How Did the Expiration of SNAP Emergency Allotments Affect Fresh Fruits and Vegetables Purchases of SNAP Households?

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Abstract

The global impact of the COVID-19 pandemic extends beyond health issues, notably affecting food accessibility worldwide. This impact is particularly severe for individuals already facing challenges in obtaining essential nutrition, especially those reliant on the Supplemental Nutrition Assistance Program (SNAP). To address this, the U.S. government introduced various pandemic-related relief measures, waivers, and flexibilities such as the emergency allotment (EA), providing additional benefits to help SNAP beneficiaries maintain access to essential food items during these challenging times. However, the termination of the EA across states started in 2021, resulted in a minimum reduction of $95 per month in SNAP benefits for each recipient. This study builds upon previous research, which established the link between SNAP benefits, food quality, and spending patterns. We employ a rich demographic information dataset from Numerator, which can identify SNAP households by using SNAP Electronic Benefit Transfer (EBT) card. We utilize Difference-in-Differences (DID) model with two-way fixed-effect (TWFE) estimator and two-stage (TSDID) estimator, to assess the impacts on monthly fresh fruits and vegetables (fresh FVs) spending of SNAP households in states that terminated EA compared to those that did not. Robustness is ensured by the use of non-SNAP households to validate the exclusivity of EA termination's effects on SNAP households. Moreover, heterogeneity analysis integrates income level, household size, children's presence, and ethnicity, providing a nuanced understanding of SNAP's influence on dietary choices across diverse households. We observe a consistent negative impact on fresh FVs spending following the termination of EA, with a reduction of approximately 4% under both DID estimators. Notably, Asian SNAP households experienced the most substantial negative impact at a reduction of 16.79%, followed by households with incomes between 100% and 130% of the federal poverty level at a reduction of 7.53%, and households with children at a reduction of 5.79%.

Key Words: SNAP, EA, DID, TWFE, Two-Stage DID

JEL Classification: I38, C21, C23,

1 Introduction

The Supplemental Nutrition Assistance Program (SNAP) is a vital social safety net in the United States, providing crucial financial support to low-income individuals and families. It plays a vital role in reducing food insecurity (Mykerezi and Mills 2010; Ratcliffe, McKernan, and Zhang 2011). The global COVID-19 pandemic has had a profound impact far beyond public health, particularly affecting the accessibility of food worldwide. Among those most severely affected are SNAP households, who face even greater challenges in securing essential nutrition. In early 2020, the U.S. government declared a state of emergency and implemented various measures to aid SNAP beneficiaries, such as the emergency allotment (EA), which provides additional benefits to ensure continued access to essential food items for SNAP households. In fiscal year 2022, the total spending on food and nutrition assistance programs reached \$183.0 billion, SNAP benefit spending constituting 65.3% of the overall spending, surged to \$119.5 billion from \$74 billion in fiscal year 2019 largely due to EA (Jones 2021; Toossi, Jones, and Hodges 2022). With the lifting of "shelter-in-place" (SIP) and the gradual return to daily life. Beginning in 2021, some states halted EA payments. By 2023, all states had stopped providing EA payments. The end of EA has raised concerns about its potential impact on the nutritional well-being of low-income individuals, especially regarding their purchases of healthier food categories like fresh fruits and vegetables (FVs). The impact of EA expiration on the spending habits of SNAP beneficiaries in different food categories remains largely unexplored. Additionally, there is a gap in understanding the consequences of gradually phasing out EA on SNAP households.

The primary objective of this study is to estimate the impact of EA expiration on the fresh FVs spending of SNAP households. We utilize transaction-level food purchase data from the Numerator data company, that enables to identify of SNAP households based on their use of SNAP Electronic Benefit Transfer (EBT) card usage to pay for their purchase partially or fully. To estimate the effects, we employ Difference-in-Differences (DID) model, comparing fresh FVs spending among SNAP households in states that terminated EA with those that did not. To validate our findings, we employ an event-study analysis (Miller 2023) to test the plausibility of the parallel trend assumption and to explore the dynamic effects. Furthermore, we conduct robustness checks using sensitivity tests with various income reference values and placebo tests with non-SNAP households to reinforce the results regarding the impact of EA termination on SNAP households.Additionally, we perform heterogeneity analysis within various household groups. Our goal is to unveil the nuanced consequences of EA expiration on the capacity of SNAP households to choose fresh FVs. Furthermore, we seek to quantify the extent to which EA expiration impacts households with varying characteristics, such as income levels, family sizes, the presence of children, and racial demographics. This comprehensive analysis enables a better understanding of how diverse groups of SNAP households are affected by this significant policy change.

Our research builds upon a foundation of prior studies that have explored the relationship between SNAP benefits, diet quality, and food spending. Some studies state that increasing SNAP benefits helps lower-income individuals afford healthy food, reduces hunger, and improves the quality and healthiness of their diets (Katare, Binkley, and Chen 2021; Andreyeva, Long, and Brownell 2010; Andreyeva, Tripp, and Schwartz 2015; Kim 2016). The latest researches find that SNAP EA positively impacts food security, guaranteeing improved access to nutritious diets for recipient households (Gregory et al. 2013; Anderson and Butcher 2016; Hoynes, McGranahan, and Schanzenbach 2015; Hastings and Shapiro 2018). These studies consistently demonstrate the significant impact of SNAP benefit levels on food expenditure patterns and their subsequent effects on diet quality. Moreover, this connection is supported by the causal effect established between SNAP benefits and increased grocery spending, particularly benefiting low-income households (Hastings and Shapiro 2018).

Our study focuses on fresh FVs because they offer superior nutrition compared to processed varieties like frozen, dried, or canned. Research supports that fresh FVs are rich in essential nutrients, making them ideal for a healthy diet (Rickman, Bruhn, and Barrett 2007; Bouzari, Holstege, and Barrett 2015). Recent research examines the effectiveness of policy responses, such as increased SNAP benefit amounts, in mitigating food insecurity and supporting food spending (Baker et al. 2020; Schanzenbach 2023; Bitler et al. 2022). Those studies highlighted the positive influence of EA payments on food spending during the pandemic.

Existing research revealed the influential role of demographics in SNAP households' spending. Murphy et al. (2016) revealed significant variations in fruits consumption patterns based on factors such as sex, age, race and income. In this paper, we incorporate income level, family size, the presence of children, and ethnicity as variables in our heterogeneity analysis. By amalgamating these characteristics with SNAP participation, we aim to deliver a more thorough and nuanced comprehension of how SNAP enrollment shapes food expenditure and dietary preferences within various household contexts.

The rest of this paper is organized as follows: Section 2 discusses our data sources. Section 3 outlines the identification of SNAP households, defines the outcome variable, specifies the period under consideration, describes the empirical model, and explains our robustness check methods. Section 4 presents the main results based on different DID estimators and models. Section 5 provides the results of event study. In Section 6, we conduct robustness checks using two methods to ensure the reliability of our findings. Section 7 provides a heterogeneity analysis that offers insights into how diverse household settings are affected by SNAP participation. Finally, Section 8 and Section 9 contains the discussions and conclusions.

2 Data

Many previous studies have sought to collectively analyze household behavior using survey data or scanner data like the Nielsen's Homescan data to gain a deeper understanding of the relationship between SNAP participation and food consumption (Just et al. 2007). In our research, the primary dataset is sourced from Numerator, a marketing research firm renowned for collecting comprehensive consumer data since 2017 (Song 2022). This dataset spans from 2019 to 2021 and encapsulates the shopping behavior of panelists who utilize a mobile application to submit photographs of their paper receipts, which are then captured and analyzed by Numerator. As He and Su (2023) and Sullivan (2023) found, the demographic composition of this dataset is close to that of the United States adult population as measured with census data. In addition, Numerator's dataset ask users to upload a photo of the complete receipt, which means that all information in each receipt, such as item-level details, including price, quantity, and item details, can be captured by Numerator. The receipt information, allowing us to identify SNAP households based on their payment method using EBT cards. This crucial feature is absent in other scanner dataset. In Numerator, each individual within the dataset is assigned a unique ID. Each unique user ID, link between transaction or item table and demographic information. This helps us focus our analysis on spending related to fresh food.

