The Effect of SNAP Disbursement Disruptions on Grocery Purchases

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Abstract

Many researchers find that SNAP participants do not spend their monthly benefits smoothly, causing food insecurity and other adverse consequences at the end of the benefit month. This study explores the impact of higher SNAP payment frequency on the cyclicality of households' grocery spending during the 2018-2019 federal government shutdown when states were allowed to issue March benefit in more than one payment. Using detailed grocery purchase data from the Nielsen Homescan Panel in a triple-difference framework, I find twice-monthly payments lead to smoother grocery spending, especially on perishable items, indicating potential smoother consumption. These findings support the policy recommendation of more frequent SNAP payment to help families stretch their monthly food budget. The research also highlights the need for future studies to examine the impact of payment frequency on consumption and other outcomes in a context with higher external validity.

Keywords: food assistance, food expenditures, transfer disbursement
JEL codes: D12, H75, I18, I38, L81

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1. Introduction

The Supplemental Nutrition Assistance Program (SNAP) is the largest food assistance program in the United States, providing direct benefits to over 41 million individuals at a cost of $108 billion in fiscal year 2021. SNAP beneficiaries receive monthly benefits through an electronic benefit transfer (EBT) card to purchase food at authorized retailers. However, the monthly payment structure creates a SNAP cycle characterized by increased spending upon benefit receipt and decreased spending until the next payment (Castner & Henke, 2011). Decreasing spending over the month is accompanied by adverse consequences such as higher food insecurity (Shapiro, 2005), worse health outcomes (Cotti et al., 2020; Seligman et al., 2014), higher crime (Carr & Packham, 2019; Foley, 2011), and lower test scores (Bond et al., 2021; Cotti et al., 2018) at the end of the benefit month[2]. To address these issues, experts have recommended increasing the frequency of benefit payments. However, the current Farm Bill limits states from issuing SNAP benefits more than once a month, making it difficult to assess the effectiveness of this approach. This study aims to investigate the impact of higher SNAP payment frequency on households' grocery spending patterns by taking advantage of the disruptions caused by the 2018-2019 federal government shutdown.

During the shutdown, the U. S. Department of Agriculture (USDA), which oversees SNAP at the federal level, is one of the agencies that experienced a funding shortfall. As a result, SNAP beneficiaries experienced disruptions in benefit payment. The February 2019 benefits were issued early in all states by January 20, 2019, and states made their own plans for the March issuance to help families cope with the extended benefit gap. While some states made lump-sum payments to all households on a single day, four states (Florida, Georgia, Indiana, and Ohio) chose to split monthly benefits into two payments issued at different times in the March benefit cycle. The difference in payment frequencies provides an opportunity to investigate whether higher SNAP payment frequency can help smooth the SNAP spending cycle and reduce the cyclicality of its associated adverse effects.

In this paper, I analyze household grocery purchases using the Nielsen Homescan dataset obtained from the Kilts Center at the University of Chicago Booth School of Business. The dataset contains detailed information on grocery purchases made by 22,504 households across the United States in 2018 and 2019, such as food category, purchase date, quantity, and price of each purchased item. There is also demographic information of these households, including household size, income, and zip code. Most importantly, I match SNAP participation status of these panelists using data from an accompanying omnibus survey administered by NielsenIQ.

[2] Benefit month refers to the interval between two monthly benefit payment.

Using a dynamic triple-difference design, the study estimates the causal effect of SNAP payment frequencies on food spending smoothness by exploiting the plausible exogenous changes in payment schedules. First, I limit the analysis to the first four weeks in the March 2019 benefit cycle counting from the day of first March payment. I measure the smoothness of food expenditures by the difference in daily spending between days in the first week and days in the three weeks that follow. A greater drop in spending indicates a less smooth spending pattern. Second, I compare this difference between SNAP participating and non-participating households with the aim of cancelling out any common time trend. To further control for within-household shopping habits generated by unobserved timing of income flows from other sources, I add expenditures on the same calendar dates one year prior to the disruption as a second control group.

The findings suggest that semi-monthly payments lead to smoother grocery spending over the March benefit month. However, there are still challenges in validating the policy recommendations from these results. The major issue pertains to the inference of the impact of payment frequency on food consumption, given that our spending data lack information on actual food consumption. It is crucial from a policy perspective that the observed smoother food spending translates into smoother food consumption under higher payment frequency. To this end, I classify foods based on their perishability and demonstrate that the smoothing effect is driven by spending responses to perishable items such as fresh fruits and vegetables. As excessive perishable foods purchased at the start of the benefit month are unlikely to be consumed later, the results indicate impulsive food consumption under monthly payments, while semi-monthly payments effectively spread out perishable food consumption.

By leveraging the unexpected disruptions as natural experiments, the paper yields novel insights into the SNAP spending cycle and the impact of increased payment frequency on shopping behaviors in this specific context. The study sheds light on the potential benefits of increasing the frequency of SNAP payments, which is a policy proposal that has been debated for some time. The research also emphasizes further examination of the effect of payment frequency on secondary outcomes. It calls for future pilot studies to examine the policy recommendation in a context with higher external validity by design. Lastly, this research highlights government stability by gauging the changes in food purchasing behaviors during SNAP disbursement disruptions. Given that government shutdowns may disproportionately affect low-income households, this analysis sheds light on their vulnerability.

The paper proceeds as follows. I review some of the prior literature on expenditure cycles in section 2. Institutional details of SNAP disruptions during the government shutdown are introduced in section 3. Section 4 lays out the conceptual framework. I describe the data on food spending in section 5. Section 6 describes the empirical approach and presents the results. Section 7 concludes.

2. Literature review

The effects of SNAP on food expenditures have been extensively studied in the literature. This literature consists of three strands. The first strand assesses the effectiveness of SNAP on improving food security, which is measured by the quantity, quality, variety, and desirableness of diets. Using variations in SNAP administration, more generous SNAP policies are found to increase food spending and reduce food insecurity (Mykerezi & Mills, 2010; Ratcliffe et al., 2011; Shaefer & Gutierrez, 2013; Yen et al., 2008). The effect of SNAP on the healthfulness of food purchases is less clear. In a systematic review, Andreyeva et al. show that SNAP participation is associated with lower diet quality. Recent studies examine how SNAP affects the healthfulness of food purchases by linking grocery store purchases to nutrients in foods. Garasky et al. (2016) find that SNAP households and non-SNAP households purchase similar foods at the grocery store. Franckle et al. (2017) find that grocery items purchased with SNAP benefits tend to be less healthful than grocery items not purchased with SNAP benefits. Grummon and Taillie (2017) find that, along several dimensions, the grocery purchases of households participating in SNAP are less healthful than the grocery purchases of income-eligible non-participating households. Harris-Lagoudakis (2019) uses supermarket retailer data to find post-SNAP adoption increases spending over meats, oils and prepared products at a higher rate over other grocery product categories.

Another strand of research explains the effectiveness of SNAP from a behavioral aspect and tests the fungibility of SNAP benefits. Research using the early rollout of the food stamp program in 1980s shows the marginal propensity to consume SNAP-eligible food (MPCF) out of food stamp benefits is 0.16 to 0.32 whereas the MPCF out of cash is 0.09 to 0.10 (Hoynes & Schanzenbach, 2009). The results of their study do not reject the hypothesis that the MPCF out of food stamps is equal to the MPCF out of cash income. In recent studies, newer estimates range from 0.3 to 0.6 based on more recent variations in the program administration (Beatty & Tuttle, 2015; Bruich, 2014; Hastings & Shapiro, 2018). Hastings and Shapiro (2018) rejects fungibility and attributes the difference in MPCF out of SNAP benefits and cash income to mental accounting where people mentally separate income sources according to different spending intentions. Their results generate policy-relevant insights – SNAP can work as a tool to help low-income households set aside budget to purchase more food for at-home consumption.

