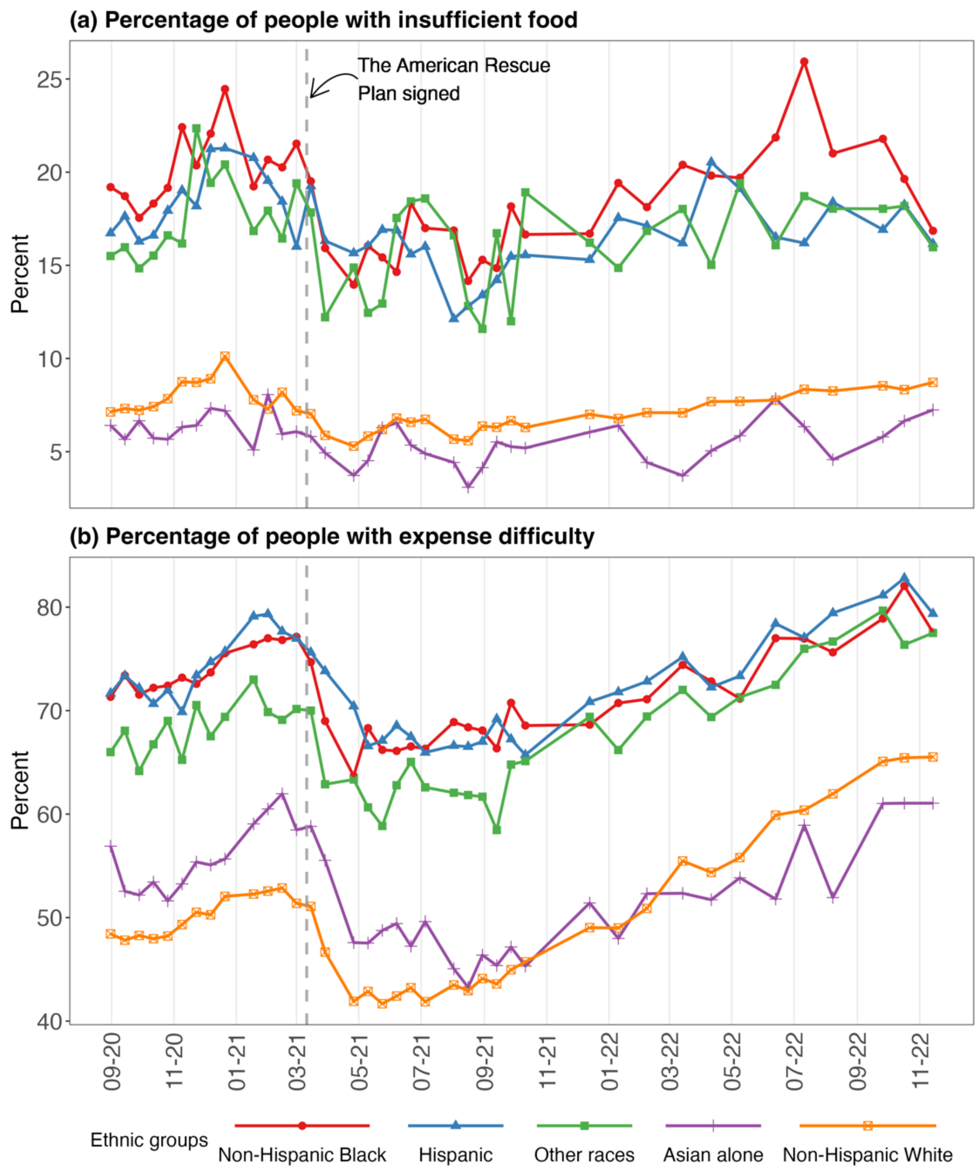


Figure 2. Trends of food insufficiency and expense difficulty by ethnic groups. All lines represent the population-weighted percentage of individuals with food insufficiency and expense difficulty. Source: HPS and authors' calculation.