The dataset comprises monthly spending on fresh FVs from October 2020 to December 2021. Across all states and throughout the study period, including those where EA benefits had ended and those where they were still being distributed. Table 1 is an overview of the summary statistics. In this table, "All state" represents the entire dataset, "With EA" includes states that continued to issue EA as of December 2021, and "Without EA" comprises data for states that ceased issuing EA by December 2021. We reclassified income levels based on intervals aligned with the federal poverty guidelines for 2020 and 2021, dividing them into three categories: less than 100% of the poverty line, 100%-130%, and 130%-185%. Based on the table, the demographic breakdown for each subgroup reveals that a majority of SNAP households have attained higher education levels, with college education being prevalent. Regarding gender, women are the primary purchasers. In terms of ethnicity, Whites represent over 50% of the dataset, followed by Hispanics, while Blacks and Asians constitute a similar percentage. Approximately 57.82% of households have children, while 42.18% do not. Household sizes with 2 to 4 members are most prevalent, accounting for approximately 20.66%, 16.48%, and 19.15%, respectively. Proportions remain consistent regardless of EA status, indicating dataset reliability. Table A1 shows the predicted EA over time by household size. Additionally, Table A3 displays the details of the selected fresh FVs along with their category descriptions.

Table A2 provides a detailed breakdown of monthly spending on fresh FVs across different household sizes from our dataset.The average monthly spending on fresh FVs by SNAP households was approximately \$200. According to the "2015-2020 Dietary Guidelines for Americans", consumers on a 2,000-calorie diet could meet federal fruit and vegetable recommendations for \$2.10 to \$2.60 per day [1]. The \$200 average spending on fresh FVs appears reasonable.

[1]Source from Stewart et al. (2016), The cost of satisfying fruit and vegetable recommendations in the dietary guidelines. Available at: https://www.ers.usda.gov/webdocs/publications/42902/56772$_e$$b27.pdf$

3 Methodology

3.1 Outcome Variables

We select user with payment method using EBT cards as SNAP household. After we select EBT card users, we find some of them has higher income level, which cannot participate program. In order to get more correct data. We use both payment method and income level to identify SNAP households. Before filter with income level, we still need one more step. Despite the richness of data provided by Numerator, we encountered a limitation regarding the income level, which was provided as a range (e.g., "Less than \$20,000," "\$20,000-\$29,999," etc.). To ensure data accuracy, we focused on SNAP households who used "SNAP" as their payment method and had a clearly defined income level. To address this, first, we divided income levels into three group for SNAP households based on the 2020 and 2021 Federal poverty guidelines (Details in Table A.4): less than 100%, 100% to 130%, 130% to 185% and 300%. Then we made use of upper bound value of each income interval (e.g., use 29,999 for "\$20,000-\$29,999" , 39,999 for "\$30,000-\$39,999") as the reference value for defining income levels. We divided these levels based on household size, using the 2020 and 2021 Federal Poverty Guidelines. The specific income level divisions can be found in the Table A.5. And now we can could effectively distinguish between SNAP and Non-SNAP households. Users who never used "SNAP EBT card" as their payment method were categorized as Non-SNAP households. We applied the same interval mean method to refine the income levels for Non-SNAP households, referring to the federal poverty line. This led to the division of Non-SNAP households into two income levels: less than 300% and over 300%. These categories correspond to lower-income and higher-income groups (see the Table A.6 for details). As Currie et al. (2001) noted, households with incomes below 300% percent of the federal poverty line are likely to be more strongly affected by welfare reform. We will conduct a robustness test on the results using transaction data from Non-SNAP households.

The transactional data provided is at a daily level, so we aggregate the daily fresh FVs spending to a monthly level. We add up the spending of unique users within the same month and state. This aggregated monthly fresh FVs spending is used as our outcome variable for analysis.

3.2 Treatment Groups

To evaluate the impact of EA expiration, we establish treatment groups based on the EA period, which spans from October 2020 to December 2021, encompassing a total of 15 periods. Since states discontinued EA benefits at different times, we categorized states without EA benefits as the "treatment group". As of December 2021, there were 8 states that had ceased EA payments (see Table 2). The month when a state first ended EA was considered its initial treated month, while states that continued EA benefits were labeled as the "control group". We introduced a dummy variable named "EA", with treatment denoting states where EA has ended, using the initial month of EA termination as their treated period (dummy variable equals 1). States maintaining EA benefits were designated as the control group, with the dummy variable EA set to 0. 8 states in Table 2 are the treatment group.

3.3 Models

3.4 Two-Way Fixed Effects

We start our empirical analysis by employing a two-way fixed effects (TWFE) estimator in a Difference-in-Differences (DID) model. We examine the change in monthly spending on fresh FVs with the staggered expiration of EA payments, using the following Equation 1:

$$Y_{ist} = \beta EA_{st} + \gamma X_{ist} + \theta_t + \delta_s + \varepsilon_{ist} \tag{1}$$

Y_{ist} is the log of real total spending on fresh FVs of SNAP households i living in state s at period t , adjusted for the logarithm of the CPI. We utilize monthly CPI data for fruits and vegetables from FRED[2]. EA_{st}, a dummy variable, indicates whether EA payments expired in the state and month of observation. If EA expired in the state s at period t, EA is equal to 1. Therefore, β could be interpreted as the impact of the termination of EA payment on spending changes in FVs. X_{ist} is all control variables including log income, log household size, whether a household has children nor not, gender, age, education level and

[2]Source from U.S. Bureau of Labor Statistics (2023). Available at: https://fred.stlouisfed.org/series/CUSR0000SAF113

ethinicity. As mentioned by Ganong and Liebman (2018), Andreyeva, Long, and Brownell (2010) and Hoynes, McGranahan, and Schanzenbach (2015), income level has impact on both SNAP benefits and food spending. Therefore, we put income level into the model. θ_t, δ_s are time and state fixed effect, respectively.

This approach accounts for the impact of EA termination across different states. It involves comparing the changes in fresh FVs spending among SNAP households within states that experienced EA termination to those states where the EA status remained unchanged. However, its effectiveness in capturing the nuances of our specific investigation into the impact of EA might be limited. The main challenge lies in the staggered and heterogeneous nature of EA expiration in varying time across different states, a scenario where TWFE may not perform optimally (Callaway and Sant'Anna 2021; Goodman-Bacon 2021; Gardner 2022). Therefore, we use an alternative DID estimator proposed by Gardner in 2022 (TSDID) to produce consistent estimates of the effect of EA expired on fresh FVs spending.

3.5 Two-Stage DID

The two-stage DID model offers several advantages over the TWFE approach, including better handling of treatment effect heterogeneity, simplicity, clear identification of average treatment effects, and flexibility in event study analysis. In the first stage, represented by Equation 2, we employ a regression model incorporating state and time fixed effects using untreated observations. This stage is designed to capture systematic differences in outcomes across different states and time periods in the absence of treatment. By estimating these effects in the initial stage, we can effectively control for any underlying differences that may exist between states and over time, thus providing a fundamental understanding of the variation in outcomes.

$$Y_{ist} = \gamma X_{ist} + \theta_t + \delta_s + \epsilon_{ist} \tag{2}$$

Where, X_{ist} represents all the characteristics of SNAP household i at state s and time t. θ_t and δ_s denote time and state fixed effects, respectively.

Moving to the second stage, ss shown in Equation 4, we utilize a regression model that includes the treatment status variable after removing the state and time effects estimated in the first stage. Where, EA_{st} is the same dummy variableas in Equation 1, β is our TSDID estimator, captures the average treatment effect on the treated groups.

$$Y_{ist} = \beta EA_{st} + \eta_{ist} \tag{3}$$

This could help us focus on capturing the average treatment effect on the treated groups, accounting for any remaining unobserved heterogeneity. By isolating the treatment effect in the second stage, we can quantify the additional impact of the treatment on the outcome variable beyond what can be explained by state and time characteristics. This two-stage approach allows us to find the treatment effect from other factors and provides a clearer estimation of the average treatment effect in the presence of staggered adoption and heterogeneous effects.

3.6 Standard Error

Various recent papers and studies in econometrics and applied microeconomics have addressed the issue of clustering standard errors in panel data and DID models to account for within-cluster correlations and ensure the reliability of empirical findings (Abadie et al. 2023; Cameron and Miller 2015).

Clustering standard errors at the monthly-state level is essential to appropriately address potential correlations among observations within the same state-month unit, capturing any within-cluster dependencies due to shared characteristics or unobserved factors. By clustering standard errors at household level, we can account for the specific clustering structure of the data and adjust standard errors to reflect the clustered nature of the observations, ensuring that the estimated treatment effects are robust and reliable. Additionally, in the context of small policy changes where effects are expected to be relatively homogeneous and within-cluster variability may be limited, considering clustering standard errors at household level can provide more precise estimates and enhance the validity of inference in the TWFE DID model analysis. For TSDID estimator, based on the "did2s" package, we also cluster at the household level.