The third strand further investigates how SNAP benefits are spent between monthly payments and identifies greater potential of SNAP on improving food security by adjusting its current payment frequency. Although SNAP is effective in increasing food spending, the rate of food insecurity remains high among participants. Intramonth food expenditures and consumption patterns may contribute to food insecurity to some extent. The SNAP cycle, which refers to the phenomenon that SNAP beneficiaries tend to deplete their benefits rapidly after receiving SNAP, has been extensively documented in the literature. Castner and Henke (2011) study the redemption pattern and estimates that 59 percent of the monthly benefits are spent on average in the first week and a quarter of households exhaust benefits within the first week following issuance. Decreased spending over the month is accompanied by a series of adverse consequences. Foley (2011) shows that crime increases over the benefit month in areas with highly time-concentrated disbursements of welfare (including SNAP), and Carr and Packham (2019) link the SNAP cycle directly to grocery store theft rates. Seligman et al. (2014) find that hospital admissions for hypoglycemia are more common at the end of the month in low-income communities, and Bond et al. (2021) show that low-income high school students get lower scores on college admissions exam if they take the exam in the last two weeks of the SNAP benefit cycle. Cotti et al. (2018) show that standardized test scores decrease for children in SNAP households at the end of the benefit month. Although researchers suggest that increasing payment frequencies can be beneficial, the opportunities to test this proposal are limited.

Prior research on monthly spending patterns has several limitations. First, studies using administrative SNAP redemption data do not track cash expenditures on food purchases. The spike in SNAP redemption may not indicate a decrease in food spending over the month. Second, studies using survey data do not observe spending or consumption over an entire benefit cycle. To interpret results as the average spending pattern among the survey population, these studies assume interview dates were randomly assigned and that the survey households were randomly observed in their benefit cycle. Research using survey data is also at risk of misreporting SNAP participation status. Third, researchers use scanner data from a single retailer to explore the monthly pattern do not track food expenditures made in other stores. Although a method of payment indicator can identify SNAP participation, most of these data do not include information regarding the date on which each household received benefits. To circumvent this problem, previous studies focus on states that issue benefits on the first day of a month. There is, however, a possibility that the so-called first-of-the-month effect may also be driven by other income streams that arrive on the first day of the month, such as paychecks, TANF, or other social welfare benefits. For example, Stephens (2003) shows that expenditure patterns vary according to when benefits other than SNAP are received, with away-from-home food spending being significantly more likely on the day of Social Security receipt. In his study, Berniell (2018) demonstrates that this pattern persists even if the timing of Social Security receipts is determined by a person's date of birth. In addition, retail scanner data used in previous studies has limited information on household characteristics and cannot account for food purchased from other stores and channels.

This paper uses Nielsen Homescan Panel to investigate the effect of the timing of SNAP on food purchases. The government shutdown generates an exogenous change in the timing of SNAP disbursement. Due to the disruption, all households in a state have the same start and end dates of a benefit cycle, which are known by the researcher. Using detailed grocery purchase data that includes purchases from different retailers, I investigate the food spending cycle as well as explore the potential barriers to consumption smoothing during the disruption.

3. Background

The SNAP, formerly known as the Food Stamp Program, is the largest food assistance program in the United States. It is not only the largest in terms of spending, but also in terms of caseload. The benefits are provided monthly through an EBT card to purchase food for at-home consumption at authorized retailers. The following sections describe the administrative details and disruptions during the partial government shutdown.

3.1 Eligibility

SNAP is a means tested program. In order to qualify for food assistance, all members of a household sharing food must have a gross income below or equal to 130% of the federal poverty level. The household net income must fall below the poverty line after deductions for working, housing, and other expenses have been made. Depending on age, disability status, and state of residence, there is also an asset limit that must be met for household eligibility. Beyond income and asset eligibility, households can automatically gain eligibility through categorical eligibility rules based on being eligible for benefits from other low-income assistance programs such as the cash assistance from Supplemental Security Income (SSI) and Temporary Assistance for Needy Families (TANF) benefits. However, the Congressional Research Service estimates that due to the categorical eligibility, only a monthly average of 4.8% of all households without an elderly or disabled member had incomes above 130% of the poverty line in fiscal year 2019 (Aussenberg & Falk, 2019).

3.2 Benefit levels

Household income and the cost of an adequate monthly diet determine benefits under the SNAP program: families with very low incomes receive higher benefits than families closer to poverty, as the poor are more likely to require assistance purchasing an adequate diet. It is assumed that families will spend 30 percent of their net income on food; SNAP contributes to the difference between that 30 percent contribution and the cost of the Thrifty Food Plan (TFP), a low-cost, nutritionally adequate diet program established by the USDA at the federal level. The TFP cost is updated every year in October to account for increasing food prices.

3.3 Payment Schedules

The benefits are loaded onto the EBT card once in a month. Although the level of benefits is determined by a federal standard, states determine their own disbursement schedules and issue benefits at different times. Table 1 lists the disbursement schedules in 2019 for the fifty states. Column 2 shows the normal disbursement outside the disruption period. Only seven states disburse their monthly benefits to all beneficiaries on the same day. Most states use a staggered payment schedule to issue benefits to different household on different dates. Individuals in these states are assigned a receipt day during the month based on their case number, birth date, Social Security number, or last name. For example, a state might distribute benefits on the day of the month corresponding to the first or last digit of a household's case number.

[Table 1 here]

3.4 Disruptions During the Shutdown

During the partial government shutdown in 2018-2019, an announcement was made on January 8, 2019, about USDA's plan to provide full SNAP benefits for February where states were required to issue February benefits by January 20, 2019. Specific early payment dates are listed in Column 3 of Table 1. Notice letters were sent out to inform the SNAP clients that the payments were early February benefits rather than extra payment. Without modifications in March issuance, approximately 15 million households could have experienced a gap between benefit receipt for February and March of more than 40 days, while more than 4 million households could have experienced a gap of more than 50 days (Rosenbaum, 2019). Although the SNAP households received the same level of benefits from January to March as what they would have received without the disruption, it could cause hardships for some families if they did not budget the early distribution over an extended period.

To address the long February SNAP gap, states developed their own plans for reducing the time between the issuance of February and March benefits. In most states, the payment was made as early as March 1st to ensure that SNAP recipients would not have to go more than 40 days before their March benefits. Some states split the March payment by issuing half of the benefits early[3], creating variation in the frequency that household receive their March SNAP payment. Their plans for March issuance were announced on February 14 by USDA.

Figure 1 describes the issuance of SNAP in all states during FY2019 using the administrative data from the USDA. The disrupted periods are marked with stars. Panel A shows the number of households and persons receiving SNAP in each month during FY2019. The number of SNAP recipients dropped sharply in February 2019 indicating most of the beneficiaries did not receive any benefit due to the early disbursement. The number does not drop to zero because households in the state of Ohio and Indiana issued half the March benefits early in February. Panel B depicts that the amount of SNAP benefits disbursed in January nearly doubled the amount disbursed in months outside the disrupted period.