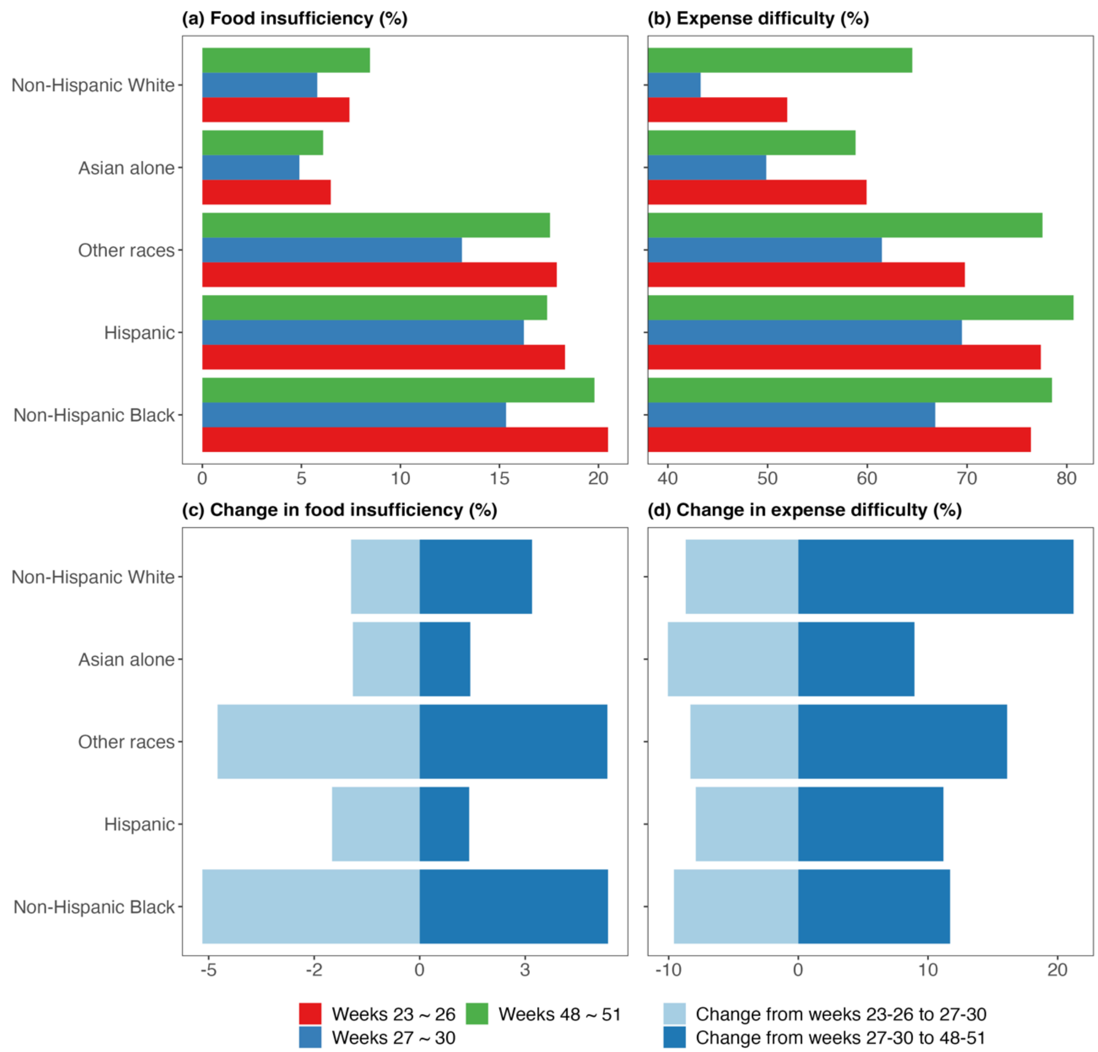


Figure 3. Food insufficiency and expense difficulty in three periods. Panels (a) and (b) compared the percentages for food insufficiency and expense difficulty at three four-week periods: HPS weeks 23-26 (January 20 to March 15, 2021), 27-30 (March 17 to May 24, 2021), and 48-51 (July 27 to November 14, 2022). Panels (c) and (d) show the change from one period to the next. All values are the population-weighted percentages. Source: HPS and authors' calculation.