3.7 Event Study

We utilize event-study analysis to confirm the absence of pre-trends and explore the dynamic effects. This analysis is conducted for both the unconditional and conditional models using two DID estimators: TWFE and TSDID. For TWFE event study results, we use Equation 3.

$$Y_{ist} = \left(\sum_{j=-m}^{n} \gamma_j \cdot D_{is(t-j)}\right) + \alpha_s + \delta_t + \beta X_{ist} + \epsilon_{ist} \tag{4}$$

Y_{ist} represents SNAP household i the monthly speding on fresh FVs in state s during period t. $D_{is(t-j)}$ is an indicator variable for event time j, meaning that the event took place j periods before this observation's time. Here, n represents the number of periods after the event, and m represents the number of periods before the event. A separate term is included for each event time. The coefficients after the event has occurred (γ_j for $j \geq 0$) capture the dynamic effects of the treatment as these effects manifest over time since the event. The coefficients γ_j for periods before the event (where $j < 0$) can be utilized to examine parallel assumptions. In the absence of anticipation effects, these pre-event terms should not have a trend in j. This event study model is estimated on data that have a panel structure. It is conventional to add two sets of fixed effects, α_s and δ_t represents state and time fixed effects respectively.

These serve the role of controlling for confounding omitted variables that vary at the state or time level. Using this two-way fixed events approach helps to isolate the effect of the event. X_{ist} are SNAP household characteristics, and ϵ_{ist} is the error term as shown in Equation 1. Based on our DID model, we want to figure out how much change we would expect without treatment compared to before treatment. A common normalization is setting $\gamma_{-1} = 0$ by excluding the dummy variable for the event at $j = -1$ from the regression. This adjustment helps isolate the treatment effect by establishing a baseline of what would have happened in the absence of the treatment. To examine the parallel trend assumption, we hypothesize that $\gamma_{-m}, \ldots, \gamma_{-1} = 0$.

For the TSDID event study, we directly extract results from the"did2s" package in R, utilizing Equation 5 to derive event study outcomes.

$$Y_{ist} = \sum_{d=-m}^{n} \delta_d \cdot 1(D_{ist} = d) + \epsilon_{ist} \tag{5}$$

Where 1() is an indicator function. δ_d is the effect of treatment duration d. Remaining notations are the same as TWFE event study model in Equation 4.

3.8 Robustness Checks and Heterogeneity Test

We aim to explore the impact of EA expiration on SNAP households. This exploration assumes that the impact is exclusive to SNAP and does not influence other individuals. If this assumption proves incorrect, it suggests that the impact on SNAP households may be due not only to EA expiration but also to other factors. To ensure the validity of the effects we've identified, we employ two methods for robustness checks. Firstly, we conduct sensitivity tests using different income reference values as our second robustness check. For SNAP households, we categorize them into three income levels: upper bound, mid-point, and lower bound. We expect that there should be no differences between these levels. Secondly, we use non-SNAP households as a placebo group in our analysis. Since these households did not receive EA payments, the cessation of EA payments should not affect them. These households are divided into three categories: all non-SNAP households, lower-income non-SNAP households (income below 300% of the poverty line), and higher-income non-SNAP households (income at or above 300% of the poverty line). Detailed information about the income level classification for SNAP and non-SNAP households with different reference values can be found in Table A5 to Table A9.

Apart from income level, the Numerator's dataset also includes rich demographic information. This wealth of information provides an opportunity for a deeper understanding of how various household characteristics may influence this impact. Our heterogeneity analysis focuses on these household characteristics, which encompass income level, education level, ethnicity, the presence of children, and household size. We have four subgroups for ethnicity: The ethnicity group was divided into four categories: "White/Caucasian", "Asian", "Black or African American" and "Hispanic/Latino". Based on the data's characteristics, to ensure the balance of each subgroup, we reclassified household size during the heterogeneity test. Given the complexity of households with six or more members, we grouped all SNAP households equal or above 6 together for analysis, labeled as "Household Size 6". This approach aims to illuminate the multifaceted impact of EA payment termination across different subgroups.

4 Main Results

Table 3 presents the differences in the impact of the expiration of EA on monthly spending on fresh FVs between SNAP households and those still receiving EA payments. The results in Table 3 illustrate the estimated impact of terminating EA payments using two DID estimators, employing both unconditional and conditional models. The first column indicates the two DID estimators, while the second column displays the results from the unconditional model, and the third column shows the results from the conditional model. Our model employs a log-level model. Given the small magnitude of these values (less than 0.15 in absolute terms), there is no need to convert the coefficient. Instead, we multiply the results by 100 and express them as percentages. For example, if the original result for the TWFE unconditional model is -0.0431, it appears as -4.31 in the table, indicating a decrease of 4.31%. Standard errors are shown in parentheses, with all values clustered at the household level.

The statistical analysis highlights a significant negative impact for both estimators. The TWFE results show consistency across unconditional and conditional models, indicating a reduction of 4.31% and 4.28%, respectively. In contrast, the TSDID results also maintain consistency but with just a lillter bit lower effect size, measuring at a decreasing of 4.11% for the unconditional model and 4.06% for the conditional model. The TWFE results consistently with TSDID results, approximately decrease 4%. All results is significant under a 90% confidence level.

In economic terms, the discontinuation of EA led to a decrease in monthly expenditure on fresh FVs among SNAP households in comparison to those who continued receiving EA benefits. Given an average monthly spending of \$200 on fresh FVs, this implies that SNAP households were spending around \$8.00 less on fresh FVs each month due to the halt in EA payments, compared to SNAP households in states where EA payments continued.

5 Event Study Results

The plots of event study visualize how the change in monthly spending on fresh FVs per household varies over time before and after the EA expired. The Conditional model results, depicted in Figure 1, are summarized with detailed numerical values provided in Table A10. For a comprehensive overview of the Unconditional event study results, please refer to Figure A1 and Table A11. In Figure 1, the vertical axis is the effects of the EA expiration on monthly spending on fresh FVs of SNAP households, estimated under the conditional model. The red lines indicate point estimates for the dynamic effects of TSDID and simultaneous 95% confidence bands for TSDID results. Similarly, the blue lines provide point estimates for γ_j in the TWFE model and simultaneous 95% confidence bands. For TSDID, Figure 1 and Figure A1 reveal no discernible pre-trend prior to the termination of EA payments. However, in the case of TWFE, a slight positive trend is observed from pre-period 11 to pre-period 6, while there is no pre-trend from pre-period 5 to the expiration of EA. This indicates that the null hypothesis cannot be rejected, suggesting no significant γ_j for $-6 \geq j \leq 0$.

Following exposure = 0 and in subsequent post-periods, both TWFE and TSDID models exhibit a significant decline in fresh FVs spending, reaching their lowest points at exposure = 6. Specifically, the TSDID model shows a 33.62% reduction, while the TWFE model indicates a decrease of 20.50%. Additionally, a minor and statistically insignificant upward trend is observed in the final period of TSDID. In contrast, TWFE exhibits fluctuations, initially increasing to non-significance at post-period 7 before showing a significant negative impact around post-period 8. This variability can be attributed to our limited treatment groups, only one state Idaho, with the 8-month post-period observed. Furthermore, as previously mentioned, TWFE may not perform optimally in cases where treatment adoption is staggered. In summary, the event study's post-period outcomes demonstrate a notable decline in fresh FVs spending post-EA payment cessation, reaching the lowest point after 6 months. However, anomalies in trends are observed towards the conclusion of the event studies, potentially influenced by the lack of data.

6 Robustness Checks Analysis

6.1 The Effects of Different Reference Values

We conducted a sensitivity test as our first robustness check, which involved adjusting the income reference values of SNAP households to create new datasets for rerunning models and analyzing their event study results. The outcomes, detailed in Table 4, reveal a consistent pattern across both the conditional and unconditional models. Notably, the upper bound results showed a slightly stronger effect in both models, with a reduction of 4.06% (4.11% for the unconditional model), compared to the mid-point results at a reduction of 3.84% (3.91% for the unconditional model) and the lower bound results at a reduction of 3.19% (3.25% for the unconditional model). This minor variation can be attributed to the composition of the datasets; the upper bound dataset excludes more households who should be classified as SNAP, while the lower bound dataset includes more individuals who should not be classified as SNAP. Consequently, the samples in the lower bound dataset may be less influenced by the expiration of EA payments. Therefore, utilizing the upper bound as the reference value is considered a reasonable choice as it helps in selecting more accurate and representative data for analysis.

Figure 2 visually presents the event study results corresponding to the different income reference values, depicted by blue, red, and green lines representing the lower bound, midpoint, and upper bound, respectively. These lines exhibit a consistent trend, with none of them demonstrating a statistically significant result. However, it's noteworthy that in the post-period (where exposure > 0), the absolute value of the green points consistently remains the lowest, indicating a subtle trend that persists throughout the result table.