[Figure 1 here]

4. Conceptual framework

Based on consumption models, the expected impact on food spending patterns can be inferred to support the projected consumption trajectory. The permanent income hypothesis suggests that a rational consumer would make consumption decisions based on their lifetime permanent income rather than their temporary income. As a result, the model anticipates a consistent consumption pattern, with temporary changes in income having little impact on consumption decisions. However, modern behavioral economics theories challenge this hypothesis by incorporating behavioral biases into the neoclassical consumption savings model. Past literature provides ample evidence that SNAP beneficiaries tend to exhaust their benefits quickly after receipt, which is a rejection of the permanent income hypothesis(Castner & Henke, 2011). Short-run impatience (Shapiro, 2005), preference for variety (Hastings & Washington, 2010), intramonth retail pricing (Goldin et al., 2022) are proposed to explain the mechanism of the observed spending dynamics. Empirical evidence suggests short-run impatience as the main driver of the spending spikes in the beginning of the month (Hastings & Washington, 2010; Shapiro, 2005). I build the conceptual model to simulate consumption behaviors incorporating present bias under different payment schedules in the following sections.

4.1 Behavioral Bias and the SNAP Cycle

[3] These states include Florida, Georgia, Indiana, and Ohio. Details from the USDA Food and Nutrition Service can be found at https://1thr423ga6tg2pem7p36a4sa-wpengine.netdna-ssl.com/wp-content/uploads/2019/02/snap-march-issuance.pdf . They are marked with stars in Table 1.

Consider a SNAP participating consumer who is planning for food purchases over the month. The consumer displays hyperbolic discounting and maximizes the following discounted utility at date t by choosing the optimal consumption level $\{c_t\}$:

$$U_t = E_t\left[u(c_t) + \beta \sum_{\tau=1}^{T-t} \delta^{\tau} u(c_{t+\tau})\right]$$

The instantaneous utility function takes the form of isoelastic utility,

$$u(c) = \frac{c^{1-\rho}}{1-\rho}$$

which means the consumer has a constant relative risk aversion of ρ. The discount structure is that the consumer at date t discounts future utility at $t + j$ by the factor $\beta\delta^{j}$. This indicates the consumer values the consumption tomorrow only $\beta\delta$ times the utility of the same level of his/her consumption today. And the consumption two days later is only $\beta\delta^2$ of the value of the same level of consumption today. A low β means the consumer is impatient in the short run choices between current utility and future utility. At $\beta = 1$, the case is reduced to exponential discounting. A low δ stands for impatience over long term choices.

For simplicity, I assume the consumer can only use SNAP payment W to purchase food. The budget constraint is given by:

$$W = \sum_{t=0}^{T} \frac{P_t \cdot C_t}{R^t}$$

where R is daily interest rate, P_t is the relative price over time, and C_t is the consumption level on date t. Following Harris and Laibson (2003), the consumption path can be derived from the Euler equation below:

$$C_t^{-\rho} = \left[C'(W_{t+1})\beta\delta + \left(1 - C'(W_{t+1})\right)\delta\right]C_{t+1}^{-\rho}$$

In the simulation study, I assume $R = 1$, because the daily interest rate is approximately zero if we evaluate the annual interest rate at the daily level. I also assume daily discount rate $\delta = 1$ for simplicity. To be consistent with the estimate of their baseline model in Laibson, Repetto, and Tobacman (2003), the measure of the short-run impatience takes the value $\beta = 0.7$. Price levels are assumed to be constant during the study period. The relative risk aversion is set at $\rho = 3.4$ to fit the estimated calorie decline in Shapiro (2005). The income stream mimics the SNAP disbursement schedules. The monthly benefit amount is normalized to one. I use the simple setting where the benefits are issued to all households on the first day of the month to illustrate the impact of disruptions in issuance.

[Figure 2 here]

Using a parametrization consistent with results from past studies on quasi-hyperbolic discounting, Panel A of Figure 2 shows the simulated optimal consumption path of a representative agent receiving SNAP on the first day of month in the first quarter of the year. The x-axis shows the days since the first day of the year. And the level of consumption is depicted on the y-axis. Consumption increases upon receipt of the payment and then drops over the rest of the month until next benefit payment, which is consistent with the observed SNAP spending cycle in past studies.

4.2 Consumption Path under Disruption

The government shutdown generates an exogenous shock to the scheduled. In 2019, February payment arrived early on January 20th. If the agent resides in a state that kept the monthly lump-sum payment, Panel B of Figure 2 shows his/her consumption path during the first quarter of 2019, where the consumption spike in February is pulled forward to the early payment in January and the spike upon March payment stays unaffected.

[Figure 3 here]

Figure 3 plots the case when the agent lives in a state that chose to split March benefits into two equal payments. Panel A shows the consumption during the three months when monthly benefits are paid on the first day of month. Panel B shows the consumption pattern when the February payment was made early and March benefit was issued at different times in equal amount. Comparing the consumption paths in Panel B of Figure 2 and Figure 3, twice-monthly benefit payment is expected to generate smoother consumption pattern than a lump sum monthly payment.

4.3 Inferring Expenditures from Consumption Path

The key caveat of the simulation study is that the model predicts consumption instead of expenditures. Factors such as the fixed costs of shopping would cause the expenditure path to deviate from the predicted consumption path. I take two approaches to address this potential issue. First, I categorize food by shelf life, as perishable foods cannot be stored for an extended period and are typically consumed and purchased around the same time. The anticipated impact on expenditures should follow closely to the predicted impact on consumption for perishable items. Second, I examine the frequency of shopping trips over the benefit month. If the fixed travel cost associated with grocery shopping trips plays a significant role in consumers' decision-making processes, it is expected that they will time their shopping trips to coincide with the arrival of their benefits and purchase groceries for the entire month to reduce the frequency of shopping trips and avoid incurring fixed costs. Consequently, we may observe a decline in expenditures over the course of the month, even if consumption remains relatively constant. However, if weekly shopping frequencies remain constant over the course of the month, it is unlikely that households are purchasing groceries for the entire month in a single trip at the time of benefit arrival. Rather, households may be stocking up on groceries for the week instead. In this case, the observed spending pattern should mirror the consumption pattern, rather than being generated by the fixed travel cost of grocery shopping trips.

5. Data and Summary Statistics

5.1 Household Characteristics

I use the Nielsen Homescan Panel data from the Kilts Center for Marketing Data at the University of Chicago Booth School of Business in this study.[4] This dataset comprises purchase records for a nationally representative panel of households spanning from 2018 to 2019. The dataset contains basic household information that is updated annually. The information contains demographic details of the household head including gender, age, race, and education. Additional household features, including the number of residents, their composition, income, as well as the number of adults and children, along with the household's zip code of residence, are also available. Nielsen aims at obtaining a nationally representative sample based on a range of demographic characteristics when recruiting panel households. Lusk and Brooks (2011) discovered that, in comparison to a random digit dial sample, Homescan panelists were typically older, more highly educated, and more likely to be white. Due to the nature of the selection process for the Homescan panel, there are two reasonable methods for interpreting the estimates in this study. Firstly, we can view the estimates as being internally valid for the sample of Homescan panelists or the population they represent. Secondly, we can assume that the estimates are valid for the entire population, on the condition that the impact of timing is uniform across different populations.

To identify relevant policy populations, the panel is merged with a supplemental survey administered by NielsenIQ, which provides additional information on household participation in SNAP. Specifically, the supplemental survey asks households in the Nielsen Homescan Panel every other quarter:

[4] The Kilts Center for Marketing at the University of Chicago Booth School of Business (n.d.). *Consumer Panel Data Overview*. NIELSEN AND NIELSENIQ MARKETING DATA. Retrieved February 26, 2023, from https://www.chicagobooth.edu/research/kilts/datasets/nielseniq-nielsen

"Are you or anyone in your household currently using or have you ever used food stamps, which includes food stamp card or voucher or cash grant from the state for food (also known as Supplemental Nutrition Assistance Program (SNAP), Electronic Debit Card (EBT card))?"

