Estimating the Impact of Emergency Allotment Expiration on Grocery Spending Patterns of SNAP Households

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Abstract

This study estimates the impact of the Supplemental Nutrition Assistance Program (SNAP) Emergency Allotment (EA) expiration on monthly grocery spending among SNAP households. Using novel transaction-level food purchase data, we employ a stacked difference-in-differences (DID) framework to estimate the causal effects of EA expiration across 16 early-terminating states relative to those maintaining benefits through December 2022. We classify food purchases into perishable, storable, and splurge categories and estimate changes in both total and category-specific spending. Results show a significant decline in overall grocery spending of 14.55%, or $30.57 per household per month. Perishable, storable, and splurge food spending declined by 15.18% ($10.46), 14.85% ($7.62), and 14.64% ($11.18), respectively. Spending reductions are proportionally distributed, suggesting that SNAP households do not shift spending across food categories in response to benefit cuts. Heterogeneity analysis reveals disproportionate effects. Smaller households experience larger declines, with single- and two-person households reducing spending by 33.00% and 17.24%, compared to 11.34% for three-person and 10.20% for four-person households. Childless households cut spending by 17.11%, versus 11.78% for those with children. Reductions are 21.40% for Black households, 13.21% for Hispanic/Latino households, and 13.12% for White households. Low-income SNAP households reduced spending by 18.18%. Our findings show that EA benefit cuts lead to spending reductions without reallocation across food categories. These results suggest that policy makers may need to take into account difference changes across households with varying demographic characteristics to ensure that program changes will have their intended effects.

Key Words: SNAP, EA, food spending, Stack DID

JEL Classification: I38, C21, C23,

Acknowledgment and Disclaimer: The conclusions drawn from the Numerator data used in this study are those of the authors and do not reflect the views of Numerator. Numerator is not responsible for and had no role in, and was not involved in, analyzing and preparing the results reported herein.

1 Introduction

The Supplemental Nutrition Assistance Program (SNAP), a federal program that provides monthly benefits to eligible low-income households to assist with food purchases, is also the largest food assistance program in the United States. In response to the economic and public health crisis of the COVID-19 pandemic, the U.S. Department of Agriculture (USDA) provided two rounds of SNAP Emergency Allotments (EA) to SNAP participants to help address temporary food needs during the pandemic. The first round of EA, implemented in March 2020, allowed states to bring all SNAP participants up to the maximum benefit for their household size. However, it means participants that are at or near the maximum SNAP benefit received little or no additional support. In January 2021, the USDA revised its guidance to provide a second round of EA, ensuring that all participants received at least an additional $95 benefits per month. State SNAP agencies could continue to provide monthly SNAP-EA to all households as long as federal and state public health emergency declarations were in effect. However, starting in 2021, states were allowed to phase out EA upon declaring the end of their emergency status. By the end of 2022, 17 states had discontinued EA payments while the remaining 33 and Washington, DC, still had it. The Consolidated Appropriations Act 2023 mandated the termination of EA after the issuance of February 2023 benefits, resulting in the cessation of EA across all states by March 2023.

This study estimates the causal effect of EA expiration on monthly grocery spending among SNAP households. Building on the stacked difference-in-differences (DID) approach developed by Wing, Freedman, and Hollingsworth (2024), using detailed panel data from the Numerator company, we construct a stacked dataset by aggregating subgroups, and then apply a DID model to this stacked data to estimate the effects. We compare SNAP households in states that ended EA early with those in states that retained benefits through December 2022. We classify food categories into perishable, storable, and splurge categories following Hastings and Washington (2010), and assess how the expiration affected both total spending and the composition of food consumed. We also examine heterogeneity by income level, household size, presence of children, and ethnicity to better understand who was most affected.

SNAP benefits increase household food spending, particularly during periods of economic distress. Studies such as Hoynes, McGranahan, and Schanzenbach (2015) and Anderson and Butcher (2016) show that SNAP benefits boosted grocery expenditures among low-income households. During the COVID-19 pandemic, benefit expansions played a vital role in stabilizing food consumption. For instance, Bitler, Hoynes, and Schanzenbach (2020) and Ganong, Noel, and Vavra (2020) document how safety-net enhancements—including EA—mitigated financial hardship and maintained food spending. Similarly, Schanzenbach and Pitts (2020) and Sanjeevi and Monsivais (2023) find that states maintaining EA witnessed lower rates of food insufficiency than those that phased it out early. However, few studies have examined the effects of EA expiration on household food spending. This gap motivates our analysis of how the termination of EA influenced overall grocery expenditures among SNAP households.

Beyond expenditure levels, SNAP benefits also affect food quality and food security. Extensive research confirms that participation in SNAP reduces the risk of food insecurity (Ratcliffe, McKernan, and Zhang 2011; Mykerezi and Mills 2010). However, its impact on dietary quality is more ambiguous. Andreyeva, Tripp, and Schwartz (2015) and Gregory et al. (2013) report that SNAP recipients tend to consume more calorie-dense and nutrient-poor foods, often driven by price constraints and limited access to healthier options. During the pandemic, EA expansions helped households better allocate budgets and maintain food sufficiency (Katare, Binkley, and Chen 2021), while the abrupt expiration of these benefits reintroduced economic strain, particularly among households with children (Dasgupta and Plum 2023; Sanjeevi and Monsivais 2023). These studies underscore the critical role of SNAP and EA in mitigating food insecurity, but most focus primarily on food sufficiency outcomes. Less is known about how the expiration of EA affected actual household grocery spending—both in total and across food categories—highlighting the need for our analysis.

Understanding how SNAP households allocate their food spending across different categories is essential for assessing the nutritional implications of benefit changes. When resources are constrained or disrupted—such as during the expiration of emergency allotments—we are curious how households allocate food spending across categories to stretch their budgets. Studies during the COVID-19 pandemic by Ellison et al. (2021), Chenarides et al. (2021), and Baker et al. (2020) showed that consumers reduced shopping frequency and increased purchases of shelf-stable, easy-to-store foods, reflecting adaptations to financial pressures. These shifts highlight how benefit levels influence not only the amount but also the composition of food spending. Further, Richterman, Roberto, and Thirumurthy (2023) and Steffen and Kim (2024) provide evidence that cuts in SNAP benefits elevated nutritional risk and exacerbated disparities in food access. These findings directly motivate our analysis of perishable, storable, and splurge categories to examine whether households shielded or sacrificed certain types of foods following the expiration of EA support.

This paper offers three primary contributions. First, we estimate the impact of EA expiration on category-specific food spending. Few studies have explored whether households reallocate spending across food categories when benefits decline. By reclassifying food spending into distinct categories, this paper investigates whether SNAP households prioritized certain types of food when benefits decreased. In addition to assessing the magnitude of spending changes, we examine compositional shifts to understand whether households shielded certain food types. This provides insight into behavioral responses to benefit losses. Second, we utilize rich, high-frequency, transaction-level data from Numerator. Unlike self-reported surveys, which are prone to underreporting and recall bias, this dataset captures actual household purchases over time, offering greater precision and granularity (Kim 2016; He and Su 2023). Numerator's large and diverse sample enables disaggregated subgroup analysis by demographic information. Third, we implement a stacked DID design (Wing, Freedman, and Hollingsworth 2024), which avoids the known biases of traditional two-way fixed effects (TWFE) models in staggered adoption settings (Goodman-Bacon 2021). Unlike TWFE and other staggered DID estimators, the stacked DID method constructs separate subgroups for each adoption cohort and pools them into a unified estimation sample, preserving the interpretability of causal effects and addressing treatment heterogeneity (Wing, Freedman, and Hollingsworth 2024; Sun and Abraham 2021; Callaway and Sant'Anna 2021).

The remainder of the paper is organized as follows. Section 2 describes the data sources and sample construction, including the staggered adoption design and the weighting procedure for the stacked dataset. Section 3 outlines the empirical strategy and presents the main regression model. It also introduces the event study framework and details the heterogeneity analysis. Section 4 presents the primary estimation results, dynamic effects, and the results of the heterogeneity analysis across key household characteristics. Sections 5 and 6 provide a discussion of the findings and conclude with implications for policy.

2 Data

2.1 Data Source

Our study utilizes consumer transaction data from Numerator, a marketing research firm that has collected detailed purchase records since 2017. The data consists of panelists who use a mobile application to submit photographs of their paper receipts. Each receipt provides detailed purchase information, such as payment method, retailer name, and transaction date. Receipts are from any retailer and capture all payment methods used, making the data are well-suited for analyzing how individuals use SNAP and non-SNAP payment during the research time. A key strength of this data is its ability to identify SNAP households by detecting whether purchases were paid partially or fully with SNAP Electronic Benefit Transfer (EBT) cards (Sullivan 2023; Song 2024). Numerator data also provides a subset of "static panelists", defined as core panelists who upload receipts consistently for at least one year, ensuring a minimum of one transaction per month over 12 consecutive months. For our analysis, we select users from the static panelists during the period from 2020 to 2022. Among these panelists, we identified SNAP households as those making at least one transaction per month using a SNAP EBT card over a consecutive period during the study period. We then re-screened these households using SNAP eligibility criteria based on state-specific Broad-Based Categorical Eligibility (BBCE) policy.