6.2 The Effects of non-SNAP households

Table 5 presents the results of two models and methods applied to non-SNAP households. Surprisingly, all estimates are opposite to those in Table 3, indicating a significant positive impact of approximately 5% under the conditional model. Only TSDID with the unconditional model shows a higher impact at around 8%. Figure 3 visually represents the event study results for non-SNAP households, with blue denoting the effects estimated with TWFE approach and red representing the effects estimated with TSDID approach, both accompanied by a 95% confidence interval. Both of them exhibits consistent results overall. When excluding the furthest period before EA cessation, the lines displayed a slow, non-significant declining trend that flattened out by the 6th period of the pre-period. However, in the 4th period of the pre-period, a very small but significant negative effect was observed. Overall, as the end of EA distribution approached, the pre-trend became more flatted. Following the termination of EA, there was an initial increase in dynamic effects, which then quickly transitioned to no effect. This pattern contrasts with the impact observed among SNAP households.

To delve deeper into the results, we categorized non-SNAP households into low-income and high-income groups based on whether their income level exceeded 300% of the poverty line. Figure 4 visualizes the event study results for the income subgroups, with blue bands representing the lower-income level and red bands representing the higher-income level, both under a 95% confidence interval. The higher-income non-SNAP households exhibit a similar trend from the pre-period to the post-period as the entire non-SNAP household group depicted in Figure 3. However, the lower-income non-SNAP households show more flattened dynamic effects after the expiration of EA. Additionally, although there are significant positive impacts observed in the first two post-periods, these effects are relatively small. Given that non-SNAP households do not experience a reduction of at least $95 per month, the positive impact may be attributed to their greater emphasis on healthy eating or other unrelated factors, which are not the focus of our study. Nevertheless, this finding underscores that the expiration of EA has a negative impact exclusively on SNAP households.

7 Heterogeneity Analysis

Our heterogeneity analysis, conducted using both TSDID and TWFE conditional model, yielded insightful results depicted in Table 7 and Table A13, respectively. These findings shed light on how various household characteristics influence the impact of EA expiration. Among the ethnic groups analyzed, Asian SNAP households experienced the most significant negative impact, with a substantial decrease of 16.79% post-EA payment cessation. The remaining ethnic groups showed non-significant and very small negative impacts. Additionally, households with incomes between 100% and 130% of the federal poverty level demonstrated a substantial negative impact of about 7.53%, while households with incomes outside this range exhibited non-significant impacts. Furthermore, our analysis considered household composition, revealing that households with children faced a significant negative impact, decreasing by 5.99% post-EA payment cessation, while households without children showed no impact. Lastly, after considering household size, none of the subgroups showed a significant impact. Overall, our heterogeneity analysis underscores the necessity of implementing targeted interventions that address the diverse needs and vulnerabilities of specific demographic groups within SNAP households.

8 Discussions

Our comprehensive analysis provides crucial insights into the consequences of EA payment expiration on SNAP households. The key findings from our study reveal a substantial decrease in fresh FVs spending among SNAP households after discontinuing EA payments, impacting diverse demographic groups. Notably, both estimators yield the same results. The TSDID estimator demonstrates an average reduction of 4.06%, significant at a 95% confidence level, while the TWFE estimator shows a reduction of 4.28%, also significant at a 95% confidence level. Given the staggered treatment group nature, our results suggest that TSDID may offer more reliable and credible estimates for interpreting the impact of EA payment expiration on SNAP households' fresh FV spending.

Our event study results show that there is no trend for the periods with the EA payment. The dynamics of the impact of EA payment cessation on SNAP households are negative. Additionally, it is worth noting that the effects after exposure = 0 show a significant downward trend, reaching underestimation in period 6 of the post-period. The significant drop in spending post-EA expiration, particularly evident at the 6th post-period, underscores the need to consider the long-term implications of the decrease in SNAP benefits. This emphasizes the importance of implementing measures to monitor and address sustained impacts on healthier food spending among SNAP households.

The sensitivity test outcomes emphasize the methodological considerations essential in assessing the impacts brought by EA expiration accurately. The choice of reference values shows that using upper bound is more rigorous.

In the context of the placebo test, the observed disparities between SNAP households and lower-income non-SNAP households underscore the complex interplay between EA effects. EA expiration only affects those low-income households that participated in SNAP. Additionally, the significant increase in spending on fresh FVs for both lower-income and higher-income non-SNAP households demonstrates that the decreasing spending on fresh FVs for SNAP households is mostly caused by the cessation of EA payments.

Our heterogeneity analysis sheds light on the nuanced effects of EA expiration on SNAP participants, revealing the complex relationship between demographic characteristics and consumption behavior. Our findings highlight that the impact of EA cessation varies significantly across different subgroups, with some groups experiencing a more pronounced decline in fresh FVs spending compared to others. These outcomes highlights the diverse consumption habits and economic sensitivities within the SNAP population, emphasizing the need for tailored interventions that consider the unique challenges and resilience factors present in each subgroup. Understanding these demographic differences, consider targeting SNAP benefits to promote healthier food choices among different SNAP subgroups.

However, our study is not without limitations. Our dataset is current as of December 2021, and it only includes eight states in the treatment group during this period. To better capture the impact of discontinuing the issuance of EAs, it is essential to expand the inclusion of states in the treatment group. Acknowledging the limitations associated with data availability, especially in post-analysis, our study emphasizes the importance of addressing these limitations to offer more comprehensive insights into long-term effects.

9 Conclusions

In conclusion, our study offers critical insights into halting EA payments on fresh FVs spending among SNAP households. The significant drop in spending after EA payments ceased highlights the financial challenges faced by SNAP households and emphasizes the importance of maintaining adequate benefits for healthier food choices. Our findings stress the need for targeted interventions that cater to the diverse requirements and vulnerabilities of specific demographic groups within the SNAP population, taking into account factors such as household size, income levels, and ethnic backgrounds.

However, it is crucial to acknowledge the limitations of our study, particularly the restricted number of states in the treatment group and data availability constraints. Future research should focus on gathering more recent data to overcome these limitations, thus providing more robust and comprehensive insights into policy effects on SNAP participants' food spending behavior. Furthermore, comparative analysis with spending in other food categories could yield valuable insights into broader consumption patterns. Ultimately, our study could contribute to the ongoing discourse on the relationship between SNAP benefits, food quality, and food spending, thereby influencing healthier dietary choices among SNAP households.

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Figures

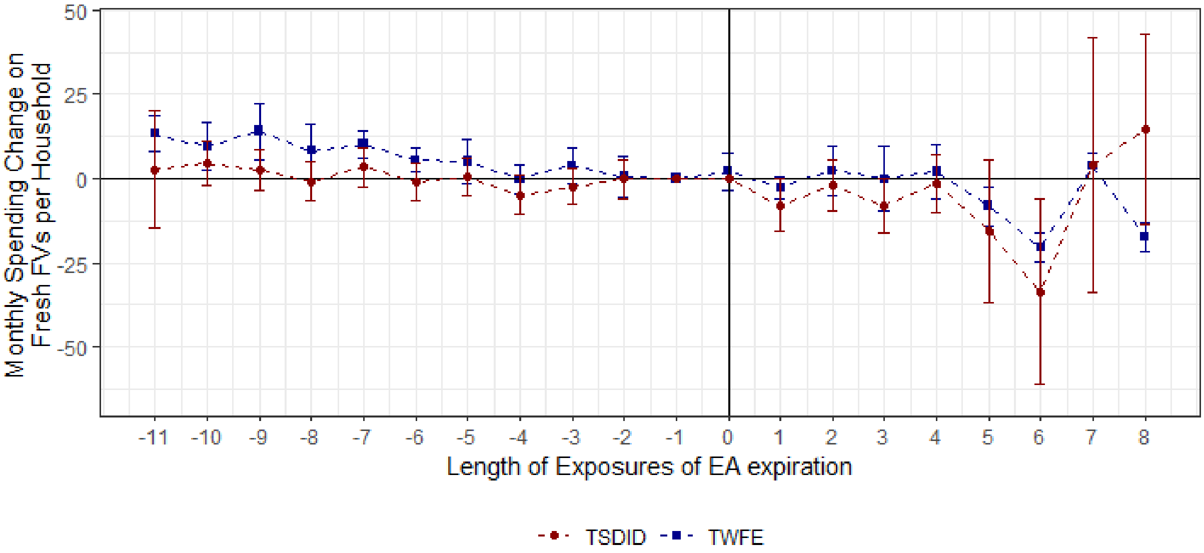


Figure 1. Event study for conditional model among SNAP households

Note: The effect of the EA expiration on monthly spending on fresh FVs of SNAP household estimated under the conditional model. TWFE refers to the impact estimated from TWFE event study models, while TSDID denotes the estimators used in "did2s" package. Red and blue lines give point estimates and simultaneous 95% confidence bands (based on household-clustered standard errors) for TSDID and TWFE results, respectively.