I obtain the survey information for the first quarter of 2018 and 2019 to identify household SNAP participation status during these periods. Based on the SNAP participation status in both years, panelists can be divided into four groups – participants in both years, non-participants in both years, participants in 2019 only, and participants in 2018 only. Table 2 shows the summary statistics of these households. Compared to non-participants, SNAP participants have lower income, are less likely to be married, less likely to be employed, less educated, more likely to be black, and less likely to be Asian than non-participants. Those who participated in only one year are younger, more likely to be married, more educated, more likely to be employed, and have higher income than two-year participants.

[Table 2 here]

5.2 Food Purchases

In the Nielsen Homescan Panel data, households recruited by Nielsen Company receive a scanner to scan the barcodes of packaged goods purchased from all outlet channels. For each product purchased, I observe the universal product classification (UPC) code, purchase date, transaction price, quantity purchased, total expenditure, as well as the coupon savings on the item.

According to the detailed item information, I categorize the purchased food into different groups. Based on the USDA guidance, SNAP benefits are mainly intended for staple foods that make up a significant portion of a person's diet and are usually prepared at home. I flag items purchased as SNAP eligible or not according to the food eligibility rules. Then these SNAP eligible items are further categorized into four major food groups – fresh fruits and vegetables, meat, dairy products, and frozen foods. Table 3 displays the mean weekly shopping frequencies and food category expenditures for four distinct household groups.

[Table 3 here]

A typical two-year SNAP participating household spends approximately $102 in grocery purchase in an average week in the first quarter of 2019. Nealy half of these expenditures were spent on SNAP eligible foods. Other expenditures were spent on non-food grocery items or ready-to-eat foods which are not eligible for SNAP benefits. For the specific food categories, a household spends $3.85 on fresh fruits and vegetables, $3.15 on meat, $6.27 on dairy products, and $11.20 on frozen items. The higher income and larger household size contribute to higher expenditures among non-participants.

[Figure 4 here]

When grocery purchases are aggregated to a weekly level, Figure 4 below shows the purchase pattern by SNAP participation during the disruption in 2019 and the same dates in 2018. The outcome displayed on the y-axis is the weekly expenditure on food eligible for SNAP benefits. Only the first four weeks in a month are included in the graph. In Panel A, the thick blue line shows the expenditures among SNAP participants in 2018. In the first three months of 2018, there is a clear decreasing pattern in the purchases of SNAP eligible food from the beginning of every month except January where expenditures in the first week are likely pulled forward by the holidays. This pattern confirms the so-called "first-of-the-month" effect, where SNAP recipients decrease their expenditures throughout the benefit month. The dashed line indicates weekly expenditures among non-participants during the same period. Their intra-month expenditures do not follow the same pattern as SNAP participants. In Panel B, the solid red line presents increased expenditures upon receipt of the early payment at the end of the third week of January in 2019. The expenditures decrease from the early payment until the beginning of March, followed by declining spending throughout March. The spending path was affected by disruptions in SNAP payment timing, whereas non-participants' spending remained relatively stable over years. Panel C presents the weekly expenditures pattern for SNAP households in 2019 by payment frequency. In March 2019, there is a steeper drop in spending among households receiving monthly SNAP payments compared to those receiving twice-monthly payments, providing graphical intuition of the smoothing effect on spending over the calendar month of twice-monthly payment. However, because the first date of March issuance varies across states, grouping daily spending by calendar dates may not accurately reflect the smoothing effect on expenditures over the benefit month.

5.3 Local Food Retailers

To explore supply side barriers, I use information on SNAP authorized retailers from the website of the USDA Food and Nutrition Service (FNS).[5] Local food prices are calculated from the Nielsen Homescan Panel following the method used in Gregory and Coleman-Jensen (2014).

[5] These data can be downloaded at https://www.fns.usda.gov/snap/retailer/historicaldata.

The historical data on authorized SNAP retailers is publicly available on the website of the FNS. The dataset includes information on the retailer such as retailer name, address, and location. The geographic information allows me to calculate the number of SNAP authorized retailers at the zip code level and match the number to the zip code of the residence of the panelists. Furthermore, the authorization and expiration dates of participating retailers are also available, allowing for a measure of how the local supply of SNAP retailers varies over time. A classification of retailer types is also included, so I can distinguish between grocery stores, convenience stores, super stores, specialty stores, and so on.

Table 4 shows the average number of SNAP authorized retailers at zip code level by household SNAP participation types. Participants who have been enrolled in the program for two years have access to approximately twenty-five SNAP retailers located within the same zip code as their household, of which approximately eleven are convenience stores and three are grocery stores. The density of SNAP stores is similar for one-year SNAP participants. However, non-participating households tend to live in zip codes with significantly fewer SNAP retailers.

[Table 4 here]

5.4 Local Food Prices

I also calculate local food prices to capture the impact of market-level changes on the purchasing power of SNAP benefits over time. Accounting for food prices is important since they can affect food demand and, consequently, purchase patterns. The Nielsen Homescan Panel data includes household level weights to project a demographically balanced panel to match the US population at the Scantrack market level[6]. For the subsample that also report random-weight goods, a separate weight is calculated for these households to be representative of the market area. The calculation follows the process used to develop the Quarterly Food-at-Home Price Database by the USDA, which uses the 1999-2006 Nielsen Homescan Panel data as the underlying price database (Todd et al., 2010)[7]. This process generates quarterly average prices of 52 food groups to conform with the USDA dietary guidelines in 35 market groups. To convert this measure to infer the purchasing power of SNAP, I aggregate these food groups into the Thrifty Food Plan (TFP) food groups to obtain the average prices of the TFP using the crosswalk developed by Oster (2018). The final price data includes quarterly average prices of 29 TFP food groups for 35 market groups covering the contiguous United States.

[6] There are 61 Scantrack markets including 52 large metropolitan areas and 9 nonmetro areas.
[7] The Quarterly Food-at-Home Price Database (QFAHPD) was developed to provide market-level food prices that can be used to study how prices affect food choices, intake, and health outcomes.

Row 4 of Table 4 lists the average food cost by SNAP participation in 2018 and 2019. While not statistically significant at the 5% level, individuals who have been enrolled in the SNAP program for two years tend to reside in areas with marginally higher food costs compared to those who are not enrolled in the program.

6. Empirical Strategy and Results

To further explore the impact of disbursement timing on expenditures, relying solely on graphical intuition is insufficient for several reasons. Firstly, I observe other factors that may affect expenditures by shifting supply or demand need to be controlled for to isolate the effect of disbursement timing. Secondly, unobserved confounding trend such as the trajectory of food supply or idiosyncratic shopping pattern generated by other income flows must also be accounted for. I address these concerns by estimating an event study model showing the weekly change in expenditures incorporating observable and time-invariant unobservable confounding factors, and then combine the event study with the difference-in-difference framework to account for the time varying unobservable confounding factors.