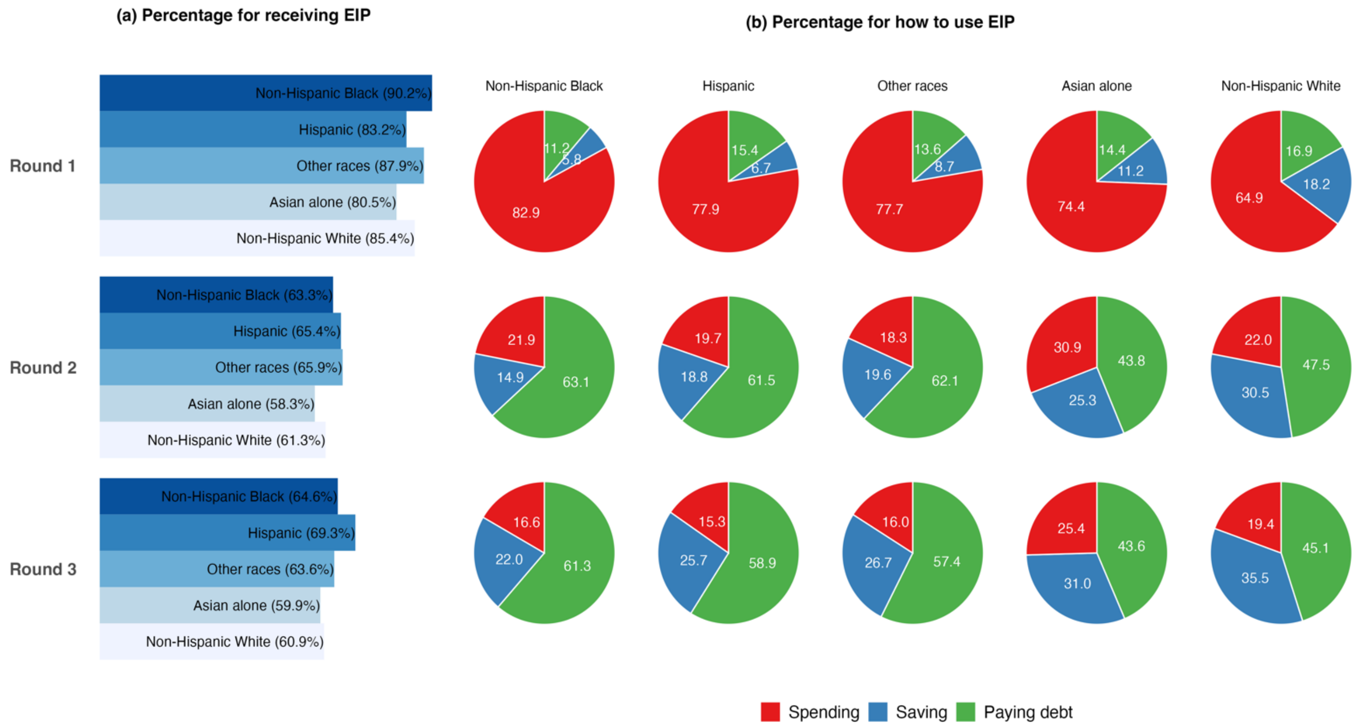


Figure 4. Percentage of individuals who received the Economic Impact Payments in three rounds of disbursement and how they used the payments. The data are collected from HPS weeks 7, 22, and 27, the respective first week when the EIP-related questions appeared in the questionnaire. The survey questions changed from the first round to the subsequent ones by adding an "in-the-last-7-days" modifier.  Source: HPS and authors' calculation.