Our sample includes 29,020 static SNAP households across all 50 states and Washington, D.C. Among these, 17 states ended EA benefits before 2023, while 33 states and Washington, D.C. continued distributing them. Summary statistics of our sample is in Table 1. The detailed methodology for this identification process is provided in the following subsection. This feature is not available in most consumer panel datasets, such as those from Nielsen or Homescan. Moreover, each panelist is assigned a unique user ID, enabling us to link purchase histories with demographic characteristics, including age, income, household composition, and education level.

2.1.1 Food Category Classification

In addition to transaction-level records, Numerator provides item-level details such as brand, product category, and product department. We use this information to collect the food category of each item. This detailed information allows us to analyze the impact of EA expiration across different food categories. Following Hastings and Washington (2010), we reclassify all grocery items into four categories: alcohol and tobacco, and three food types—perishable, storable, and surplus. Appendix Table A1, A2 and A3 summarizes the reclassification results. This step addresses potential censoring issues inherent in Numerator's predefined classifications. Based on this reclassification, we define our primary outcome variables as monthly total grocery spending and monthly spending in each of the three food categories.

2.1.2 BBCE Screening

We use payment method information to identify SNAP households by detecting purchases made with SNAP EBT cards. However, we find that some households classified as SNAP participants report income levels exceeding the eligibility threshold. This discrepancy arises for two main reasons. First, SNAP EBT cards operate similarly to debit card, allowing purchases without requiring identity verification beyond PIN entry, which means anyone possessing the card and PIN can use the benefits (Investopedia 2024; National Council on Aging 2024). Second, income data are self-reported through Numerator's survey, which may not always align with actual SNAP eligibility. These inconsistencies may result from: households misreporting their income in the survey, or households accurately reporting their income but still using a SNAP EBT card despite exceeding the income limit. Both cases suggest that our sample may include households that are not income-eligible for SNAP.

To address this issue, we apply an additional screening criterion based on BBCE policy. BBCE allows states to expand SNAP eligibility by raising the income threshold, enabling more low-income individuals to qualify for benefits even if they do not receive direct cash assistance. We use the state-specific gross income limits under BBCE as a secondary eligibility screen. While most states set this limit at or below 200% of the Federal Poverty Guidelines (FPG), some states set thresholds at 185%, 175%, 165%, or 130% of the FPG (see Appendix Table A4 for details). We re-screen SNAP households using these adjusted thresholds and construct a more valid sample.

To further examine how household characteristics shape the effects of EA expiration on food expenditures, we conduct a heterogeneity analysis based on key demographics: household size, presence of children, ethnicity, and income level (see Appendix Table A5 for details). To ensure meaningful subgroup comparisons, we reclassify these household characteristics based on the distribution of our data. Households are categorized into four ethnicity groups: "White/Caucasian", "Asian", "Black or African American" and "Hispanic/Latino" For household size, given the complexity of larger households, those with six or more members are grouped into a single category labeled "Household Size 6" Income level is classified into four groups: "Low Income" (below 100% FPG), "Medium Income" (100%–130% FPG), "High Income" (130%–185% FPG), and "Over Income(Non-SNAP Eligible)" (above 185% FPG). This classification facilitates a structured heterogeneity analysis, allowing us to assess the differential effects of EA expiration across distinct household subgroups.

2.2 Staggered Adoption Design

2.2.1 Identification of EA Expiration Time

To account for variation in EA expiration dates across states, we employ a staggered adoption design. We define the treatment and control groups as follows: the treatment group includes SNAP households in states that terminated EA payments between 2021 and 2022, while the control group consists of households in states that continued distributing EA payments through March 2023. These latter states serve as a comparison group, as they had not yet experienced treatment during the study period. This design allows us to estimate the causal effect of EA expiration by comparing monthly SNAP household spending across treatment and control states. The first month without EA payments is designated as the treatment start period for each state. Table 2 lists the first expiration months for the states that opted out of the EA program prior to 2023. For instance, Idaho ended EA in May 2021, Florida in August 2021, Tennessee in January 2022. SNAP households from those 17 states are in treatment group and SNAP households from states that continued EA payments (including 33 states, Washington, D.C., and Rhode Island) are in control group.

To address overlapping treatment timings across states, we define a formal structure. Let $s = 1, \ldots, S$ index treatment groups, where $S = 9$, and let $t = 1, \ldots, 26$ denote calendar months from November 2020 to December 2022. Define A_s as the calendar month in which treatment group s lost EA benefits, where $A_s = a$ indicates the specific treatment month in research period, and $A_s = \infty$ for households live in those state that still giving EA benefits. For instance, Missouri's EA expired in September 2021, which corresponds to research period 18 in our sample. Thus, Missouri is assigned to treatment subgroup $s = 5$, with $A_5 = 18$ (See Table 2).

2.2.2 Event Window

To examine the impact of EA expiration on household food spending, we define a symmetric 13-month event window centered on each state's EA expiration month. Let e denote event time, where $e = 0$ represents the first month without EA payments. The event window spans from $e = -6$ to $e = 6$, covering six months before and six months after expiration. Formally, $e \in [\kappa_{\text{pre}}, \kappa_{\text{post}}]$, where $\kappa_{\text{pre}} \in [-6, -1]$ and $\kappa_{\text{post}} \in [1, 6]$. In total, we identify 10 event windows of equal length but with different start and end months, corresponding to 10 treatment subgroups across 17 states. Each treatment subgroup is defined by its EA expiration month, as shown in Table 3.

For further analysis, we match each treatment subgroup to a control subgroup composed of SNAP households from states that continued EA payments. Each treatment subgroup is paired with its control counterpart, forming what we refer to as a "subgroup".[1] We use three treatment subgroups—Idaho, Tennessee, and Georgia—and Texas as a control state to illustrate this process. To ensure valid subgroup matching, we apply the same procedure to all treatment subgroups. As shown in Figure 1, SNAP households in Texas who used a SNAP EBT card at least once per month between November 2020 and November 2021 are eligible to serve as controls for Idaho. However, the same households may not be eligible for Georgia's control subgroup due to differing event windows. For Tennessee, SNAP

[1]Here is how we define "treatment subgroup", "control subgroup" and "subgroup": (1) treatment subgroup: A specific group of SNAP households live in states that adopted EA expiration in the same month. (2) control subgroup: A subset of the control group that is matched to a specific treatment subgroup based on defined criteria. (3) subgroup: A combination of one treatment subgroup and its corresponding matched control subgroup.

households in Texas who used an EBT card at least once per month between July 2021 and July 2022 are included. Thus, some households may qualify for multiple subgroups (e.g., Idaho and Tennessee) but not others (e.g., Georgia), depending on the alignment of their usage periods (Figures 2 and 3 provide further illustration).

This matching framework ensures that treatment and control groups are comparable. Ultimately, we retain 9 treatment subgroups across 16 states, excluding later-adopting states (e.g., Alaska) due to insufficient post-treatment data. We define Ω_κ as the trimmed set of 9 subgroups. Note that overlap exists in control subgroups because certain control households are reused across multiple subgroups. We address this overlap in the next section.

2.3 Stacked Dataset

We construct a household-by-month panel dataset where each observation reflects monthly food spending or 3 categories-specific spending for a SNAP household. Each treatment subgroup s is defined by a group of states that lost EA in the same month. Following Wing, Freedman, and Hollingsworth (2024), we pool all subgroups into a single stacked dataset. This structure enables appropriate comparisons between treated units and not-yet-treated controls within each subgroup, enhancing internal validity.

To address potential imbalances in sample size across treatment and control subgroups, we implement a reweighting scheme. Each treatment subgroup($D_s^a = 1$) is given a stack weight of 1. Each control subgroup($D_s^a = 0$) is assigned a stack weight based on the relative representation of treatment and control subgroups within the stack. The stack weights Q_s^a for subgroup $A_s = a$ is defined as:

$$Q_s^a = \begin{cases} 1, & \text{if } D_s^a = 1 \\ \frac{N_a^D}{N_{\Omega_\kappa}^D} \cdot \frac{N_a^C}{N_{\Omega_\kappa}^C}, & \text{if } D_s^a = 0 \end{cases}$$

This ensures that treatment and control observations are proportionally balanced within our stack dataset. Specifically, the control stack weight $Q_s^a(D_s^a = 0)$ is a product of:

- Treatment subgroup share: $\frac{N_a^D}{N_{\Omega_\kappa}^D}$. [2]

- Control subgroup share: $\frac{N_a^C}{N_{\Omega_\kappa}^C}$.[3]

Here, N_a^D and N_a^C are the numbers of observations in treatment and control subgroups that lost EA in month a. $N_{\Omega_\kappa}^D = \sum_{a\in\Omega_\kappa} N_a^D$ and $N_{\Omega_\kappa}^C = \sum_{a\in\Omega_\kappa} N_a^C$ denote the total number of treatment and control observations across all subgroups Ω_κ.[4]

To ensure no single subgroup dominates the overall estimate, we calculate a "Stack Share" for each subgroup—defined as the subgroup's total share of observations in the stacked dataset: $\frac{N_a^C+N_a^D}{N_{\Omega_\kappa}^C+N_{\Omega_\kappa}^D}$. This metric prevents larger states or treatment cohorts from exerting disproportionate influence. As shown in Table 3, the May 2021 subgroup (Idaho) comprises 10.42% of the sample, while the June 2022 subgroup (Indiana and Georgia) accounts for 11.59%. These proportions reflect the number of observations contributed by each treatment month to the full stacked dataset. Appendix Table A6 shows more details of each subgroup's weights and shares. For example, subgroup 4 (August 2021: South Dakota, Florida, Nebraska, Montana) has a Treatment Share of 33.73% but a much smaller Control Share of only 11.02%. To compensate for this imbalance, control units in this subgroup are upweighted by the product of these two shares, resulting in a control weight of $Q_s^a(D_s^a = 0) = 306.11\%$. In contrast, subgroup 1 (May 2021: Idaho) has a smaller Treatment Share of just 1.64%, but a relatively large Control Share of 10.65%, yielding a much smaller control weight of $Q_s^a(D_s^a = 0) = 15.43\%$. These weights ensure balance within each subgroup. Meanwhile, Stack Share—defined as the proportion of total observations contributed by each subgroup—is 11.59% for subgroup 4 and 10.42% for subgroup 1, reflecting their relative sizes in the full stacked dataset. Together, these weights and shares ensure that each subgroup contributes to the estimation in proportion to its presence in the stacked sample, and that treatment-control balance is maintained within each subgroup.