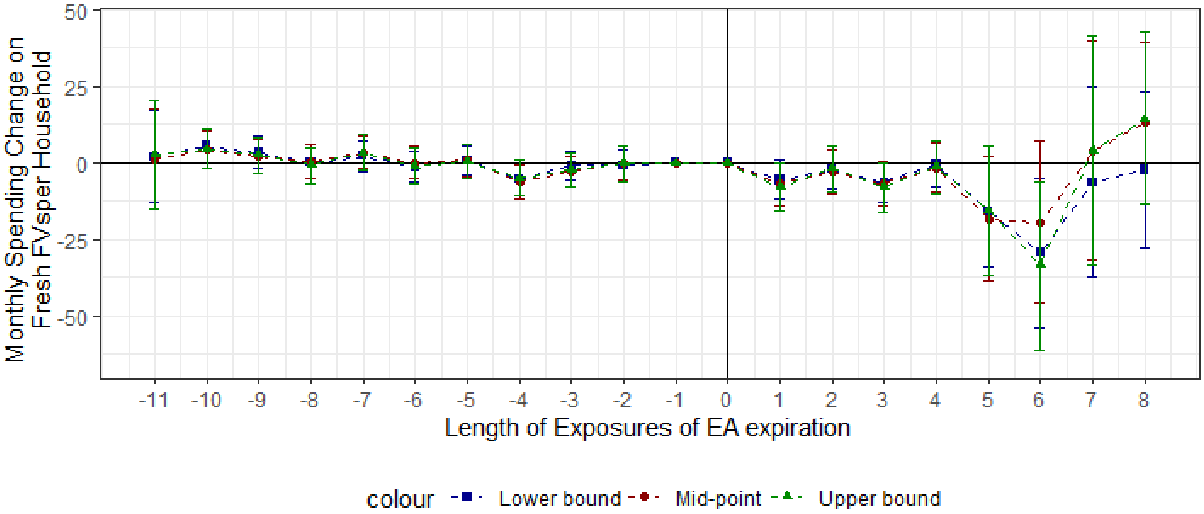


Figure 2. Event study for conditional model among SNAP households with different reference values

Note: The effect of the EA expiration on monthly spending on fresh FVs estimated under the TSDID conditional model. Blue, red, green lines give point estimates, along with simultaneous 95% confidence bands (based on household-clustered standard errors), corresponding to the lower bound, mid-point, and upper bound as reference values, respectively.

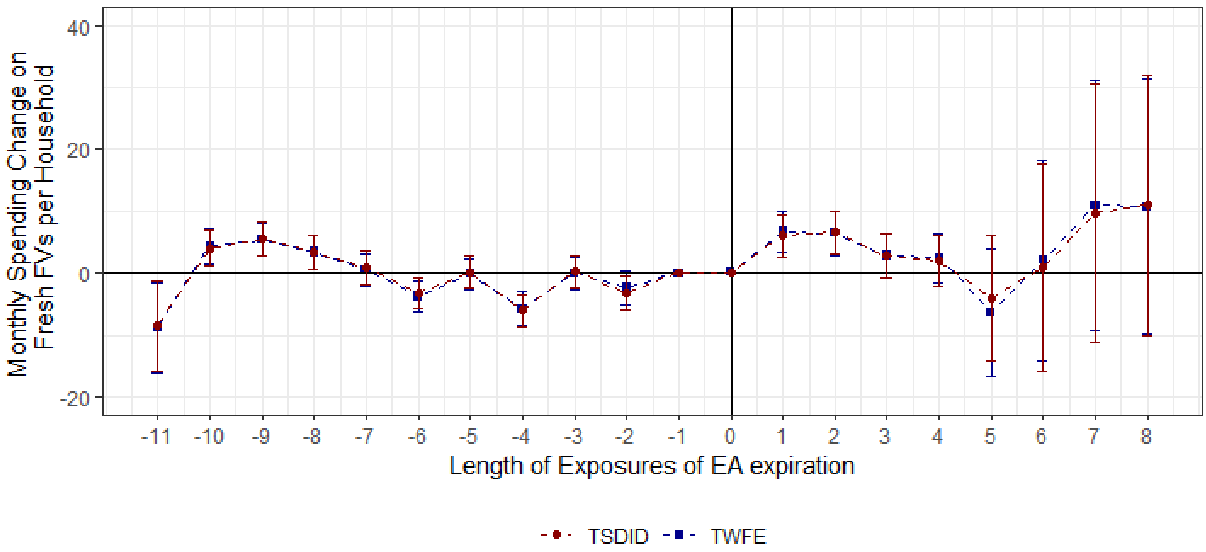


Figure 3. Event study for conditional model among non-SNAP households

Note: The effect of the EA expiration on monthly spending on fresh FVs of non-SNAP household estimated under the conditional model. TWFE refers to the impact estimated from TWFE event study models, while TSDID denotes the estimators used in "did2s" package. Red and blue lines give point estimates and simultaneous 95% confidence bands (based on household-clustered standard errors) for TSDID and TWFE results, respectively.

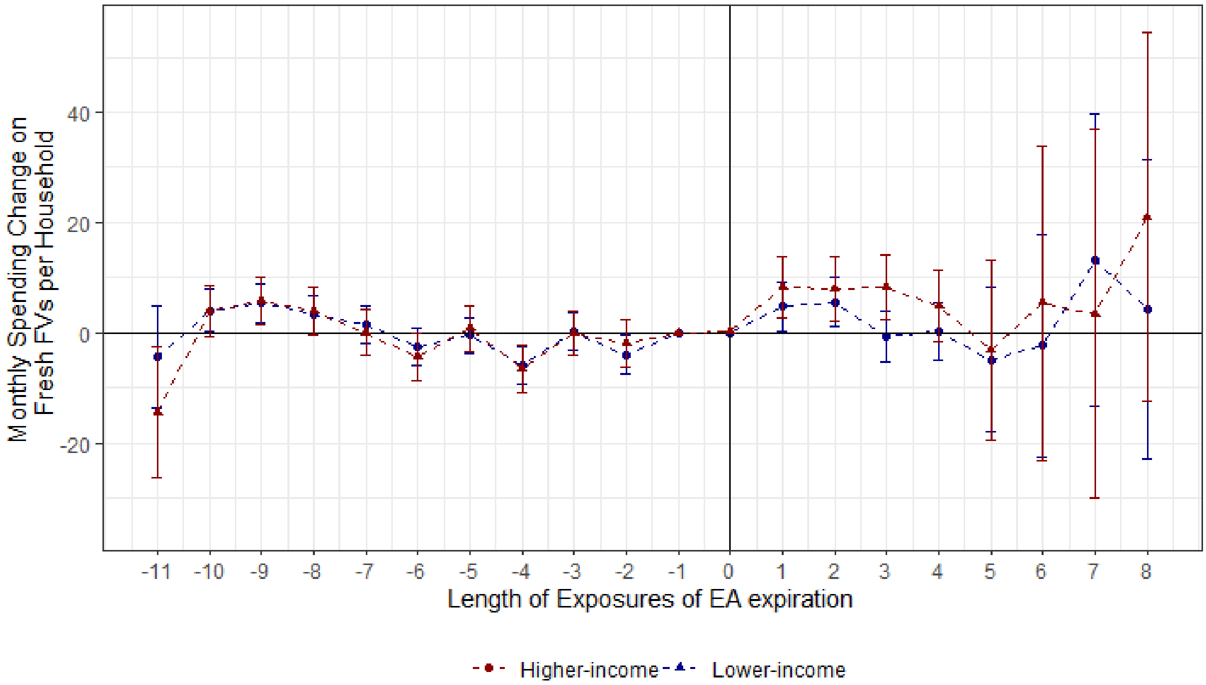


Figure 4. Event study for TSDID conditional model among non-SNAP households with different income level

Note: The effect of the EA expiration on monthly spending on fresh FVs of non-SNAP household estimated under the TSDID conditional model. Red and blue lines give point estimates and simultaneous 95% confidence bands (based on household-clustered standard errors) for higher-income and lower-income non-SNAP household, respectively.