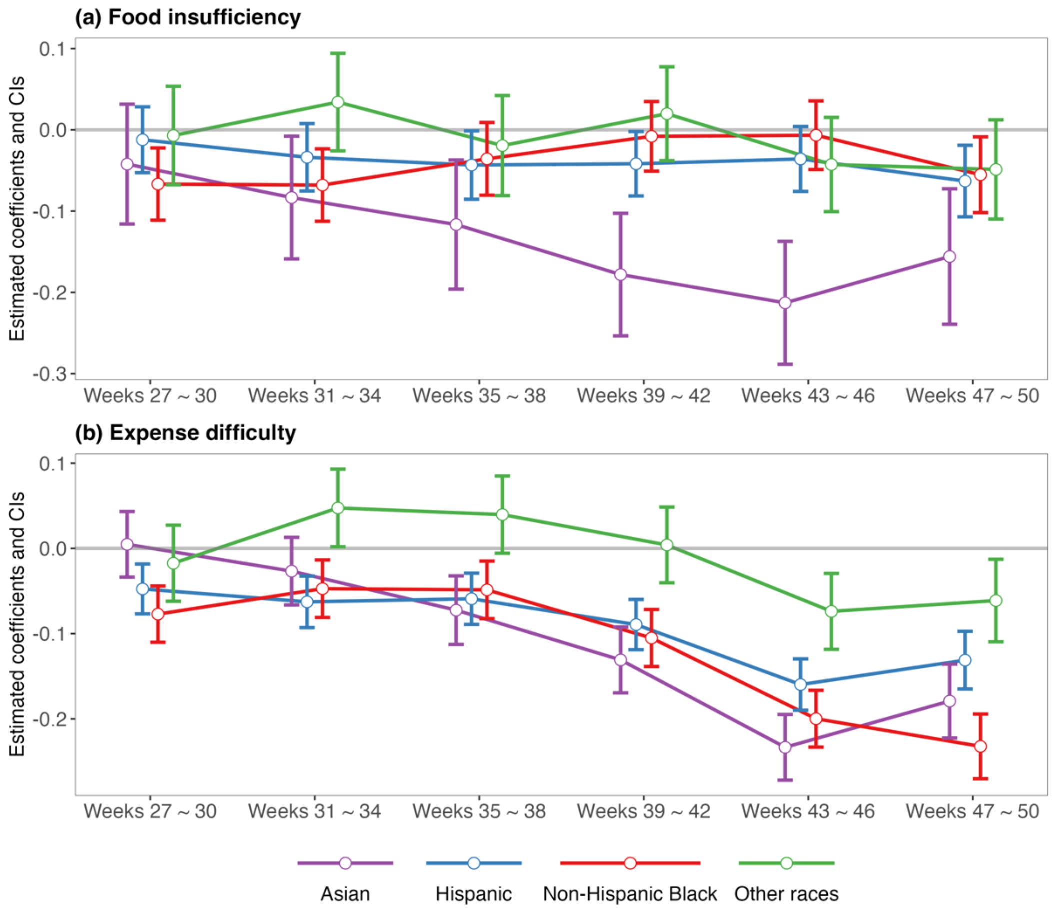


Figure 5. Estimated quasi-DiD effects for ethnic minority groups the four-week estimation. The regression model is equation (1), excluding the polynomial of time. The data include HPS weeks 23–26 (January 20–March 15, 2021) as the reference point and each four-week data since then. More detailed results are shown in Tables A4 and A5. Source: HPS and authors' calculation.