[2] This represents the proportion of observations in treatment subgroup a relative to the total number of treatment observations across all subgroups in Ω_κ.

[3] This represents the proportion of observations in control subgroup a relative to the total number of control observations across Ω_κ.

[4] As shown in Table 3 and Table A6, N_a^D and N_a^C are the number of treated and control units within subgroup a, and $N_{\Omega_\kappa}^D$ and $N_{\Omega_\kappa}^C$ denote their respective totals across the stack.

3 Empirical Strategy

The staggered timing of EA phase-outs across states naturally lends itself to a stacked DID design, which compares treated and untreated SNAP households over aligned event windows. In this section, we detail how we apply this stacked dataset to estimate both dynamic and average treatment effects within a DID model

Compared to traditional approaches, the stacked DID framework offers several important advantages. It resolves the negative weighting issues that can arise in TWFE models (Goodman-Bacon 2021; De Chaisemartin and d'Haultfoeuille 2023), directly targets the trimmed average treatment effect on the treated (ATT), and accommodates flexible integration of covariate adjustment, matching, and robust inference procedures (Wing, Freedman, and Hollingsworth 2024). These features make it particularly well-suited for evaluating the effects of SNAP EA expiration, where treatment timing varies by state and heterogeneity in treatment effects is expected across both time and household characteristics.

3.1 Main Model

To estimate the causal effect of EA expiration, we employ a stacked DID framework using our constructed dataset. The model is specified as follows:

$$Y_{ist} = \beta_{st} D^{a}_{st} + \gamma X_{ist} + \lambda_t + \delta_s + \epsilon_{ist} \tag{1}$$

Where, Y_{ist} represents one of our four outcome variables: monthly spending on all groceries and three specific food categories, for SNAP household i in state s at period t. β_{st}[5] denotes

[5]In Wing, Freedman, and Hollingsworth (2024) paper, he computed a trimmed aggregate ATT for each event time using weighted group-period ATTs:

$$\theta^{e}_{\kappa} = \sum_{a \in \Omega_{\kappa}} ATT(a, a+e) \times \frac{N^{D}_{a}}{N^{D}_{\Omega_{\kappa}}}$$

This convex combination produces θ^{e}_{κ}, a summary estimate of causal effects across subgroups. The weights are fixed over time, allowing changes in θ^{e}_{κ} to reflect true dynamic effects. Based on our staggered adoption design, the θ^{e}_{κ} is the same as β_{st} from our main model, to show the average treatment effect on the treated (ATT).

the causal effect of EA expiration for the state in subgroup s at period t. D^a_{st} [6] is a binary indicator equal to 1 if state s is treated at time t relative to first EA expiration period a. X_{ist} includes all household-level controls such as income level, household size, ethinicity, the presence of children and so on. λ_t and δ_s represent time and state fixed effects, respectively. Standard errors are clustered at the household level.

3.2 Event Study

To capture dynamic treatment effects, we estimate an event-study specification by replacing D^a_{st} with a series of event-time indicators relative to EA expiration:

$$Y_{ise} = \sum_{\substack{h=-\kappa_{pre}\ldots\kappa_{post} \\ h\neq -1}} [\alpha^a_e D^a_{se} \times \mathbf{1}[e = h]] + \gamma X_{ist} + \lambda_t + \delta_s + \epsilon_{ist} \tag{2}$$

Where α^a_e is the coefficient for the interaction term at event tme e. $h = -1$ is omitted and serves as the reference period. This specification allows us to trace the evolution of treatment effects over time relative to the expiration time of the EA. All models use stacking weights Q^a_s to appropriately aggregate across subgroups. For each $a \in \Omega_\kappa$ for each event time $e \in \{-\kappa_{pre} \ldots \kappa_{post} | e \neq -1\}$. For $\kappa_{pre} > 0$, the specification includes impacts in the pre-treatment time periods. When the no anticipation and common trend assumptions hold in each subgroups, these pre-treatment effects will equal zero. Similarly, for $\kappa_{post} > 0$ the event study traces out the aggregated ATTs over the post treatment event times for a balanced set of adoption subgroups. Changes in the α^a_e over post-treatment periods $e = 0, 1, \ldots, \kappa_{post}$ measure time varying treatment effects without concerns about changes in composition.

[6] Here, D^a_{st} is different with what we define D_{sa} before:

$$\mathbf{D}^a_{st} = \begin{pmatrix} D^1_{st} \\ D^2_{st} \\ D^3_{st} \\ \vdots \\ D^{26}_{st} \end{pmatrix}$$

.
For treatment group, D^a_{st} equals 0 for $t < a$ and 1 for $t >= a$; For control group, D^a_{st} remains 0 all the periods

3.3 Heterogeneity Analysis

To provide a more comprehensive understanding of how household characteristics influence the effects of EA expiration on food expenditures, we conduct a heterogeneity analysis based on key demographic attributes, including household size, presence of children, ethnicity, and income level. Our classification facilitates a structured heterogeneity analysis and enables us to assess the differential responses to EA expiration across distinct demographic subgroups. Table 1 presents the summary statistics for the full sample ("All States") as well as separately for states that ended EA before January 2023 ("States Without EA") and those that continued EA through December 2022 ("States With EA"). The distributions across key characteristics remain largely consistent across the three groups, suggesting comparability in demographic composition and supporting the validity of our empirical comparisons.

4 Results

4.1 Main Results

Table 4 presents the estimated impact of EA expiration on monthly grocery expenditures for SNAP households. The results indicate a significant reduction in overall spending, with declines observed across all food categories. Our model employs a log-level specification, and given that all coefficient estimates are around 0.15 in absolute terms, there is no need for an exact exponential transformation. The results show a significant reduction in total spending of 14.55%, with similarly large declines across food categories: 15.18% for perishables, 14.85% for storables, and 14.64% for splurge foods. All estimates are statistically significant at the 99% level, and standard errors are clustered at the household level.

Table 5 translates these percentage reductions into dollar amounts based on pre-treatment averages. The 14.55% decline corresponds to a \$30.57 monthly decrease in total food spending. Category-specific declines amount to \$10.46 for perishables, \$7.62 for storables, and \$11.18 for splurge foods. These reductions are proportionally distributed. Prior to treatment, perishable, storable, and splurge categories accounted for 32.78%, 24.43%, and 36.33% of total expenditures, respectively. Their shares of the total after EA expiration were 34.22%, 24.93%, and 36.67%, indicating no evidence of selective food shielding.

4.2 Event Study Results

The event study design allows us to trace the evolution of treatment effects over time, checking that the parallel trends assumption holds and that there are no anticipatory behavioral changes before EA expiration. Figure 4 to Figure 7 display the estimated treatment effects for total spending, perishable, storable, and splurge categories, respectively.

Figure 4 presents the event study estimates for monthly total spending. Prior to treatment ($e < 0$), the estimated coefficients remain close to zero, with overlapping confidence intervals, supporting the assumption that the pre-trends were parallel between treated and control households. Starting from $e = -1$, impacts begin to decline significantly, with treatment effects growing more negative over time. By $e = 6$, total spending has fallen by approximately 20 percentage points. Figures 5, 6, and 7 show the event study results by food category. The patterns for perishable, storable, and splurge spending closely mirror those for total grocery expenditures. As shown in Figures 5, estimates for perishable spending remain near zero in the pre-treatment period, confirming no anticipatory responses, and decline significantly after stop paying EA benefits. For post-treatment, total spending shows a sharp and sustained decline, reaching nearly -21% by event month 5. Similar patterns emerge across food categories, with storable and perishable categories experiencing the largest declines—exceeding -21% and -20%, respectively. These findings reinforce the main results: households in the our sample reduced food spending substantially across all categories, with no evidence of compositional reallocation.