6.1 Expenditures Paths by Payment Frequencies

I group daily expenditures into weeks and employ an event study approach to estimate the change of daily expenditures in the weeks before and after the March payment. I estimate the event study model as follows with 2019 expenditures data among SNAP participants:

$$y_{it} = \beta_0 + \sum_{k=-3,k\neq-1}^{5} \beta_{1k} \cdot 1[Week_{it} = k] + \delta \cdot X_{it} + \pi_t + c_i + \varepsilon_{it} \qquad (1)$$

where y_{it} is the logged daily expenditure. $1[Week_{it} = k]$ is the indicator of date t falling into the kth week from the date of March payment in 2019 or the number of weeks counting from the same date in 2018 if t falls in year 2018. I control for factors affecting shopping patterns in X_{it}. These include household characteristics such as age, marital status, education, race of the household head, presence of children in the household, as well as the number of SNAP retailers at the same zip code and local TFP costs. Average temperature, and precipitation are also included to address factors that affect shopping trips. π_t includes holidays and day-of-week fixed effects. c_i is the unobserved household fixed effect. ε_{it} is an error term. I use robust standard errors throughout the analysis.

[Figure 5 here]

Figure 5 illustrates the dynamic effects of the March payment on household spending on SNAP eligible foods, separately for SNAP participants under monthly payment and twice-monthly payment. For households receiving March benefits as a lump sum, the spending path aligns with the predicted consumption pattern in the conceptual model. Specifically, spending levels remained constant in the three weeks prior to payment, which is reasonable since households may have depleted their February benefits due to the early payment in January. After the arrival of March benefits, there was a significant increase in expenditures on SNAP eligible items, which gradually declined to pre-payment levels later in the month. On the other hand, for households receiving twice-monthly payments, the spending path following the first March payment did not show a significant increase upon receipt. Instead, expenditure levels remained relatively unchanged throughout the month, indicating the smoothing effect of semi-monthly payments on spending.

To investigate the potential smoothing effect of SNAP payments on household food consumption, I estimated equation (1) using expenditures by food categories, including fresh fruits and vegetables, dairy products, meat, frozen foods, and shelf-stable foods. Since perishable foods have a limited shelf life, consumption of these items should more closely follow expenditures compared to shelf-stable foods. Figure 6 presents the results of the regression analyses by food categories.

[Figure 6 here]

The findings suggest that households receiving monthly SNAP payments experienced a significant increase in spending on all food categories upon receipt of the March payment, followed by a significant decline in subsequent weeks. In contrast, the changes in expenditures post-payment were smaller for households receiving twice-monthly payments, indicating a smoothing effect on spending across all food categories. Notably, the results for fresh foods and dairy show constant levels of consumption of these most perishable items, despite fluctuations in overall spending.

The assumption for a causal interpretation of the event study estimates described above lies in there being no systematic changes over time except for SNAP payment. Under this assumption, the above estimates the causal effect of March SNAP payment on expenditures among SNAP participants in 2019. There are potential threats to this assumption. First, promotions or food stock at local retailers could shift food demand systematically within the month. Second, unobserved timing of other incomes could contribute to certain intramonth shopping patterns. For example, states that split March benefits mandate semi-monthly paychecks and other states have various payday requirements. The different timing of paychecks could cause the spending pattern across states to divert. I address potential violations of the assumption in the next section.

6.2 How SNAP Caused a Change in the Spending Trajectories

I estimate the contribution of SNAP payment to the observed spending path by controlling for unobserved confounding trends. To control for unobserved seasonality that homogenously affect all consumers, I use expenditures of non-participants as a control group. To account for the effect of idiosyncratic monthly spending pattern within households generated by unobserved income flows and fixed shopping habits, the expenditures of the same households in 2018 serve as a second control group. I limit the analysis to households that participated in the SNAP program in 2019 but not in 2018, which allows for the identification of the effect of SNAP payment rather than a change in the payment across years if they received benefits in both years.[8] The estimation equation is shown in equation (2).

$$y_{it} = \beta_0 + \sum_{k=-3,k\neq-1}^{5} \beta_{1k} \cdot 1[Week_{it} = k] + \beta_2 \cdot SNAP_i + \beta_3 \cdot Y2019_t + \sum_{k=-3,k\neq-1}^{5} \beta_{4k} \cdot 1[Week_{it} = k] \cdot SNAP_i + \beta_5 \cdot SNAP_i \cdot Y2019_t + \sum_{k=-3,k\neq-1}^{5} \beta_{6k} \cdot 1[Week_{it} = k] \cdot Y2019_t + \sum_{k=-3,k\neq-1}^{5} \beta_{7k} \cdot 1[Week_{it} = k] \cdot SNAP_i \cdot Y2019_t + \delta \cdot X_{it} + \pi_t + c_i + \varepsilon_{it} \quad (2)$$

where $SNAP_i$ indicates households that only participated in SNAP in 2019 but not 2018. The remaining households did not participate in SNAP in both years. $Y2019_t$ equals one if date t falls into 2019. Other notations remain the same as in equation (1).

The parameter of interest is $\{\beta_{7k}\}$, which traces out the percentage change in spending by participation across years in the weeks before and after the benefit payment. Under the assumption that the difference in household purchasing pattern by SNAP participation would have evolved the same as in 2018 without the SNAP payment in 2019, $\{\beta_{7k}\}$ represents the causal effect of the March SNAP payment on the spending in the same week across years.

In Figure 7, the point estimates of the weekly change in expenditures on SNAP eligible items compared to the week prior to the March payment, along with their 95% confidence intervals, are presented by payment frequency. For SNAP households under monthly payments, the

[8] Analyzing the cross-year change in expenditures among households that participated in both 2018 and 2019 is an alternative approach to estimate the effect of a change in SNAP payment frequency. However, it is not feasible in this case because the SNAP payment dates for individual households in 2018 are not observed. The states that issued twice-monthly payments in 2019 used staggered issuance schedules during normal times, making it impossible to identify the start dates of the same benefit cycle in 2018. Although the start dates of the March benefit cycle in 2019 are identifiable because the first half was paid on the same day for all households, the lack of information to match payment dates with these households hinders the analysis.

spending in the first week after payment remained significantly higher than pre-payment levels and gradually decreased throughout the month. Although the pattern of dynamic effects were consistent with those estimated in section 6.1, unobserved trends due to contemporaneous seasonality and idiosyncratic shopping patterns over the month partly mitigated the spending patterns generated by SNAP disbursement. While the dynamic effects are similar to the pattern estimated in section 6.1 without accounting for unobserved trends, the magnitude of the increase in spending on SNAP eligible items is higher. This indicates that the spending pattern generated by SNAP disbursement were partly mitigated by unobserved trend caused by seasonality and idiosyncratic shopping patterns over the month.

Figure 7 also plots the case with households receiving twice-monthly payment. Prior to the March payment, I do not detect any significant changes in expenditures compared to the last week before the payment. While the arrival of the first half of the March benefit did not induce a significant increase in expenditures, there was a significant increase two weeks after the payment of the first half benefit. These results suggest that twice-monthly SNAP payment contributed to a smoother spending trajectory by increasing expenditures in the latter half of the benefit month.

[Figure 7 here]

Figure 8 shows the estimation results by food category. For households receiving lump-sum payment, the March payment led to a significantly increase in expenditures on fresh fruits and vegetables, as well as shelf stable foods in the week of payment, suggesting that the monthly lump-sum payment of SNAP benefits drives an intra-monthly spending cycle characterized by increased purchases of fresh and shelf-stable foods upon benefit receipt. Given the limited shelf life of fresh produce, this also implies an increase in consumption at the beginning of the month. The higher expenditures on shelf-stable foods suggest that stocking up was also a driver of the observed spending pattern.