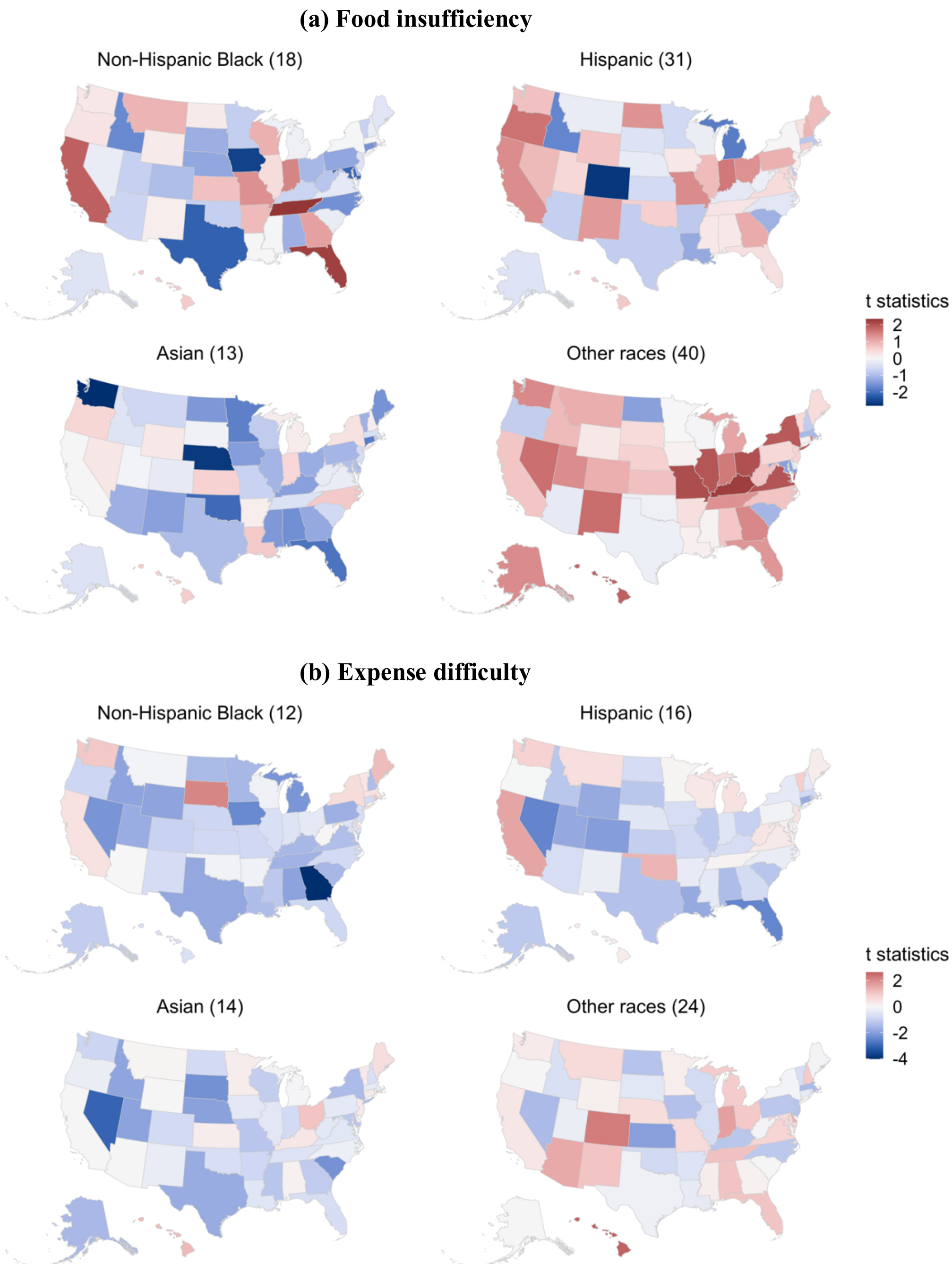


Figure 6. State variation of food insufficiency and expense difficulty after the ARPA by ethnic minority groups in comparison with non-Hispanic White. The regression model is equation (1), excluding the state dummy variables. The colors show the quasi-DiD coefficients, divided by their standard errors, i.e., making them t statistics. The darker colors, either blue or red, indicate a higher level of statistical significance. Source: HPS and authors' calculation.