4.3 Heterogeneity Analysis

We explore heterogeneity in EA expiration effects within the sample (Results in Table 6). Results from different household size indicate that smaller households experienced the largest reductions in food expenditures, with single-person and two-person households reducing spending by 33.00% and 17.24%, respectively. The decline is significant but smaller for three-person (11.34%) and four-person (10.20%) households, while effects for larger households (five or more persons) were minimal and statistically insignificant. These findings suggest that smaller households relied more heavily on EA benefits, whereas larger households may have had greater financial flexibility. Households without children experienced a spending decline of 17.11%, compared to 11.78% for households with children. The smaller decline for families with children may reflect access to additional food assistance programs, such as WIC and school meal programs, which could have mitigated the impact of EA expiration. In contrast, childless households, lacking access to these supplementary programs, may have faced greater financial strain. Spending reductions also varied by ethnicity. "Black or African American" households experienced the largest decline (21.40%), followed by "Hispanic/Latino" (13.21%) and "White/Caucasian" (13.12%) households. The different magnitutions of reductions among different race households suggests greater financial vulnerability, reflecting broader disparities in food security and economic resilience. Income level also played a significant role in shaping responses to EA expiration. "Low Income" households reduced spending by 18.18%, while "High Income" and "Over Income" households also show a decline of 11.35% and 8.55% respectively. "Medium Income" households exhibited no statistically significant change. These results highlight disproportionate effects among some households.

5 Discussion

The findings from this study provide important evidence on how the sudden loss of SNAP EA affects household food purchasing. Our results show that while spending falls in categories of perishable, storable, and splurge, the relative shares of these categories remain stable. Table 7 and Table 8 provides further insight into the composition and magnitude of the monthly spending response. This implies that households do not prioritize their food choices, even under tighter budgets. Such inelastic food allocation is consistent with Andreyeva, Long, and Brownell (2010), who found limited responsiveness to price and budget shifts among low-income populations. When benefits were reduced, nutritional adjustments were constrained by rigid preferences and limited access to affordable alternatives.

Table 7 and Table 8 also provides the dollar value of the decline by food category, shows that category shares remained highly stable before and after EA expiration, revealing that reductions were broadly proportional to baseline shares. Further confirming that while total food expenditure declined, households did not make strategic trade-offs across those three food categories.

However, unlike Dasgupta and Plum (2023); Steffen and Kim (2024), estimated $180 per month lost SNAP benefits after the termination of EA. We on average observe spending drop of $30.57 per month that captures only 17% of the befits reduction. Several explanations may account for this discrepancy. First, SNAP households may balance their budgets by reducing both food and non-food spending. The total drop in EA payments may lead to cutbacks in other areas such as transportation, housing, or utilities, leaving food expenditures partially protected. Second, the Numerator dataset may not capture all grocery spending. Not all purchases made with SNAP benefits are recorded, and households may not upload all receipts. Third, SNAP households might access alternative resources such as food pantries, informal support networks, or short-term borrowing to buffer the immediate impact.

Heterogeneity analysis reveals particularly large impacts for single-person, childless, and minority households, echoing findings from Bitler et al. (2022) and Song (2024) that emphasized unequal resilience across demographic groups. These effects reinforce the concern that vulnerable subpopulations are least equipped to absorb the policy shock. The event study also shows that these spending declines persist without recovery over a six-month horizon, underscoring the enduring nature of the adjustment. In sum, EA expiration triggers broad and lasting cutbacks in grocery spending, with no evidence of substitution across food types.

6 Conclusion

The expiration of EA reduced SNAP households' purchasing power during a period of elevated food prices and economic uncertainty. This study shows that SNAP participants responded by reducing grocery spending across all food categories, but without changing the overall composition of their food baskets. These patterns suggest limited flexibility to optimize nutritional value when benefits are cut.

The findings highlight two key implications. First, even partial benefit reductions can have effects on household consumption, especially for some households. Second, the absence of compositional shifts despite lower spending points to strong consumption rigidity—driven either by fixed dietary needs or a lack of affordable substitutes.

As policymakers consider future SNAP reforms, especially during and after economic shocks, they may wish to consider not only the level of support but also to its stability and responsiveness. EA payments played a substantial role in SNAP households' food purchasing decisions during the pandemic, and their elimination significantly affected food purchases, particularly among the lowest income households. Designing policies that smooth transitions and protect food purchasing power may be needed to safeguard nutrition and health for some populations.

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Figures

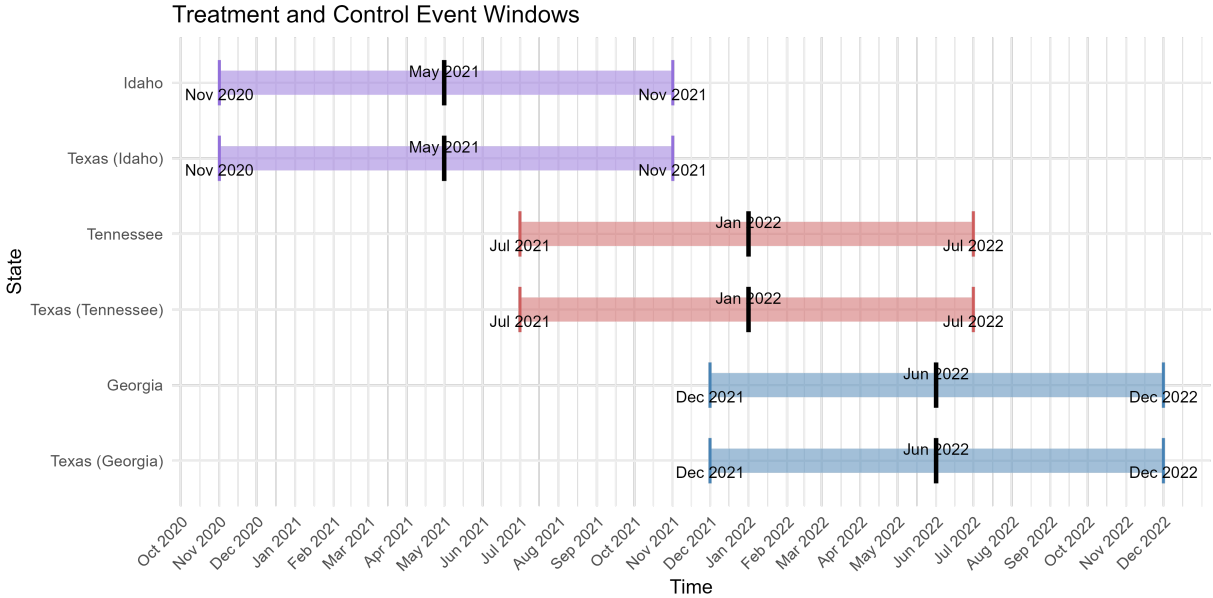

Figure 1. Defining SNAP Households in different Treatment and Control Subgroup

Note: This figure illustrates how we define the event window for three treatment subgroups based on their respective EA expiration months. For each state, the event window spans 13 months: six months before and six months after the EA expiration month. As shown in the figure, Idaho's event window (purple) begins in November 2020 (six months before May 2021, the EA expiration month) and ends in November 2022 (six months after May 2021). Similarly, Tennessee's event window (red) starts in July 2021 and ends in July 2022, while Georgia's event window (blue) runs from January 2021 to January 2022. Each treatment subgroup is matched with an appropriate control subgroup based on this standardized event window.

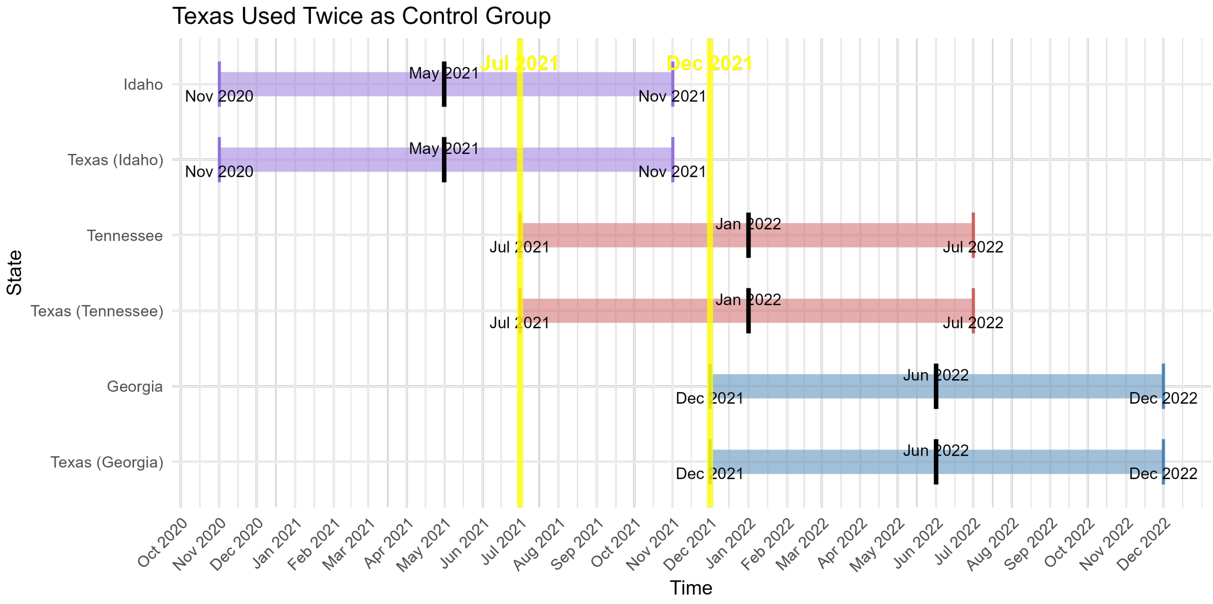

Figure 2. SNAP Households in Control Subgroup Used Twice

Note: This figure illustrates the reuse of SNAP households in Texas. The two vertical yellow lines indicate that SNAP households in Texas during July 2021 and December 2021 are used twice: once as part of the control subgroup for Idaho and once for Tennessee.