For households under twice-monthly payments, the higher payment frequency caused expenditures on fresh fruits and vegetables to increase two weeks after receipt. However, the effect on spending over shelf-stable foods is not significantly different from zero throughout the March benefit cycle. These findings indicate the spending cycle was smoothed out by higher expenditures on fresh foods and meat later in the month. These results have important implications for policymakers seeking to optimize the timing and frequency of SNAP benefits to improve food security for low-income households, as they provide evidence of smoother consumption under higher payment frequency.

6.3 Testing the Smoothing Effect

I measure the smoothness of the spending trajectory by the difference between the average daily expenditures in the first week after payment and three weeks that follow. Specifically, I estimate the following regression by ordinary least squares:

$$y_{it} = \alpha_0 + \alpha_1 \cdot Week1_{it} + \alpha_2 \cdot Y2019_t + \alpha_3 \cdot SNAP_i + \alpha_4 \cdot Week1_{it} \cdot Y2019_t + \alpha_5 \cdot Week1_{it} \cdot SNAP_i + \alpha_6 \cdot Y2019_t \cdot SNAP_i + \alpha_7 \cdot Week1_{it} \cdot Y2019_t \cdot SNAP_i + \delta \cdot X_{it} + c_i + \varepsilon_{it} \quad (3)$$

where $Week1_{it}$ is the indicator of the first seven days following the date of March payment in 2019 and the same seven calendar dates in 2018. Other notations are consistent with previous definitions. I use robust standard errors throughout the analysis. The sample period is restricted to the first four weeks following March benefit payment. We are interested in the estimate of α_7, which is a measure of the smoothness of the spending path in March, accounting for the unobserved within-household time effect and across-household seasonal trend. A significantly positive $\hat{\alpha}_7$ indicates a declining spending path caused by the SNAP payment.

I present the results of the regressions of equation (3) in Table 5. Column (1) reports the estimation results with households residing in states that used a twice monthly payment. Column (2) presents the results for households in states that issued monthly payment in March. 2019. Under a monthly lump-sum payment, the spending on a typical day in the first week following benefit payment was 12% higher than that of an average day in the subsequent weeks, while the difference across weeks was no significant under a twice-monthly payment scheme.

[Table 5 here]

These results provide measures of the SNAP spending cycle. We can compare the estimate with monthly payment scheme to the results generated from other data sources. A closely related study is Beatty et al. (2019), where they find an average household spends 8% more if the day of requisition is in the first week of the benefit cycle in a similar estimation specification. Shapiro (2005) estimates the daily decline in the value of food consumption to be 7% using food intake survey data. This is equivalent to a 7.3% decline in food value if we group dates into weeks. Despite the difference in the study population and identifying assumptions, our estimate with the population under monthly payment during the disruption is consistent with these earlier findings.

To formally test whether there was a smoothing effect of higher payment frequencies, I add an interaction of an indicator of split benefits to the estimation equation (3). The coefficient on the four-way interaction term shows the effect of splitting benefits into twice-monthly payments.

$$y_{it} = \gamma_0 + \gamma_1 \cdot Week1_{it} + \gamma_2 \cdot Y2019_t + \gamma_3 \cdot SNAP_i + \gamma_4 \cdot Split_i + \gamma_5 \cdot Week1_{it} \cdot Y2019_t + \gamma_6 \cdot Week1_{it} \cdot SNAP_i + \gamma_7 \cdot Week1_{it} \cdot Split_i + \gamma_8 \cdot Y2019_t \cdot SNAP_i + \gamma_9 \cdot Y2019_t \cdot Split_i + +\gamma_{10} \cdot SNAP_i \cdot Split_i + \gamma_{11} \cdot Week1_{it} \cdot Y2019_t \cdot SNAP_i + \gamma_{12} \cdot Week1_{it} \cdot Y2019_t \cdot Split_i + \gamma_{13} \cdot Week1_{it} \cdot SNAP_i \cdot Split_i + \gamma_{14} \cdot Y2019_t \cdot SNAP_i \cdot Split_i + \gamma_{15} \cdot Week1_{it} \cdot Y2019_t \cdot SNAP_i \cdot Split_i + \delta \cdot X_{it} + c_i + \varepsilon_{it} \quad (4)$$

Table 6 shows the results of the four-way interaction regression model. The coefficient on the four-way interaction term captures the difference in the smoothness of the spending cycle caused by the higher frequency of payment. In all specifications, the first week spending spike is 20% lower for households that received March benefits in two payments than those received one-time monthly payment. Under the assumption that the SNAP cycle would have been the same as in monthly-payment states for households receiving split disbursement if it were monthly payment, this estimate has a causal interpretation.

[Table 6 here]

Table 7 presents the estimation results by food categories. Decomposing the effect of receipt frequencies into food categories, I find the effect is most extensive with fresh food expenditures, where the first-week spending spike was 10% lower under twice-monthly payment than the lump-sum payment. These findings provide supporting evidence that higher payment frequency caused smoother spending over the benefit month. Furthermore, there are indications of smoother expenditures translating into smoother consumption of fresh fruit and vegetables under the twice-monthly payment, providing a policy-relevant insight that higher SNAP payment frequency could improve food security for SNAP beneficiaries.

[Table 7 here]

7. Conclusion

This study investigates the impact of higher SNAP payment frequency on households' grocery spending patterns, taking advantage of the disruptions caused by the 2018-2019 federal government shutdown. The findings suggest that semi-monthly payments lead to smoother grocery spending over the benefit month, particularly in perishable food items such as fresh fruits and vegetables, indicating potential smoother consumption out of this category. These results provide policy-relevant insights where higher payment frequency could be a cost-effective way to help SNAP beneficiaries stretch food budget over the month.

While the findings offer support for the policy proposal of increasing the frequency of SNAP payments, the research also highlights the need for future pilot studies to examine the policy recommendation in a context with higher external validity by design. Additionally, the study is limited in the inference of the impact on food consumption because of the lack of consumption data. The study stresses the significance of delving deeper into the direct impact of payment frequency on food consumption, along with any correlated secondary outcomes.

Finally, this analysis sheds light on the vulnerability of low-income households during government shutdowns and emphasizes the need for government stability. The results show significant changes in food purchases during a short-lived disruption in SNAP benefit payment. Due to the fact that families who rely on public assistance are disproportionately affected by shutdowns, it is crucial to ensure adequate funding for the social safety net in order to protect the health and well-being of the country's most vulnerable population.