Tables

Table 1. Summary Statistics

	All States	**States Without EA**	**States With EA**
Income Level			
<100%	36.06%	36.33%	34.43%
100%-130%	33.99%	33.91%	34.50%
130%-185%	29.95%	29.76%	31.07%
Education Level			
Advanced	4.75%	4.76%	4.65%
College	51.44%	51.25%	52.63%
High School	34.11%	34.23%	33.40%
Less than high school	9.69%	9.75%	9.32%
Gender			
Female	84.75%	84.65%	85.38%
Male	13.65%	13.68%	13.45%
Other	1.60%	1.67%	1.18%
Ethnicity			
Asian	8.03%	8.73%	3.68%
Black or African American	12.07%	12.14%	11.65%
Hispanic/Latino	17.63%	17.46%	18.65%
Other	6.23%	6.27%	5.98%
White/Caucasian	56.04%	55.40%	60.03%
Present of Child			
With children	42.18%	41.91%	43.88%
Without children	57.82%	58.09%	56.12%
Household Size			
1	12.36%	12.27%	12.88%
2	20.66%	20.39%	22.29%
3	16.48%	16.47%	16.55%
4	19.15%	19.24%	18.59%
5	14.74%	14.82%	14.24%
6	8.52%	8.57%	8.19%
7	8.10%	8.24%	7.27%

Note: "All state" represents the entire dataset, while "With EA" represents the dataset for states that continued to issue EA as of December 2021, and "Without EA" represents the data for states that ceased issuing EA as of December 2021. Income level is reclassified based on the income interval of the original data according to the federal poverty guidelines in 2020 and 2021.

Table 2. Initial Month of EA Payment Cessation Across Different States

Month	State
April 2021	Idaho
June 2021	North Dakota
July 2021	Arkansas
August 2021	Florida, Montana, Nebraska, South Dakota
September 2021	Missouri

Note: Source from USDA website: https://www.fns.usda.gov/disaster/pandemic/covid-19. In December 2021, a total of 8 states have stopped issuing EA payments.

Table 3. TWFE and TSDID results (SNAP)

	Unconditional	Conditional
TWFE	-4.31 *	-4.28 *
	(2.50)	(2.50)
TSDID	-4.11 *	-4.06 *
	(2.50)	(2.50)

Note: All models include state and month fixed effects. "Unconditional" refers to the estimates without any additional conditions, while "Conditional" includes all covariates: log income level, log household size, age, education, gender, race, and children. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level. ***p<0.01, **p<0.05, *p<0.1.

Table 4. TSDID results (SNAP with different reference values)

	Unconditional	Conditional
Upper bound	-4.11 *	-4.06 *
	(2.50)	(2.50)
Mid-point	-3.91 *	-3.84
	(2.34)	(2.33)
Lower bound	-3.25	-3.19
	(2.11)	(2.11)

Note: All models include state and month fixed effects. "Unconditional" refers to the estimates without any additional conditions, while "Conditional" includes all covariates: log income level, log household size, age, education, gender, race, and children. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level. ***p<0.01, **p<0.05, *p<0.1.

Table 5. TWFE and TSDID results (Non-SNAP)

	Unconditional	Conditional
TWFE	5.13 ***	4.96 ***
	(1.12)	(1.14)
TSDID	8.09 ***	5.02 ***
	(1.94)	(1.16)

Note: All models include state and month fixed effects. "Unconditional" refers to the estimates without any additional conditions, while "Conditional" includes all covariates: log income level, log household size, age, education, gender, race, and children. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level. ***p<0.01, **p<0.05, *p<0.1.

Table 6. TSDID results (Non-SNAP with different income level)

	Unconditional	Conditional
Higher-income	3.37 *	3.09 *
non-SNAP	(1.41)	(1.45)
Lower-income	8.09 ***	7.98 ***
non-SNAP	(1.94)	(1.93)

Note: "Unconditional" refers to the estimates without any additional conditions, while "Conditional" includes all covariates: log income level, log household size, age, education, gender, race, and children. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level. ***p<0.01, **p<0.05, *p<0.1.

Table 7. Heterogeneity results(TSDID Conditional model)

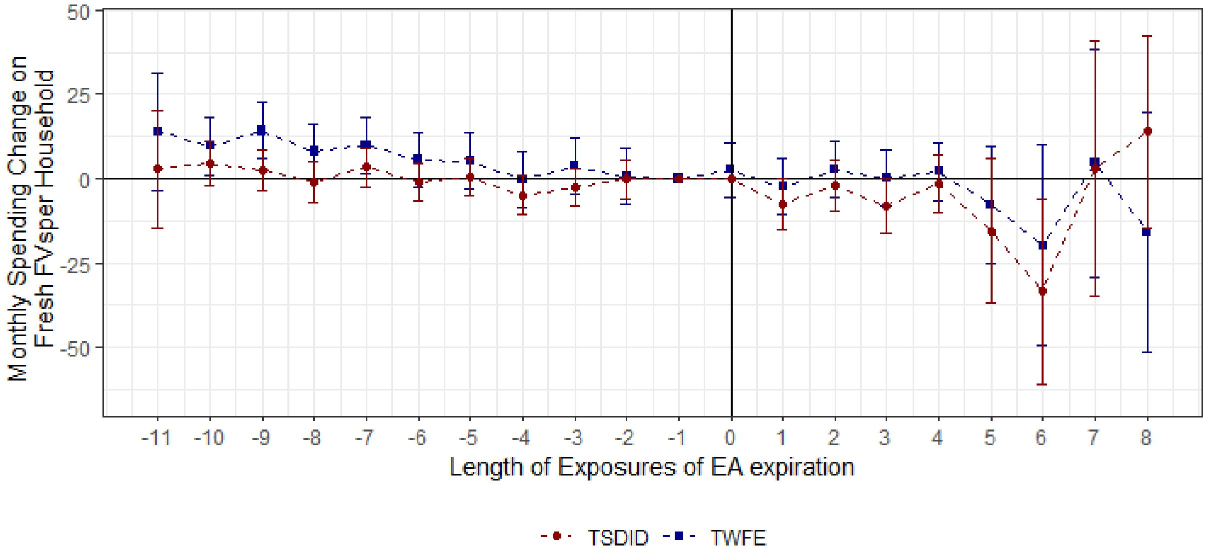
	Coefficients	Std. Error
Income Level		
$< 100\%$	-0.30	(4.37)
$100\% - 130\%$	-7.53 *	(4.42)
$130\% - 185\%$	-3.72	(4.20)
Ethnicity		
White/Caucasian	-2.94	(3.30)
Black or African American	-2.60	(6.42)
Asian	-16.79 *	(8.63)
Hispanic/Latino	-4.33	(5.77)
Child		
With children	-5.79 *	(3.76)
Without children	-2.48	(3.35)
Household Size		
1	-7.49	(7.76)
2	-6.70	(5.03)
3	0.77	(5.93)
4	-8.27	(6.14)
5	7.59	(6.58)
6	-6.90	(5.90)

Note: Income level is reclassified based on the income interval of the original data according to the federal poverty guidelines in 2020 and 2021. We divide it into three levels, $<$ 100%: less than 100% poverty line, 100%-130 %: greater than or equal to 100% and less than 130% poverty lnie, 130%-185%: greater than or equal to 130% and less than 185% poverty lnie. Household size 6 includes Household sizes 6 and 7. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level. ***p<0.01, **p<0.05, *p<0.1.

Appendix

Figures

Figure A1. Event study for unconditional model among SNAP households



Note: The effect of the EA expiration on monthly spending on fresh FVs of SNAP household estimated under the conditional model. TWFE refers to the impact estimated from TWFE event study models, while TSDID denotes the estimators used in "did2s" package. Red and blue lines give point estimates and simultaneous 95% confidence bands (based on household-clustered standard errors) for TSDID and TWFE results, respectively.

Tables

Table A1. Predicted EA payments over time by household size(in Dollar)

Household Size	2020	2021	2022	2023
1	65	121	149	167
2	126	175	215	241
3	138	186	228	257
4	214	256	314	353
5	249	292	359	403
Average	110	162	199	223

Note: Data source from the report conducted by Schanzenbach (2023)

Table A2. Monthly Spending on fresh FVs across Household Sizes

Household Size	Monthly Spending on Fresh FVs ($ per Household)	Proportion of Household Size in the Total Household
1	149	12.36%
2	165	20.66%
3	194	16.48%
4	213	19.15%
5	244	14.74%
6	246	8.52%
7	266	8.10%
Average	200	

Note: The values presented in this table are calculated by the author using data from the dataset.