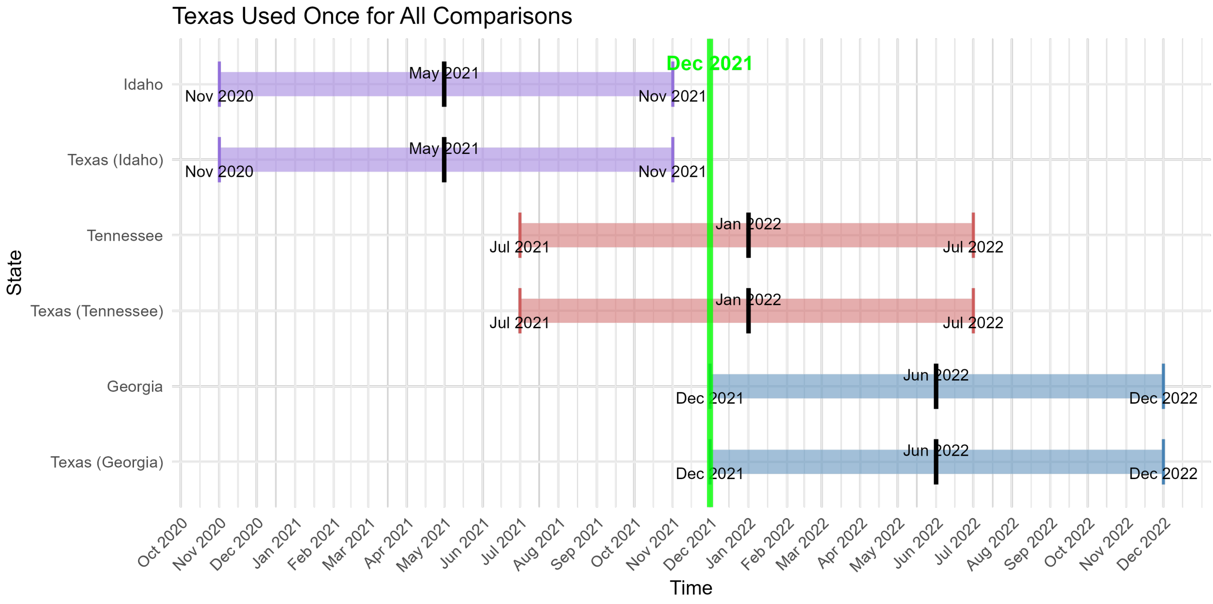

Figure 3. SNAP Households in Control Subgroup Used Once

Note: The green vertical lines in this figure indicate that SNAP households in Texas are only used once as a control subgroup. Specifically, households before December 2021 (excluding December) are used as the control group for Idaho, while those after December 2021 (excluding December) serve as the control group for Georgia. The non-overlapping time periods ensure that these households are only used once in each control subgroup.

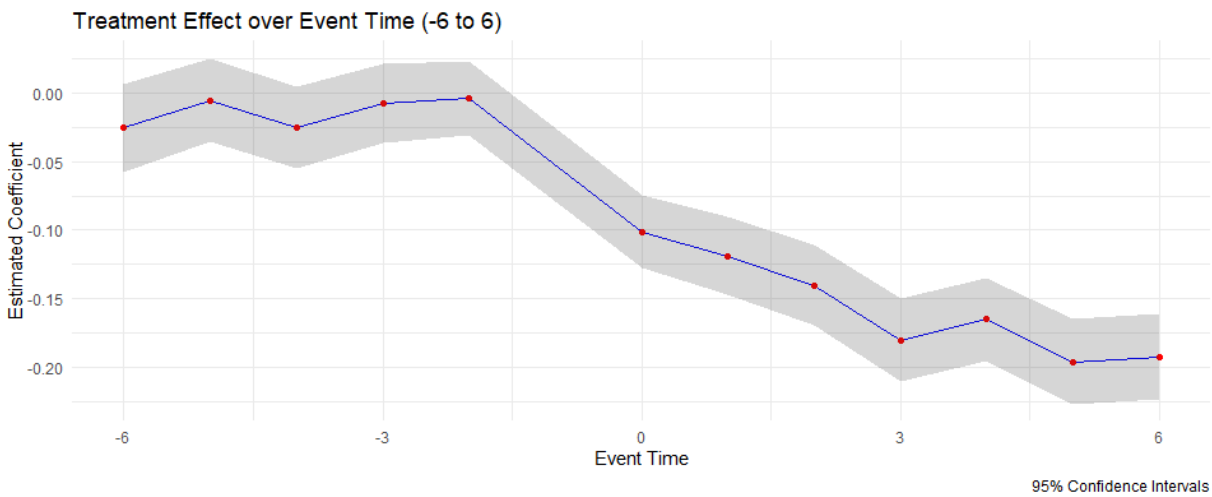

Figure 4. Event Study for Monthly Total Grocery Spending

Note: This figure plots event study estimates of monthly total grocery spending using our sample. Red points represent the estimated treatment effects at each event time. The blue line connects these point estimates to show the overall trend. The gray shaded area indicates the 95% confidence intervals around each estimate.

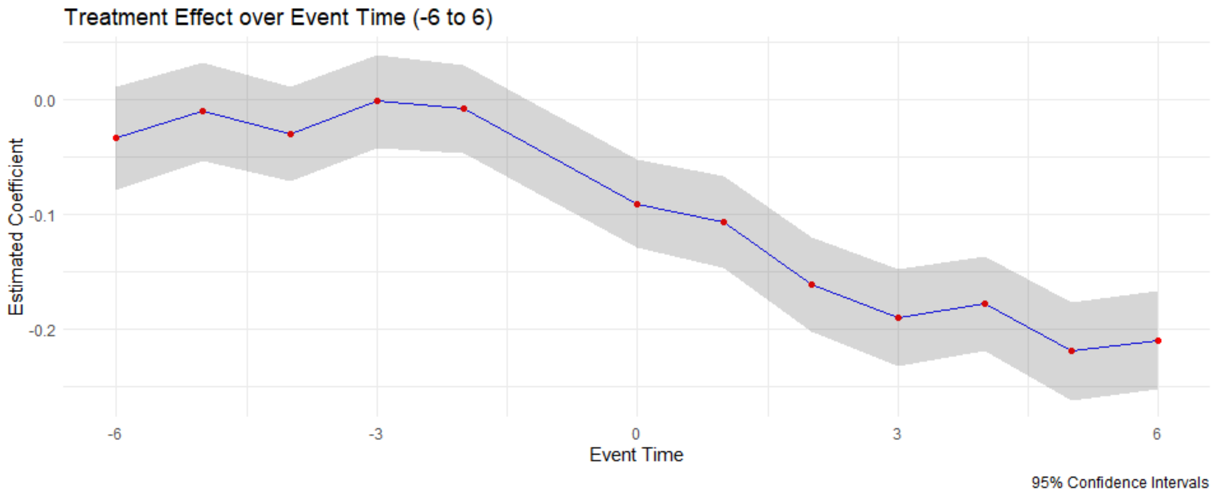

Figure 5. Event Study for Monthly Perishable Spending

Note: This figure plots event study estimates of monthly perishable spending using our sample. Red points represent the estimated treatment effects at each event time. The blue line connects these point estimates to show the overall trend. The gray shaded area indicates the 95% confidence intervals around each estimate.

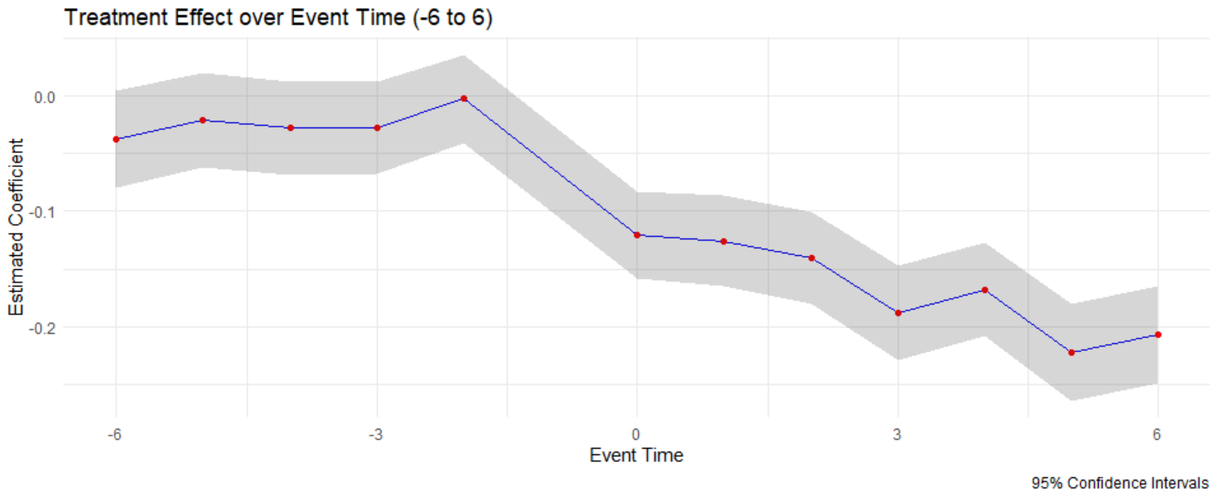

Figure 6. Event Study for Monthly Storable Spending

Note: This figure plots event study estimates of monthly storable spending using our sample. Red points represent the estimated treatment effects at each event time. The blue line connects these point estimates to show the overall trend. The gray shaded area indicates the 95% confidence intervals around each estimate.