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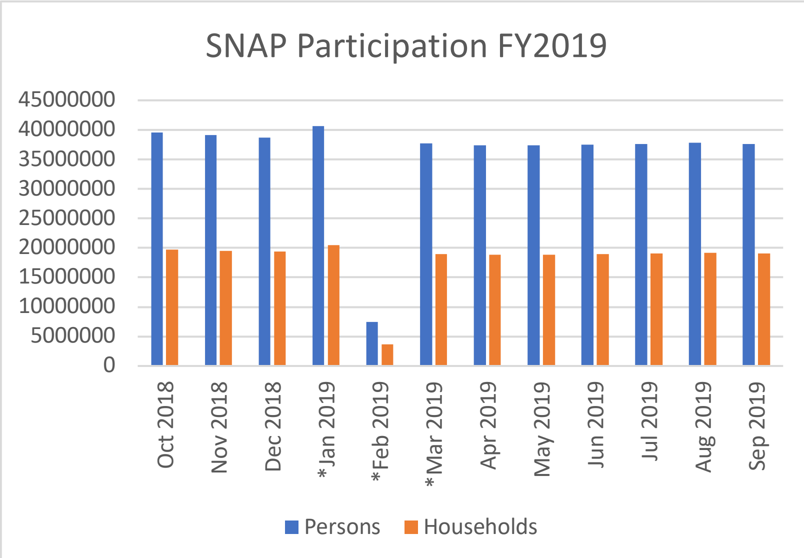
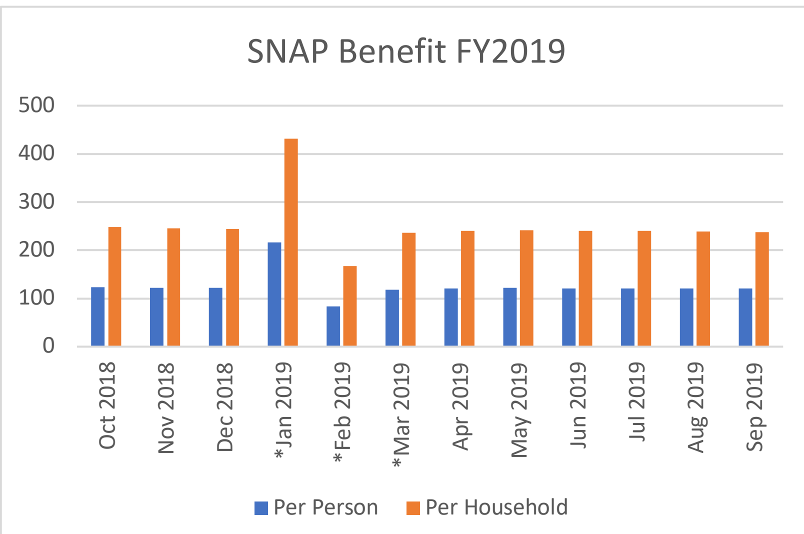
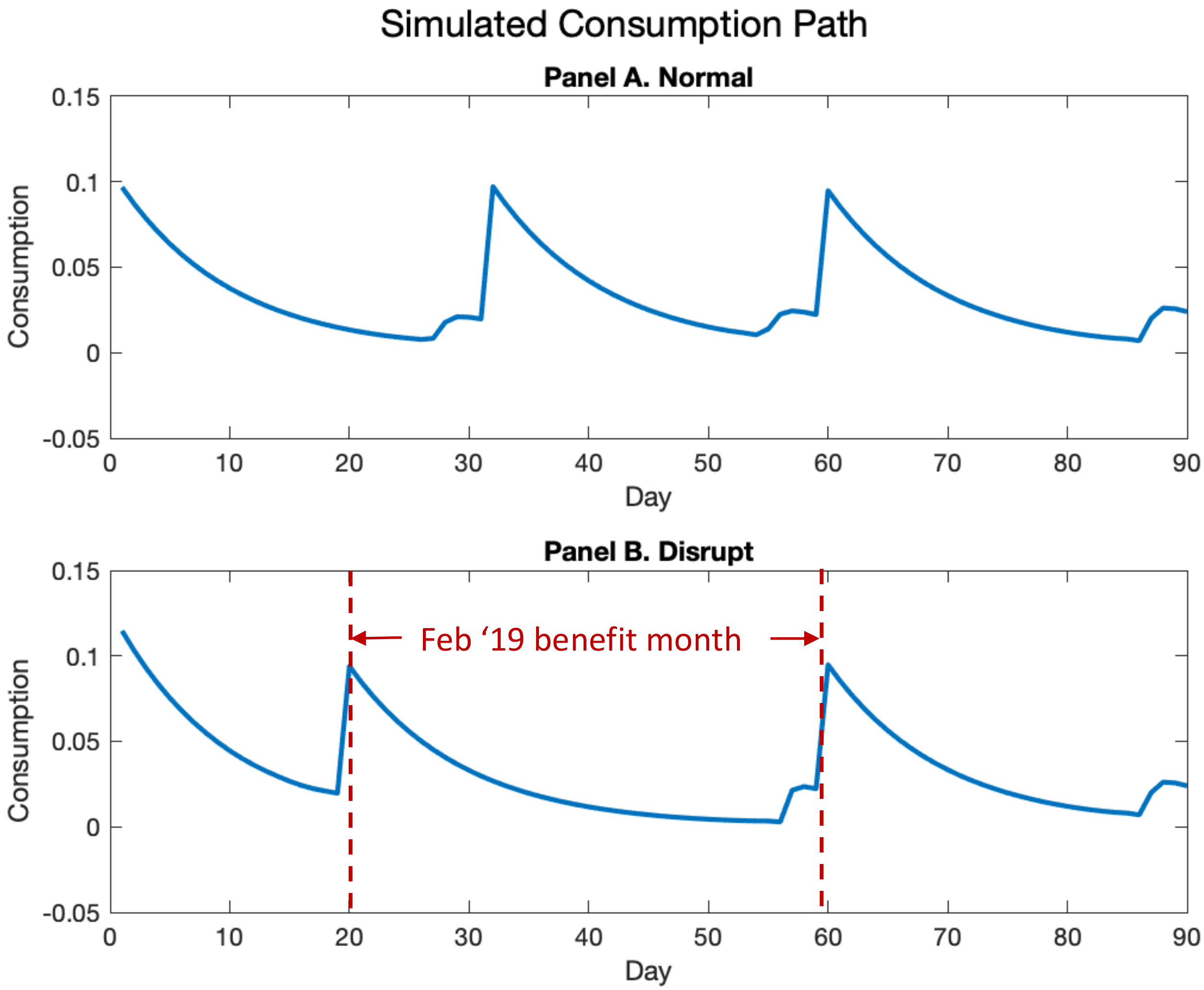
Figure 1. The disruption in SNAP disbursement