## Appendix

Table A1. Descriptive statistics of categorical variables

| Variable | HPS weeks | Weighted percent | Unweighted percent |
|---|---|---|---|
| Food insufficiency | 1 ~ 51 | 10.41 | 6.38 |
| Expense difficulty | 13 ~ 51 | 57.25 | 46.33 |
| Receiving EIP | 7 ~ 12 | 85.81 | 82.64 |
| Receiving EIP | 22 ~ 26 | 53.37 | 48.10 |
| Receiving EIP | 27 ~ 33 | 23.32 | 19.16 |
| Using EIP: spending | 7 ~ 12 | 72.95 | 67.68 |
| Using EIP: spending | 22 ~ 26 | 25.77 | 27.34 |
| Using EIP: spending | 27 ~ 33 | 20.93 | 23.12 |
| Using EIP: saving | 7 ~ 12 | 12.46 | 15.85 |
| Using EIP: saving | 22 ~ 26 | 22.43 | 26.22 |
| Using EIP: saving | 27 ~ 33 | 27.70 | 30.46 |
| Using EIP: paying debt | 7 ~ 12 | 14.59 | 16.47 |
| Using EIP: paying debt | 22 ~ 26 | 51.80 | 46.44 |
| Using EIP: paying debt | 27 ~ 33 | 51.37 | 46.43 |
| Hispanic | 1 ~ 51 | 17.10 | 9.08 |
| Non-Hispanic Black | 1 ~ 51 | 11.38 | 7.43 |
| Asian, alone | 1 ~ 51 | 5.24 | 4.70 |
| Other races, alone | 1 ~ 51 | 3.81 | 3.63 |
| Household income: less than $25,000 | 1 ~ 51 | 15.05 | 10.59 |
| Household income: $25,000 - $34,999 | 1 ~ 51 | 11.50 | 8.73 |
| Household income: $35,000 - $49,999 | 1 ~ 51 | 12.60 | 10.86 |
| Household income: $50,000 - $74,999 | 1 ~ 51 | 17.75 | 17.42 |
| Household income: $75,000 - $99,999 | 1 ~ 51 | 13.25 | 14.55 |
| Household income: $100,000 - $149,999 | 1 ~ 51 | 15.19 | 18.29 |
| Household income: $150,000 - $199,999 | 1 ~ 51 | 6.95 | 8.92 |
| Household income: greater than $200,000 | 1 ~ 51 | 7.71 | 10.65 |
| Female | 1 ~ 51 | 51.56 | 59.24 |
| Less than high school | 1 ~ 51 | 8.23 | 2.08 |
| High school diploma or GED | 1 ~ 51 | 30.79 | 11.68 |
| Some college/associate's degree | 1 ~ 51 | 30.38 | 31.88 |
| Rental housing | 1 ~ 51 | 28.90 | 23.75 |
| Owning mortgage | 1 ~ 51 | 45.40 | 48.69 |
| Unemployed | 1 ~ 51 | 43.39 | 41.06 |
| With children under 18 | 1 ~ 51 | 38.59 | 34.16 |
| Married | 1 ~ 51 | 55.00 | 57.91 |
| Widowed, divorced, or separated | 1 ~ 51 | 18.43 | 22.55 |

Table A2. Descriptive statistics of continuous variables

| Variable | Mean | SD | Mode | Min | Max |
|---|---|---|---|---|---|
| Age | 52 | 16 | 66 | 17 | 88 |
| Household size | 3 | 2 | 2 | 1 | 10 |

Table A3. Percentage of receiving three rounds of EIP in the HPS data.

| Round of EIP | HPS weeks | Start date | End date | Weighted percentage | Unweighted percentage | Change in survey questions |
|---|---|---|---|---|---|---|
| Round 1 | 7 | Jun 11, 20 | Jun 16, 20 | 85.5 | 82.5 | The survey questions during these survey weeks do not include the modifier "in the last 7 days" in reference to the answering period, which implies a period from the receipt of EIP to answering the survey. |
| | 8 | Jun 18, 20 | Jun 23, 20 | 86.1 | 82.8 | |
| | 9 | Jun 25, 20 | Jun 30, 20 | 86.4 | 83.2 | |
| | 10 | Jul 02, 20 | Jul 07, 20 | 86.0 | 82.5 | |
| | 11 | Jul 09, 20 | Jul 14, 20 | 85.6 | 82.3 | |
| | 12 | Jul 16, 20 | Jul 21, 20 | 85.3 | 82.3 | |
| Round 2 | 22 | Jan 06, 21 | Jan 18, 21 | 62.2 | 57.9 | The survey questions during these survey weeks include the modifier "in the last 7 days" in reference to the answering period, resulting in lower percentages of receiving EIP after the first week of each round. |
| | 23 | Jan 20, 21 | Feb 01, 21 | 63.2 | 59.1 | |
| | 24 | Feb 03, 21 | Feb 15, 21 | 53.9 | 49.1 | |
| | 25 | Feb 17, 21 | Mar 01, 21 | 46.9 | 40.6 | |
| | 26 | Mar 03, 21 | Mar 15, 21 | 40.8 | 34.6 | |
| Round 3 | 27 | Mar 17, 21 | Mar 29, 21 | 62.7 | 56.3 | |
| | 28 | Apr 14, 21 | Apr 26, 21 | 26.9 | 21.3 | |
| | 29 | Apr 28, 21 | May 10, 21 | 19.2 | 14.3 | |
| | 30 | May 12, 21 | May 24, 21 | 16.3 | 12.0 | |
| | 31 | May 26, 21 | Jun 07, 21 | 14.0 | 10.0 | |
| | 32 | Jun 09, 21 | Jun 21, 21 | 12.6 | 8.9 | |
| | 33 | Jun 23, 21 | Jul 05, 21 | 11.6 | 7.7 | |