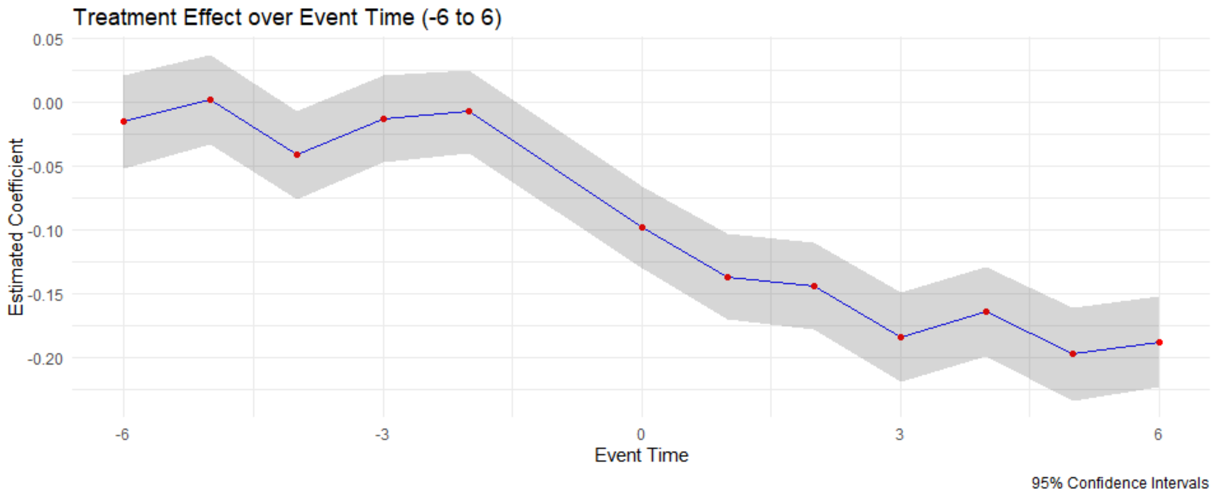

Figure 7. Event Study for Monthly Splurge Spending

Note: This figure plots event study estimates of monthly splurge spending using our sample. Red points represent the estimated treatment effects at each event time. The blue line connects these point estimates to show the overall trend. The gray shaded area indicates the 95% confidence intervals around each estimate.

Tables

Table 1. Summary Statistics

	All States	**States Without EA**	**States With EA**
Household Size			
1	15.38%	15.38%	15.37%
2	25.04%	27.10%	24.71%
3	17.52%	17.98%	17.42%
4	17.44%	16.43%	17.59%
5	11.83%	11.01%	11.95%
6 and more	12.80%	12.10%	12.96%
Presence of Child			
Without Child	48.40%	49.34%	48.25%
With Child	51.60%	50.66%	51.75%
Ethnicity			
White/Caucasian	55.20%	61.97%	53.82%
Asian and others	7.58%	3.60%	8.44%
Black or African American	16.24%	19.02%	15.65%
Hispanic/Latino	20.99%	15.42%	22.10%
Income Level			
Low Income	56.08%	56.33%	55.92%
Medium Income	8.71%	8.42%	8.80%
High Income	29.62%	29.82%	29.60%
Non-SNAP Eligible	5.58%	5.43%	5.68%

Note: "All States" represents the entire dataset, while "States With EA" represents the dataset for states that continued to issue EA as of December 2021, and "States 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**	$A_s = a$
May 2021	Idaho	$A_1 = 7$
June 2021	North Dakota	$A_2 = 8$
July 2021	Arkansas	$A_3 = 9$
August 2021	South Dakota, Florida, Nebraska, Montana	$A_4 = 10$
September 2021	Missouri	$A_5 = 11$
January 2022	Tennessee, Mississippi	$A_6 = 15$
April 2022	Iowa	$A_7 = 18$
May 2022	Kentucky, Wyoming, Arizona	$A_8 = 19$
June 2022	Indiana, Georgia	$A_9 = 20$

Note: Source from USDA website: https://www.fns.usda.gov/disaster/pandemic/covid-19. In December 2022, a total of 16 states had stopped issuing EA payments. We define A_s as the research period in which treatment group s lost EA benefits, with $A_s = a$ denoting that period and $A_s = \infty$ for groups that never experienced EA expiration.

Table 3. Event Window and Stack Share

Subgroup(A_s)	Treated States	Treatment Month	Event Start Date	Event End Date	Stack Share (%)	Control States
1	Idaho	2021-05	2020-11-01	2021-11-30	0.104242877	Alabama, California, Colorado, Connecticut, District of Columbia, Delaware, Hawaii, Illinois, Kansas, Louisiana, Massachusetts, Maryland, Maine, Michigan, Minnesota, North Carolina, New Hampshire, New Jersey, New Mexico, Nevada, New York, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, Texas, Utah, Virginia, Vermont, Washington, Wisconsin, West Virginia
2	North Dakota	2021-06	2020-12-01	2021-12-31	0.105359703	
3	Arkansas	2021-07	2021-01-01	2022-01-01	0.107243683	
4	South Dakota, Florida, Nebraska, Montana	2021-08	2021-02-01	2022-02-28	0.115945301	
5	Missouri	2021-09	2021-03-01	2022-03-31	0.110409664	
6	Tennessee, Mississippi	2022-01	2021-07-01	2022-07-31	0.114146181	
7	Iowa	2022-04	2021-10-01	2022-10-31	0.111799635	
8	Kentucky, Wyoming, Arizona	2022-05	2021-11-01	2022-11-30	0.114930384	
9	Indiana, Georgia	2022-06	2021-12-01	2022-12-31	0.115922571	

Note: This table presents subgroup assignments based on the timing of EA expiration. It includes treatment states, treatment month, event window of the full stacked sample. Control states remain the same across all subgroups and are listed in the first row.

Table 4. Main Results

Category	Estimate	Std. Error
Perishable	-15.18 ***	1.08
Storable	-14.85 ***	1.03
Splurge	-14.64 ***	0.92
Total Spending	-14.55 ***	0.82

Note: All models include state and month fixed effects and control for household characteristics as covariates. Estimates represent percentage point changes (multiplied by 100). Standard errors are clustered at the household level. ***p<0.01, **p<0.05, *p<0.1.

Table 5. Estimated Changes in Monthly Food Spending per Household by Category After EA Expiration

Category	Estimate (%)	Avg. Before ($)	% of Total Before	Change ($)	% of Total Decline
Perishable	-15.18	68.89	32.78%	-10.46	34.22%
Storable	-14.85	51.33	24.43%	-7.62	24.93%
Splurge	-14.64	76.35	36.33%	-11.18	36.57%
Total Spending	-14.55	210.13	100.0%	-30.57	100.0%

Note: All models include state and month fixed effects and control for household characteristics as covariates. Estimates represent percentage changes.

Table 6. Heterogeneity Results

Group	Estimate	Std. Error
Household Size		
1	-33.00 ***	2.87
2	-17.24 ***	2.00
3	-11.34 ***	2.48
4	-10.20 ***	2.63
5	-2.82	3.17
6 and more	-5.70	3.10
Child Status		
Without Child	-17.11 ***	1.42
With Child	-11.78 ***	1.39
Income Level		
Low Income	-18.18 ***	1.28
Medium Income	-3.91	3.73
High Income	-11.35 ***	1.85
Over Income	-8.55 *	4.47
Ethnicity		
White/Caucasian	-13.12 ***	1.19
Asian and Others	-5.43	5.83
Black or African American	-21.40 ***	2.49
Hispanic/Latino	-13.21 ***	2.74

Note: Income level is reclassified based on the income interval of the original data according to the federal poverty guidelines. Household size 6 includes Household sizes 6 and 7. All values are in percentage points. Standard errors are clustered at the household level. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