Table A3. Category description

	CATEGORY_DESCRIPTION	MAJOR_CATEGORY_DESCRIPTION
1	Fresh Pineapple	Fruits
2	Fresh Garlic	Vegetables
3	Fresh Asparagus	Vegetables
4	Fresh Brussels Sprouts	Vegetables
5	Vegetable Trays & Mixed Fresh Vegetables	Vegetables
6	Fresh Feijoa	Fruits
7	Fresh Cut Flowers	Flowers & Indoor Plants
8	Fresh Tomatoes	Vegetables
9	Fresh Broccoli	Vegetables
10	Fresh Blueberries	Fruits
11	Fresh Spinach	Vegetables
12	Fresh Cucumber	Vegetables
13	Fresh Kale	Vegetables
14	Fresh Peas	Vegetables
15	Fresh Carrots	Vegetables
16	Fresh Pearl Onions	Vegetables
17	Fresh Potatoes	Vegetables
18	Fresh Papayas	Fruits
19	Fresh Green Beans	Vegetables
20	Fresh Apples	Fruits
21	Fresh Avocado	Vegetables
22	Fresh Gai Lan	Vegetables
23	Fresh Bell Peppers	Vegetables
24	Fresh Melons	Fruits
25	Fresh Mangos	Fruits
26	Fresh Herbs	Vegetables
27	Fresh Grapes	Fruits
28	Fresh Squash	Vegetables
29	Fresh Cauliflower	Vegetables
30	Fresh Celery	Vegetables
31	Fresh Lettuce	Vegetables
32	Fresh Blackberries	Fruits
33	Fresh Pumpkin	Vegetables
34	Fresh Onions	Vegetables
35	Fresh Corn	Vegetables
36	Fresh Mushrooms & Truffles	Vegetables
37	Fresh Pears	Fruits
38	Fresh Citrus Fruits	Fruits
39	Fresh Okra	Vegetables
40	Fresh Cactus	Fruits
41	Fresh Grape Tomatoes	Vegetables
42	Fresh Cabbage	Vegetables
43	Fresh Zucchini	Vegetables
44	Fresh Fennel	Vegetables
45	Fresh Raisins	Fruits
46	Fresh Peaches	Fruits
47	Fresh Apricots	Fruits
48	Fresh Berries	Fruits
	Fresh Sweet Yam	Vegetables
50	Fresh Dates	Fruits
51	Fresh Prunes	Fruits
52	Fresh Turnips	Vegetables
53	Fresh Bananas	Fruits
54	Fresh Strawberries	Fruits
55	Fresh Peppers	Vegetables
56	Fresh Yu Choy	Vegetables
57	Fresh Bok Choy	Vegetables
58	Fresh Cherries	Fruits
59	Fresh Currants	Fruits
60	Fresh Chili Peppers	Vegetables
61	Fresh Persimmon	Fruits
62	Fresh Sugar Cane	Fruits
63	Fresh Plums	Fruits
64	Fresh Coconut	Fruits
65	Fresh Beans (Legumes)	Legumes
66	Fresh Kiwano	Fruits
67	Fresh Sweet Peppers	Vegetables
68	Fresh Tamarindo	Fruits
69	Fresh Eggplants	Vegetables
70	Fresh Pitahaya	Fruits
71	Fresh Parsnips	Vegetables
72	Fresh Nectarines	Fruits
73	Fresh On Choy	Vegetables
74	Fresh Figs	Fruits
75	Fresh Yams	Vegetables
76	Fresh Jalapeno Peppers	Vegetables
77	Fresh Beets	Vegetables
78	Fresh Rambutan	Fruits
79	Fresh Butternut Squash	Vegetables
80	Fresh Pomegranate	Fruits
81	Fresh Greens	Vegetables
82	Fresh Vegetables	Vegetables
83	Fresh Gourd	Vegetables
84	Fresh Raspberries	Fruits
85	Fresh Bean Sprouts	Vegetables
86	Fresh Guava	Fruits
87	Fresh Broccoli Sprouts	Vegetables
88	Fresh Horse Radish	Vegetables
89	Fresh Radishes	Vegetables
90	Fresh Soursop	Fruits
91	Fresh Beans (Vegetables)	Vegetables
92	Fresh Taro Root	Vegetables
93	Fresh Mustard Greens	Vegetables
94	Fresh Kiwi	Fruits
95	Fresh Leeks	Vegetables
96	Fresh Kohlrabi	Vegetables
97	Fresh Cranberries	Fruits
98	Fresh Arracacha	Vegetables
99	Fresh Tomatillos	Vegetables
100	Fresh Limequats	Fruits
101	Fresh Scallions	Vegetables
102	Fresh Sprouts	Vegetables
103	Fresh Olives	Vegetables
104	Fresh Pak Choy	Vegetables
105	Fresh Broccoflower	Vegetables
106	Fresh Malanga	Vegetables
107	Fresh Longan	Fruits
108	Fresh Lotus Root	Vegetables
109	Fresh Rhubarb	Vegetables
110	Fresh Sapodillo	Fruits
111	Fresh Physalis	Fruits
112	Fresh Bitter Gourd	Vegetables
113	Fresh Plumcot	Fruits

Note: Data from Numerator.

Table A4. Federal Poverty Line

Household Size	100%	130%	185%	300%
1	13000	16900	24050	39000
2	17500	22750	32375	52500
3	22000	28600	40700	66000
4	26500	34450	025	79500
5	31100	40430	57535	93300
6	35600	46280	65860	106800
7	40200	52260	74370	120600

Note: Income levels are classified as 100%, 130%, 185%, and 300% relative to the federal poverty line. The table shows various income thresholds for different household sizes. For example, for a household size of 1, an income of $13,000 is considered at 100% of the poverty line, $16,900 at 130%, $24,050 at 185%, and $39,000 at 300%. Similar calculations apply to other household sizes.

Table A5. Income Level Classification for SNAP

Income Level	<= $20, 000	$20, 000– – $29, 999	$30, 000– – $39, 999	$40, 000– – $, 999	$50, 000– – $59, 999	$60, 000– – $69, 999	$70, 000– – $79, 999	$80, 000– – $89, 999	$90, 000– – $99, 999	$100, 000– – $124, 999	$125, 000– – $1, 999	$150, 000– – $174, 999	$175, 000– – $199, 999	$200, 000– – $224, 999	$225, 000– – $2, 999
Lower Bound	0	20000	30000	40000	50000	60000	70000	80000	90000	100000	125000	150000	175000	200000	225000
Mid-Point	20000	25000	35000	45000	55000	65000	75000	85000	95000	112500	137500	162500	187500	212500	237500
Upper Bound	20000	29999	39999	999	59999	69999	79999	89999	99999	1299	1999	1799	199999	2299	2999

Note: The table represents income levels based on a reference value. The reference value, lower bound, mid-point, and upper bound are provided for each income category. For example, for the income category of "$20,000-$29,999", the lower bound is 20,000, the mid-point is 25,000, and the upper bound is 29,999. These categories allow for classifying income levels accurately in the analysis.

Table A6. Non-SNAP Income Level by Different Household Size

Household Size	Income Level															
	<= $20000	$20, 000– – $29, 999	$30, 000– – $39, 999	$40, 000– – $, 999	$50, 000– – $59, 999	$60, 000– – $69, 999	$70, 000– – $79, 999	$80, 000– – $89, 999	$90, 000– – $99, 999	$100, 000– – $124, 999	$125, 000– – $1, 999	$150, 000– – $174, 999	$175, 000– – $199, 999	$200, 000– – $224, 999	$225, 000– – $2, 999	$250000+
1	L	L	L	H	H	H	H	H	H	H	H	H	H	H	H	H
2	L	L	L	L	H	H	H	H	H	H	H	H	H	H	H	H
3	L	L	L	L	L	L	H	H	H	H	H	H	H	H	H	H
4	L	L	L	L	L	L	L	H	H	H	H	H	H	H	H	H
5	L	L	L	L	L	L	L	L	H	H	H	H	H	H	H	H
6	L	L	L	L	L	L	L	L	L	H	H	H	H	H	H	H
7	L	L	L	L	L	L	L	L	L	L	H	H	H	H	H	H

Note: This table represents different non-SNAP households' income levels by household size. "L" stands for income level upper bound below 300% poverty line, and "H" for those higher than 300% poverty line.

Table A7. Mid-Point Income Classification

Household Size	<= 20000	20,000–29,999	30,000–39,999	40,000–,999	50,000–59,999	60,000–69,999	70,000–79,999
1	2	3	0	0	0	0	0
2	2	3	0	0	0	0	0
3	1	2	3	0	0	0	0
4	1	1	3	0	0	0	0
5	1	1	2	3	3	0	0
6	1	1	1	2	3	3	0
7	1	1	1	2	3	3	0

Note: The table represents mid-point income classifications for different households. Each row corresponds to a different household, and each column represents the mid-point income level within a specific income range, e.g., use 25,000 as the reference value for income level equals "$20,000-$29,999". The numbers in the table indicate the mid-point income level category for each household. "1" represents reference value < 100%, "2" represents reference value >= 100% and < 185%, "3" represents reference value >= 185%.

Table A8. Upper Bound Income Classification

Household Size	<= 20000	20,000–29,999	30,000–39,999	40,000–,999	50,000–59,999	60,000–69,999	70,000–79,999
1	2	3	0	0	0	0	0
2	2	3	0	0	0	0	0
3	1	3	0	0	0	0	0
4	1	2	3	0	0	0	0
5	1	1	2	3	0	0	0
6	1	1	2	3	3	0	0
7	1	1	1	2	3	3	0

Note: The table represents upper bound income classifications for different households. Each row corresponds to a different household, and each column represents the upper bound income level within a specific income range, e.g., use 29,000 as the reference value for income level equals "\$20,000-\$29,999". The numbers in the table indicate the upper bound income level category for each household. "1" represents reference value < 100%, "2" represents reference value >= 100% and < 185%, "3" represents reference value >= 185%.