Notes: This table shows that the percentages of receiving the EIP drop from the first round to the second and third rounds due to the change in how the survey question was asked. In the first round, the survey question does not limit the time window of receiving the EIP, while in the second and third rounds, the question limits the time window to the last seven days. Sources: The HPS and authors' calculation.

Table A4. Estimated coefficients in probit models for food insufficiency using data from four HPS weeks

| | Weeks 27 ~ 30 | Weeks 31 ~ 34 | Weeks 35 ~ 38 | Weeks 39 ~ 42 | Weeks 43 ~ 46 | Weeks 47 ~ 50 |
|---|---|---|---|---|---|---|
| Intercept | -2.158*** | 2.974** | 0.133 | -3.901*** | -3.565*** | -1.484* |
| | (0.597) | (0.906) | (1.040) | (0.416) | (0.313) | (0.622) |
| Non-Hispanic Black | 0.317*** | 0.317*** | 0.317*** | 0.316*** | 0.314*** | 0.317*** |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) |
| Hispanic | 0.198*** | 0.187*** | 0.196*** | 0.197*** | 0.189*** | 0.189*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.015) |
| Asian, alone | 0.049+ | 0.047+ | 0.058* | 0.060* | 0.058* | 0.060* |
| | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.026) |
| Other races, alone | 0.313*** | 0.309*** | 0.313*** | 0.314*** | 0.310*** | 0.312*** |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) |
| After ARPA | -0.100*** | 0.136*** | -0.013 | -0.163*** | -0.102** | 0.233** |
| | (0.013) | (0.033) | (0.044) | (0.030) | (0.036) | (0.085) |
| After ARPA * Hispanic | -0.012 | -0.034 | -0.043* | -0.042* | -0.036+ | -0.063** |
| | (0.021) | (0.021) | (0.021) | (0.020) | (0.020) | (0.022) |
| After ARPA * Non-Hispanic Black | -0.067** | -0.068** | -0.036 | -0.008 | -0.007 | -0.055* |
| | (0.023) | (0.023) | (0.023) | (0.022) | (0.022) | (0.024) |
| After ARPA * Asian | -0.042 | -0.083* | -0.117** | -0.178*** | -0.213*** | -0.156*** |
| | (0.038) | (0.039) | (0.041) | (0.038) | (0.039) | (0.043) |
| After ARPA * Other races | -0.007 | 0.034 | -0.019 | 0.020 | -0.043 | -0.049 |
| | (0.031) | (0.031) | (0.031) | (0.029) | (0.030) | (0.031) |
| All controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Num.Obs. | 457116 | 437756 | 442933 | 455922 | 452379 | 396245 |
| AIC | 151902 | 150054 | 146756 | 160398 | 162711 | 146985 |
| Log.Lik. | -75871 | -74947 | -73298 | -80119 | -81275 | -73413 |
| RMSE | 0.214 | 0.218 | 0.214 | 0.222 | 0.225 | 0.228 |

Notes: (1) The regression model is equation (1), excluding the polynomial of time. (2) The data include HPS weeks 23–26 (January 20–March 15, 2021) as the reference point and each four-week data since then. (3) Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5. Estimated coefficients in probit models for expense difficulty using data from four HPS weeks