Table 7. Monthly Average Grocery Spending Before EA Expiration

State	Treat Month	Total Grocery Spending	Perishable	Storable	Splurge	% Perishable	% Storable	% Splurge
AR	7/1/2021	184	58.30	47.20	68.90	31.68%	25.65%	37.45%
AZ	5/1/2022	256	90.20	60.50	86.70	35.23%	23.63%	33.87%
FL	8/1/2021	210	78.00	47.10	66.00	37.14%	22.43%	31.43%
GA	6/1/2022	235	81.80	58.00	79.70	34.81%	24.68%	33.91%
IA	4/1/2022	226	71.40	57.50	82.10	31.59%	25.44%	36.33%
ID	5/1/2021	169	56.20	44.20	58.10	33.25%	26.15%	34.38%
IN	6/1/2022	267	88.60	65.10	95.80	33.18%	24.38%	35.88%
KY	5/1/2022	238	76.30	59.30	89.60	32.06%	24.92%	37.65%
MO	9/1/2021	182	56.30	44.20	68.30	30.93%	24.29%	37.53%
MS	1/1/2022	198	65.00	51.10	69.50	32.83%	25.81%	35.10%
MT	8/1/2021	165	53.80	36.40	63.40	32.61%	22.06%	38.42%
ND	6/1/2021	166	50.90	40.80	64.50	30.66%	24.58%	38.86%
NE	8/1/2021	215	64.90	48.50	81.40	30.19%	22.56%	37.86%
SD	8/1/2021	201	61.80	47.70	80.40	30.75%	23.73%	40.00%
TN	1/1/2022	223	72.20	55.70	81.50	32.38%	24.98%	36.55%
WY	5/1/2022	227	76.60	57.90	85.70	33.74%	25.51%	37.75%
Average		210.13	68.89	51.33	76.35	32.69%	24.42%	36.43%

Note: This table presents monthly average household grocery spending prior to EA expiration in states that ended EA before 2023, using the BBCE200 sample. Spending is reported by category—perishable, storable, and splurge foods—as well as each category's share of total food expenditures. All values are calculated by the author.

Table 8. Monthly Average Grocery Spending After EA Expiration

State	Treat Month	Total Grocery Spending	Perishable	Storable	Splurge	% Perishable	% Storable	% Splurge
AR	7/1/2021	181	57.60	48.50	65.10	31.82%	26.80%	35.97%
AZ	5/1/2022	252	89.10	58.60	83.80	35.36%	23.25%	33.25%
FL	8/1/2021	208	77.50	48.10	65.30	37.26%	23.13%	31.39%
GA	6/1/2022	221	76.20	55.40	75.10	34.48%	25.07%	33.98%
IA	4/1/2022	196	64.00	45.10	73.30	32.65%	23.01%	37.40%
ID	5/1/2021	179	58.80	43.90	61.10	32.85%	24.53%	34.13%
IN	6/1/2022	271	87.80	68.50	97.00	32.40%	25.28%	35.79%
KY	5/1/2022	227	72.50	57.00	86.80	31.94%	25.11%	38.24%
MO	9/1/2021	183	58.00	44.90	67.10	31.69%	24.54%	36.67%
MS	1/1/2022	184	60.40	45.10	65.20	32.83%	24.51%	35.43%
MT	8/1/2021	150	47.70	36.00	54.90	31.80%	24.00%	36.60%
ND	6/1/2021	151	43.00	37.40	63.30	28.48%	24.77%	41.92%
NE	8/1/2021	202	60.00	49.50	73.10	29.70%	24.50%	36.19%
SD	8/1/2021	235	70.00	56.10	86.90	29.79%	23.87%	36.98%
TN	1/1/2022	210	69.10	50.80	75.90	32.90%	24.19%	36.14%
WY	5/1/2022	228	71.80	59.00	85.90	31.49%	25.88%	37.68%
Average		204.88	66.47	50.24	73.74	32.34%	24.53%	36.11%

Note: This table presents monthly average household grocery spending after EA expiration in states that ended EA before 2023, using the BBCE200 sample. Spending is reported by category—perishable, storable, and splurge foods—as well as each category's share of total food expenditures. All values are calculated by the author.

Appendix Tables

Table A1. Category Labels

MAJOR CATEGORY DESCRIPTION	DEPARTMENT DESCRIPTION	Label
All Other Salty Snacks	Snack	Splurge
All Other Seasonal Candy	Candy (Snacks)	Splurge
Bacon	Meat	Perishable
Bag of Ice	Ice	Storable
Baked Goods	Deli & Prepared Foods	Splurge
Baking Chips & Bars	Baking & Cooking	Splurge
Baking Ingredients	Baking & Cooking	Storable
Baking Mixes	Baking & Cooking	Splurge
Baking Nuts, Seeds, Coconut & Fruit	Baking & Cooking	Splurge
Baking Powder & Soda	Baking & Cooking	Storable
Barley	Beans & Grains	Storable
Beans	Canned	Storable
Beef	Meat	Perishable
Beer	Alcohol Beverages	Alcohol and Tobacco
Beverage Powders & Enhancers	Beverages	Splurge
Breakfast Cereal	Breakfast	Storable
Bulk & Bagged Rice (Non-Instant Rice)	Beans & Grains	Storable
Butter & Margarine	Dairy	Perishable
Canned & Powdered Milk	Baking & Cooking	Storable
Canned Fruit	Canned	Storable
Canned Meat & Seafood	Canned	Storable
Canned Vegetables	Canned	Storable
Canning Supplies	Baking & Cooking	Storable
Capers	Condiments	Storable
Caviars & Roes	Seafood & Fish	Perishable
CBD Beverages	Cannabis Beverages	Splurge
Cheese	Dairy	Perishable
Cheese-Deli	Deli & Prepared Foods	Perishable
Chili	Shelf Stable Meals	Storable
Chili Topping	Condiments	Storable
Chips	Snack	Splurge
Christmas & Winter Holiday Candy	Candy (Snacks)	Splurge
Chutneys	Condiments	Storable
Clams	Seafood & Fish	Perishable
Coatings	Batters	Baking
Cooking	Storable	
Cocktail Components	Alcohol Beverages	Alcohol and Tobacco
Coconut Water	Beverages	Splurge
Coffee	Beverages	Splurge
Cold Cuts-Deli	Deli & Prepared Foods	Perishable
Cold Cuts-Mainstream	Meat	Perishable
Combo Condiment Packs	Condiments	Storable
Cookie	Gingerbread Kits	Baking & Cooking
Storable		
Corn Meal & Polenta	Baking & Cooking	Storable
Couscous	Beans & Grains	Storable
Crab	Seafood & Fish	Perishable
Crackers	Snack	Splurge
Crusts	Baking & Cooking	Storable
Cup of Ice	Deli & Prepared Foods	Storable
Deli Tray	Deli & Prepared Foods	Perishable
Dessert Snacks	Snack	Splurge
Desserts	Deli & Prepared Foods	Splurge
Dips	Condiments	Storable
Dried Fruit & Fruit Snacks	Snack	Splurge
Drinks & Mixes	Beverages	Splurge
Dry Beans	Beans & Grains	Storable
Dry Meal Kits (Non-Grain)	Shelf Stable Meals	Storable
Easter Candy	Candy (Snacks)	Splurge
Egg Pasta	Pasta & Noodles	Storable
Eggnog	Dairy	Perishable
Eggs	Dairy	Perishable
Ethnic Fruits & Vegetables	Produce	Perishable
Exotic	Meat	Perishable
Fish	Seafood & Fish	Perishable
Flavored Syrups	Beverages	Splurge
Flour & Blends	Baking & Cooking	Storable
Flowers	Produce	Perishable
Food Gifts	Misc. Food	Perishable
Fountain Beverages	Deli & Prepared Foods	Splurge
Fresh Meat Alternatives	Meat	Perishable
Fresh Seafood	Seafood & Fish	Perishable
Frosting	Baking & Cooking	Splurge
Frozen Appetizers	Frozen Foods	Storable
Frozen Bakery	Frozen Foods	Splurge
Frozen Breakfast Food	Frozen Foods	Storable
Frozen Desserts	Frozen Foods	Splurge
Frozen Dinners & Meals	Frozen Foods	Storable

Note: Data from Numerator.

Table A2. Category Labels (Continued)