Table A9. Lower Bound Income Classification

Household Size	<= 20000	$20,000-$ $29,999$	$30,000-$ $39,999$	$40,000-$ $,999$	$50,000-$ $59,999$	$60,000-$ $69,999$	$70,000-$ $79,999$
1	1	3	0	0	0	0	0
2	1	2	3	0	0	0	0
3	1	1	2	3	0	0	0
4	1	1	2	3	0	0	0
5	1	1	2	2	3	0	0
6	1	1	1	3	3	3	0
7	1	1	1	1	2	3	3

Note: The table represents lower bound income classifications for different households. Each row corresponds to a different household and each column represents the lower bound income level within a specific income range, e.g., use 20,000 as the reference value for income level equals "$20,000-$29,999". The numbers in the table indicate the upper bound income level category for each household. "1" represents reference value < 100%, "2" represents reference value >= 100% and < 185%, "3" represents reference value >= 185%.

Table A10. Event Study for TWFE and TSDID among SNAP households(Conditional Models)

Exposure	TWFE	CI (TWFE)	TSDID	CI (TSDID)
-11	13.26	(8.12, 18.4)	2.68	(-14.88, 20.24)
-10	9.58	(2.47, 16.68)	4.46	(-2.06, 10.98)
-9	14.06	(5.73, 22.38)	2.43	(-3.57, 8.43)
-8	8.21	(0.07, 16.35)	-0.82	(-6.72, 5.09)
-7	10.08	(6.04, 14.13)	3.32	(-2.43, 9.07)
-6	5.46	(1.87, 9.05)	-1.08	(-6.79, 4.63)
-5	4.97	(-1.76, 11.69)	0.32	(-5.19, 5.83)
-4	-0.25	(-4.58, 4.08)	-4.92	(-10.73, 0.89)
-3	3.92	(-1.4, 9.23)	-2.36	(-7.82, 3.1)
-2	0.47	(-5.44, 6.38)	-0.27	(-6.08, 5.55)
-1	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)
0	2.10	(-3.55, 7.75)	0.02	(-0.06, 0.09)
1	-2.69	(-5.88, 0.5)	-7.86	(-15.5, -0.22)
2	2.29	(-5.17, 9.75)	-2.04	(-9.71, 5.64)
3	-0.08	(-9.58, 9.42)	-8.14	(-16.09, -0.18)
4	1.98	(-6.2, 10.17)	-1.40	(-9.92, 7.13)
5	-8.11	(-13.9, -2.32)	-15.57	(-36.74, 5.59)
6	-20.50	(-24.96, -16.03)	-33.62	(-61.14, -6.11)
7	3.62	(-0.15, 7.39)	4.04	(-33.56, 41.64)
8	-17.43	(-21.69, -13.16)	14.51	(-13.63, 42.65)

Note: The dataset includes information from all individuals participating in SNAP, with the upper bound serving as the reference value. TWFE indicates the impact of EA expiration using the TWFE conditional model, while TSDID represents the impact using two-statge DID conditional model. CI denotes the 95% confidence interval. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level.

Table A11. Event Study for TWFE and TSDID among SNAP households(Unconditional Models)

Exposure	TWFE	CI (TWFE)	TSDID	CI (TSDID)
-11	13.93	(-3.56, 31.43)	2.76	(-14.84, 20.37)
-10	9.75	(1.16, 18.34)	4.45	(-2.07, 10.98)
-9	14.14	(5.80, 22.49)	2.55	(-3.45, 8.55)
-8	8.02	(-0.25, 16.29)	-0.98	(-6.89, 4.93)
-7	9.93	(1.69, 18.16)	3.27	(-2.49, 9.03)
-6	5.53	(-2.68, 13.73)	-1.05	(-6.76, 4.67)
-5	5.16	(-3.05, 13.36)	0.33	(-5.19, 5.84)
-4	-0.18	(-8.44, 8.09)	-4.85	(-10.66, 0.96)
-3	3.75	(-4.44, 11.94)	-2.53	(-7.99, 2.93)
-2	0.69	(-7.45, 8.83)	-0.21	(-6.03, 5.61)
-1	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)
0	2.57	(-5.54, 10.67)	0.02	(-0.06, 0.09)
1	-2.41	(-10.61, 5.79)	-7.75	(-15.39, -0.11)
2	2.71	(-5.49, 10.90)	-2.10	(-9.79, 5.58)
3	0.23	(-8.03, 8.48)	-8.21	(-16.16, -0.26)
4	2.09	(-6.59, 10.78)	-1.74	(-10.29, 6.81)
5	-7.81	(-25.24, 9.61)	-15.52	(-36.86, 5.82)
6	-19.83	(-49.56, 9.89)	-33.47	(-61.07, -5.87)
7	4.64	(-29.24, 38.51)	3.03	(-34.82, 40.89)
8	-15.81	(-51.22, 19.59)	13.92	(-14.53, 42.37)

Note: The dataset includes information from all individuals participating in SNAP, with the upper bound serving as the reference value. TWFE indicates the impact of EA expiration using the TWFE unconditional model, while TSDID represents the impact using two-statge DID conditional model. CI denotes the 95% confidence interval. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level.

Table A12. Event Study for TWFE and TSDID among non-SNAP households(Conditional Models)

Exposure	TWFE	CI (TWFE)	TSDID	CI (TSDID)
-11	-8.86	(-16.09, -1.63)	-8.55	(-15.85, -1.25)
-10	4.33	(1.46, 7.20)	3.93	(1.02, 6.84)
-9	5.34	(2.67, 8.01)	5.46	(2.75, 8.17)
-8	3.37	(0.70, 6.03)	3.43	(0.73, 6.14)
-7	0.51	(-2.08, 3.11)	0.86	(-1.78, 3.49)
-6	-3.80	(-6.38, -1.23)	-3.26	(-5.86, -0.66)
-5	-0.19	(-2.74, 2.35)	0.15	(-2.42, 2.73)
-4	-5.77	(-8.42, -3.12)	-6.13	(-8.82, -3.44)
-3	-0.03	(-2.60, 2.54)	0.19	(-2.41, 2.80)
-2	-2.44	(-5.16, 0.29)	-3.17	(-5.93, -0.42)
-1	0.00	(0.00, 0.00)	0.00	(0.00, 0.00)
0	0.10	(0.06, 0.14)	0.10	(0.06, 0.14)
1	6.68	(3.31, 10.05)	6.07	(2.64, 9.50)
2	6.40	(2.92, 9.88)	6.51	(2.98, 10.03)
3	2.79	(-0.76, 6.35)	2.87	(-0.74, 6.48)
4	2.42	(-1.57, 6.40)	2.01	(-2.05, 6.06)
5	-6.42	(-16.61, 3.77)	-4.13	(-14.32, 6.07)
6	2.05	(-14.20, 18.30)	0.86	(-15.85, 17.57)
7	10.92	(-9.38, 31.22)	9.76	(-11.11, 30.62)
8	10.67	(-9.97, 31.30)	10.99	(-10.07, 32.06)

Note: The dataset includes information from all individuals not participating in SNAP, with the upper bound serving as the reference value. TWFE indicates the impact of EA expiration using the TWFE conditional model, while TSDID represents the impact using two-statge DID conditional model. CI denotes the 95% confidence interval. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level.

Table A13. Heterogeneity results(TWFE Conditional model)

	Coefficients	Std. Error
Income Level		
< 100%	-0.56	(4.32)
100% – 130%	-7.90 *	(4.13)
130% – 185%	-3.84	(4.00)
Ethnicity		
White/Caucasian	-2.91	(3.11)
Black or African American	-3.65	(6.60)
Asian	-17.39 **	(7.75)
Hispanic/Latino	-4.37	(5.61)
Child		
With children	-5.69	(3.54)
Without children	-2.98	(3.26)
Household Size		
1	-7.22	(NA)
2	-7.13	(4.93)
3	1.19	(5.91)
4	-8.08	(5.28)
5	7.72	(6.47)
6	-8.54	(6.06)

Note: Income level is reclassified based on the income interval of the original data according to the federal poverty guidelines in 2020 and 2021. We divide it into three levels, < 100%: less than 100% poverty line, 100%-130 %: greater than or equal to 100% and less than 130% poverty lnie, 130%-185%: greater than or equal to 130% and less than 185% poverty lnie. Household size 6 includes Household sizes 6 and 7. All values are converted to percentage points, multiple by 100. Standard errors in parentheses, cluster at household level. ***p<0.01, **p<0.05, *p<0.1.