| | Weeks 27 ~ 30 | Weeks 31 ~ 34 | Weeks 35 ~ 38 | Weeks 39 ~ 42 | Weeks 43 ~ 46 | Weeks 47 ~ 50 |
|---|---|---|---|---|---|---|
| Intercept | 5.252*** | 1.508** | 3.280*** | -4.026*** | -4.326*** | 1.792*** |
| | (0.341) | (0.537) | (0.616) | (0.245) | (0.187) | (0.378) |
| Non-Hispanic Black | 0.366*** | 0.360*** | 0.348*** | 0.357*** | 0.373*** | 0.376*** |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| Hispanic | 0.275*** | 0.265*** | 0.255*** | 0.262*** | 0.275*** | 0.269*** |
| | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) | (0.011) |
| Asian, alone | 0.150*** | 0.150*** | 0.142*** | 0.156*** | 0.169*** | 0.163*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| Other races, alone | 0.272*** | 0.262*** | 0.257*** | 0.266*** | 0.280*** | 0.277*** |
| | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) | (0.016) |
| After ARPA | -0.110*** | -0.135*** | -0.011 | -0.271*** | -0.176*** | 0.826*** |
| | (0.007) | (0.020) | (0.026) | (0.017) | (0.022) | (0.052) |
| After ARPA * Hispanic | -0.048** | -0.063*** | -0.059*** | -0.089*** | -0.160*** | -0.131*** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.017) |
| After ARPA * Non-Hispanic Black | -0.077*** | -0.047** | -0.049** | -0.105*** | -0.200*** | -0.232*** |
| | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) | (0.019) |
| After ARPA * Asian | 0.005 | -0.027 | -0.072*** | -0.131*** | -0.233*** | -0.179*** |
| | (0.020) | (0.020) | (0.021) | (0.020) | (0.020) | (0.022) |
| After ARPA * Other races | -0.017 | 0.047* | 0.040+ | 0.004 | -0.074** | -0.061* |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.025) |
| All controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Num.Obs. | 456933 | 437710 | 443010 | 456076 | 452613 | 396295 |
| AIC | 498089 | 470627 | 475463 | 495834 | 502858 | 437873 |
| Log.Lik. | -248965 | -235234 | -237652 | -247837 | -251349 | -218857 |
| RMSE | 0.428 | 0.424 | 0.424 | 0.427 | 0.433 | 0.431 |

Notes: (1) The regression model is equation (1), excluding the polynomial of time. (2) The data include HPS weeks 23–26 (January 20–March 15, 2021) as the reference point and each four-week data since then. (3) Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A6. Estimated coefficients in probit models for receiving and using the ARPA EIP

| | Receiving EIP | Saving | Pay debt | Spending |
|---|---|---|---|---|
| Intercept | -1.042*** | -0.060 | -0.319*** | -0.987*** |
| | (0.066) | (0.082) | (0.082) | (0.093) |
| Non-Hispanic Black | 0.025 | -0.348*** | 0.373*** | -0.102** |
| | (0.024) | (0.032) | (0.030) | (0.034) |
| Hispanic | 0.019 | -0.218*** | 0.284*** | -0.131*** |
| | (0.022) | (0.027) | (0.026) | (0.030) |
| Asian, alone | 0.053+ | -0.136*** | 0.075* | 0.073+ |
| | (0.029) | (0.038) | (0.037) | (0.040) |
| Other races, alone | 0.016 | -0.237*** | 0.282*** | -0.091* |
| | (0.032) | (0.041) | (0.039) | (0.045) |
| Inverse Mill's ratio | | 0.338*** | -0.412*** | 0.065+ |
| | | (0.032) | (0.034) | (0.035) |
| Income groups | Yes | No | No | No |
| Other controls | Yes | Yes | Yes | Yes |
| Num.Obs. | 58016 | 32428 | 32428 | 32428 |
| AIC | 67288 | 40818 | 42046 | 32986 |
| Log.Lik. | -33570 | -20341 | -20955 | -16425 |
| RMSE | 0.444 | 0.467 | 0.477 | 0.405 |

Notes: (1) This table shows the estimation results of separate probit models. The first column represents the probit model in which the dependent variable is the probability of receiving the ARPA EIP, the second to the fourth columns represent the probit models in which the dependent variables are the probability of using EIP in saving, paying debt, or spending, respectively. (2) All the models use the data from HPS week 27. The second to the fourth models confine the sample to individuals who received EIP. Therefore, we included the inverse Mill's ratio in these models. The inverse Mill's ratios are computed with a shortened probit model from the first column by only including the variables for household incomes, sizes, and children under 18. (3) Significance levels: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.