MAJOR CATEGORY DESCRIPTION	DEPARTMENT DESCRIPTION	Label
Frozen Fruit	Frozen Foods	Storable
Frozen Juice	Frozen Foods	Storable
Frozen Meat	Frozen Foods	Storable
Frozen Onion Rings	Frozen Foods	Storable
Frozen Pasta & Noodles	Frozen Foods	Storable
Frozen Pizza	Frozen Foods	Storable
Frozen Potato Snacks	Frozen Foods	Storable
Frozen Sandwiches/Handhelds	Frozen Foods	Storable
Frozen Seafood	Frozen Foods	Storable
Frozen Soups	Frozen Foods	Storable
Frozen Vegetables	Frozen Foods	Storable
Fruits	Produce	Perishable
Glazed & Coated Nuts & Fruit	Snack	Splurge
Grains, Rice & Pasta Dishes-Shelf Stable	Shelf Stable Meals	Storable
Halloween Candy	Candy (Snacks)	Splurge
Herbs, Spices & Seasonings-Blends	Herbs & Spices	Storable
Herbs, Spices & Seasonings-Single	Herbs & Spices	Storable
Home Brewing & Wine Making	Beverages	Alcohol and Tobacco
Honey	Condiments	Storable
Horseradish	Condiments	Storable
Hot Cocoa	Beverages	Splurge
Hot Dogs	Meat	Perishable
Hot Sauce	Condiments	Storable
Ice Cream & Novelties	Frozen Foods	Splurge
Ice Cream Cones & Cups	Baking & Cooking	Splurge
Icings, Toppings & Decorations	Baking & Cooking	Splurge
In-Store Bakery Alternatives	In-Store Bakery (Bread & Alternatives)	Splurge
In-Store Bakery Bread	In-Store Bakery (Bread & Alternatives)	Splurge
In-Store Bakery Bread Crumbs & Stuffing	In-Store Bakery (Bread & Alternatives)	Splurge
In-Store Bakery Breakfast Bakery	In-Store Bakery (Bread & Alternatives)	Splurge
In-Store Bakery Desserts	In-Store Bakery (Bread & Alternatives)	Splurge
In-Store Bakery Rolls & Buns	In-Store Bakery (Bread & Alternatives)	Splurge
In-Store Bakery Sweet Goods	Bakery Sweet Goods	Splurge
Instant Breakfast Drink	Breakfast	Storable
Jam, Jelly, Preserves, Marmalade, Fruit	Nut Butters	Condiments
Storable		
Juices	Beverages	Splurge
Ketchup	Condiments	Storable
Kombucha	Beverages	Splurge
Lamb	Meat	Perishable
Legumes	Produce	Perishable
Lentils	Beans & Grains	Storable
Liquid Aminos	Condiments	Storable
Lobster	Seafood & Fish	Perishable
Mayonnaise & Mayonnaise Dressings	Condiments	Storable
Meal Combo-Adult	Meat	Perishable
Meal Combo-Kids	Meat	Perishable
Meat Based Meal Kits	Fresh Meal Kits	Perishable
Meat Snacks	Snack	Splurge
Meatballs	Meat	Perishable
Milk, Cream, & Milk Substitutes	Dairy	Perishable
Mussels	Seafood & Fish	Perishable
Mustard	Condiments	Storable
Nectars	Beverages	Splurge
Non-Alcoholic Cider	Beverages	Splurge
Non-Seasonal Candy	Candy (Snacks)	Splurge
Noodles	Pasta & Noodles	Storable
Nutrition and Wholesome Bars	Snack	Splurge
Nuts & Seeds (Produce)	Produce	Perishable
Oil & Shortening	Baking & Cooking	Storable
Oysters	Seafood & Fish	Perishable
Packaged Bakery Alternatives	Packaged Bakery (Bread & Alternatives)	Storable
Packaged Bakery Desserts	Packaged Bakery (Bread & Alternatives)	Splurge
Packaged Bread	Packaged Bakery (Bread & Alternatives)	Storable
Packaged Bread Crumbs & Stuffing	Packaged Bakery (Bread & Alternatives)	Splurge
Packaged Breakfast Bakery	Packaged Bakery (Bread & Alternatives)	Splurge
Packaged Cookies	Snack	Splurge
Packaged Dry Soups - Shelf Stable	Shelf Stable Meals	Storable
Packaged Meals-Refrigerated	Refrigerated Foods	Perishable
Packaged Pasta-Refrigerated	Refrigerated Foods	Perishable
Packaged Portable Sweet Snacks	Snack	Splurge
Packaged Rolls & Buns	Packaged Bakery (Bread & Alternatives)	Storable
Packaged Sides-Refrigerated	Refrigerated Foods	Perishable
Packaged Soups-Refrigerated	Refrigerated Foods	Perishable
Packaged Sweet Bakery Goods	Bakery Sweet Goods	Splurge
Packaged Wet Soups - Shelf Stable	Shelf Stable Meals	Storable
Pasta	Pasta & Noodles	Storable

Note: Data from Numerator.

Table A3. Category Labels (Continued)

MAJOR CATEGORY DESCRIPTION	DEPARTMENT DESCRIPTION	Label
Pates	Meat	Perishable
Pea, Bean, & Vegetable Snacks	Snack	Splurge
Pea/Bean/Vegetable Snacks	Snack	Splurge
Peas	Beans & Grains	Storable
Pepper & Peppercorns	Herbs & Spices	Perishable
Perishable Snack Packs	Produce	Perishable
Pickled Marinated Vegetables	Condiments	Storable
Pickled Peppers	Condiments	Storable
Pickles	Condiments	Storable
Pie, Pie & Cobbler Fillings	Baking & Cooking	Splurge
Popcorn	Snack	Splurge
Pork	Meat	Perishable
Poultry	Meat	Perishable
Prebiotic & Probiotic Soda	Beverages	Splurge
Prepared Meals	Deli & Prepared Foods	Perishable
Pretzels	Snack	Splurge
Puffed Snacks	Snack	Splurge
Quinoa	Beans & Grains	Storable
Ramen	Pasta & Noodles	Storable
Ready to Drink Alcohol Beverages	Alcohol Beverages	Alcohol and Tobacco
Ready to Eat Meals	Shelf Stable Meals	Storable
Refreshers (Candy)	Candy (Snacks)	Splurge
Refrigerated Beverages	Beverages	Splurge
Refrigerated Dough	Dairy	Perishable
Refrigerated Meat Snacks	Meat	Perishable
Relishes	Condiments	Storable
Rice Cakes	Snack	Splurge
Salad Dressings & Toppings	Condiments	Storable
Salad Dressings & Toppings-Ref	Deli & Prepared Foods	Storable
Salad Mixes & Salad Kits	Produce	Perishable
Salt & Salt Substitutes	Herbs & Spices	Storable
Sandwich Spreads	Condiments	Storable
Sauces	Baking & Cooking	Storable
Sausage	Meat	Perishable
Scallops	Seafood & Fish	Perishable
Shelf Stable Dairy	Dairy	Storable
Shelf Stable Olives	Condiments	Storable
Shelf Stable Tray Meals	Shelf Stable Meals	Storable
Shrimp & Prawns	Seafood & Fish	Perishable
Side Dishes-Shelf Stable	Shelf Stable Meals	Storable
Sides	Deli & Prepared Foods	Perishable
Single Serve Breakfast	Breakfast	Storable
Smoked & Cured Fish	Seafood & Fish	Perishable
Snack Food	Snack	Splurge
Snack Mix	Snack	Splurge
Snack Seeds, Nuts & Trail Mixes (Snack)	Snack	Splurge
Soba	Pasta & Noodles	Storable
Soft Drinks	Beverages	Splurge
Soups	Deli & Prepared Foods	Storable
Soy Sauce	Condiments	Storable
Sparkling Juice & Ciders	Beverages	Splurge
Spirits	Alcohol Beverages	Splurge
Sports & Energy Drinks	Beverages	Splurge
Stocks & Broths	Shelf Stable Meals	Storable
Sugar, Sugar Substitutes & Sweeteners	Baking & Cooking	Storable
Syrups	Baking & Cooking	Storable
Tea	Beverages	Storable
THC Beverages	Cannabis Beverages	Storable
Thickeners	Baking & Cooking	Storable
Toaster Pastries	Breakfast	Splurge
Tonic & Club Soda	Beverages	Splurge
Udon	Pasta & Noodles	Storable
Valentine Candy	Candy (Snacks)	Splurge
Variety Packs	Snack	Splurge
Variety Packs (Snack)	Snack	Splurge
Veal	Meat	Perishable
Vegetables	Produce	Perishable
Vinegars	Baking & Cooking	Storable
Wasabi	Condiments	Storable
Water	Beverages	Storable
Whipped Cream Toppings	Dairy	Splurge
Whipped Toppings	Frozen Foods	Splurge
Wine	Alcohol Beverages	Alcohol and Tobacco
Worcestershire Sauce	Condiments	Storable
Yeast & Leaveners	Baking & Cooking	Storable
Yogurt & Yogurt Drinks	Dairy	Perishable
Yogurt Covered Snacks	Snack	Splurge

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. Subgroup Shares and Decomposition of Weighting Terms

Subgroup(A_s)	**Treated States**	**Treatment Month**	Stack Share $\frac{N_a^C+N_a^D}{N_{\Omega_\kappa}^C+N_{\Omega_\kappa}^D}$	Treatment Share $\frac{N_a^D}{N_{\Omega_\kappa}^D}$	Control Share $\frac{N_a^C}{N_{\Omega_\kappa}^C}$	$Q_s^a(D_s^a=1)$	$Q_s^a(D_s^a=0)$	Treatment Share (%)
1	Idaho	2021-05	10.42%	1.64%	10.65%	1	15.43%	6.25%
2	North Dakota	2021-06	10.54%	0.61%	10.79%	1	5.68%	6.25%
3	Arkansas	2021-07	10.72%	3.50%	10.91%	1	32.10%	6.25%
4	South Dakota, Florida, Nebraska, Montana	2021-08	11.59%	33.73%	11.02%	1	306.11%	25.00%
5	Missouri	2021-09	11.04%	7.58%	11.13%	1	68.12%	6.25%
6	Tennessee, Mississippi	2022-01	11.41%	12.42%	11.39%	1	109.02%	12.50%
7	Iowa	2022-04	11.18%	3.06%	11.39%	1	26.83%	6.25%
8	Kentucky, Wyoming, Arizona	2022-05	11.49%	16.29%	11.37%	1	143.32%	18.75%
9	Indiana, Georgia	2022-06	11.59%	21.16%	11.34%	1	186.52%	12.50%

Note: This table decomposes the stack weight components used in stack dataset.