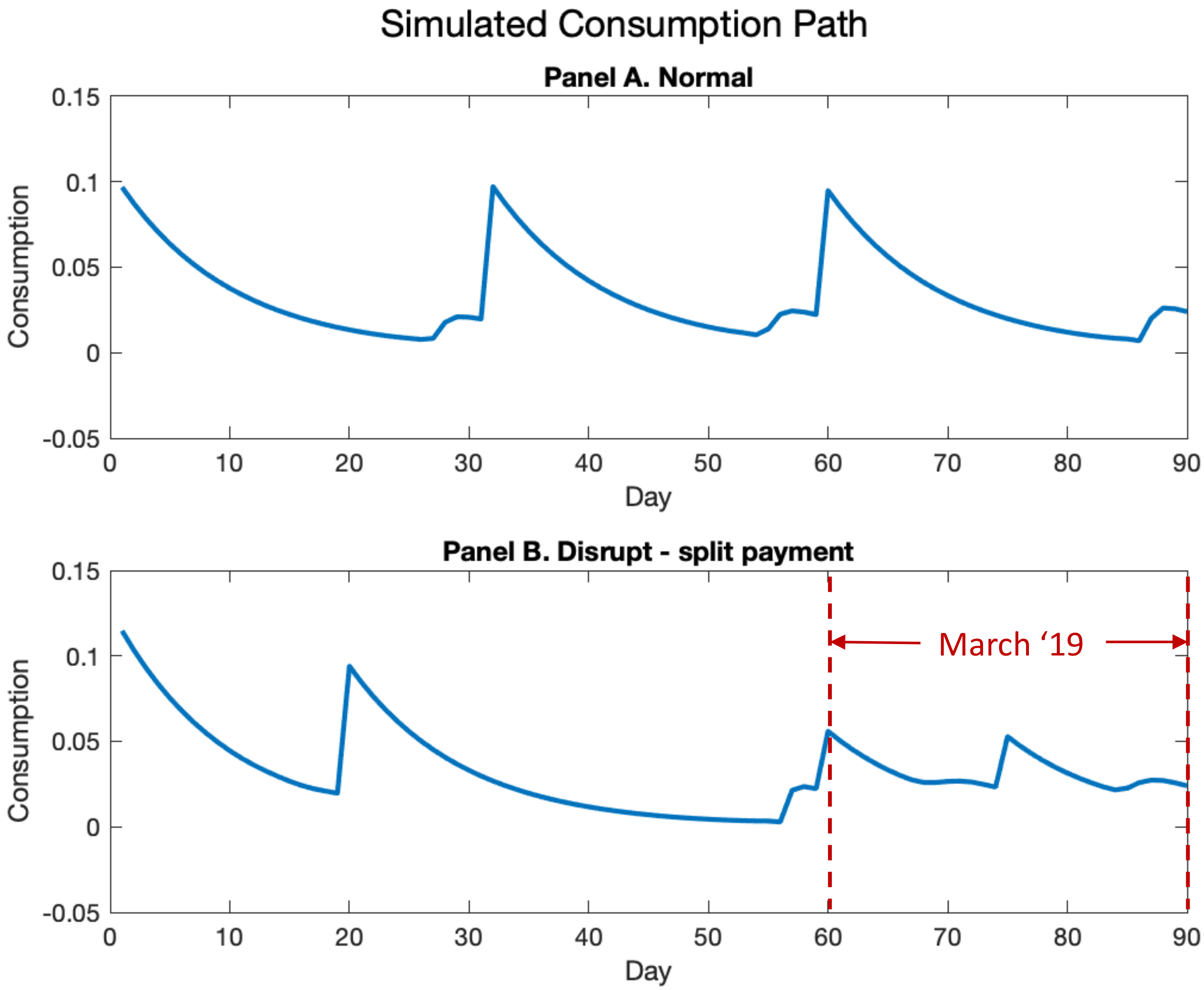
Note: The data is obtained from the monthly SNAP data table maintained by the Food and Nutrition Service of USDA (https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap). Due to the partial Federal government shutdown, most of the February 2019 SNAP benefits were issued early in the month of January 2019. February's data reflects the participation and issuance that was early March issuance in Ohio and Indiana and not part of the early February issuance. As a result, March 2019's participation and benefits show a significant increase over the previous month.

Figure 2. Simulated impact of early payment



Note: The figures depict the simulated consumption paths under hyperbolic discounting. The horizontal axis represents the days elapsed from the first day of a year. The vertical axis shows the daily share of consumption during the benefit month. Panel A shows the case of the hypothetical normal disbursement at the first of each month. Panel B plots the case where the February disbursement occurs early in the latter half of January, and disbursement returns to normal in March.

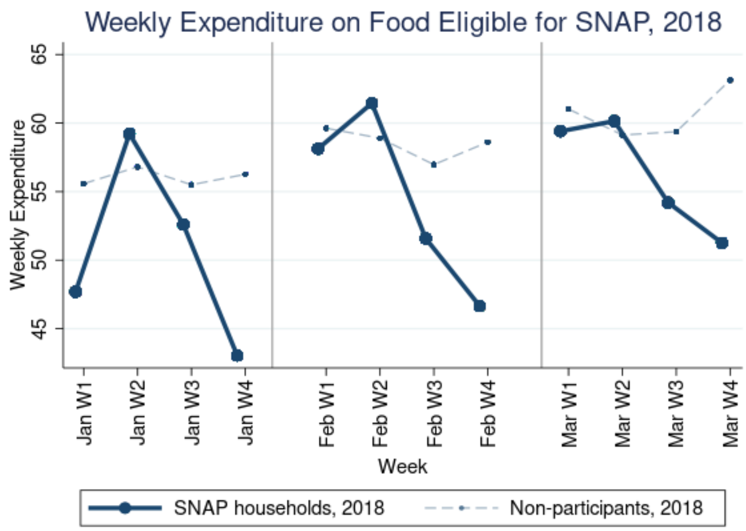
Figure 3. Simulated impact of semi-monthly payment



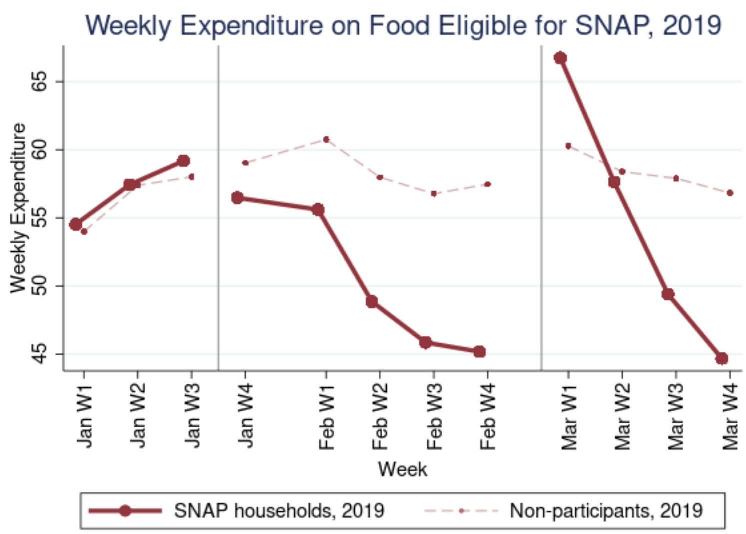
Note: The figures depict the simulated consumption paths under hyperbolic discounting. The horizontal axis represents the days elapsed from the first day of a year. The vertical axis shows the daily share of consumption during the benefit month. Panel A shows the case of the hypothetical normal disbursement at the first of each month. Panel B plots the case where the February disbursement occurs early in the latter half of January, and March benefit is split into two payments on different days.

Figure 4. Weekly expenditure on SNAP eligible items

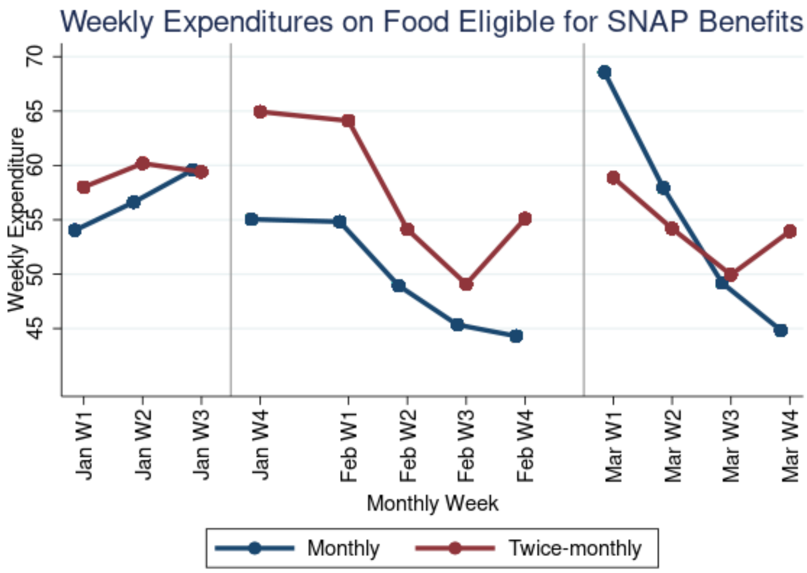
Panel A. Average Expenditures in 2018 By SNAP Participation



Panel B. Average Expenditures in 2019 By SNAP Participation

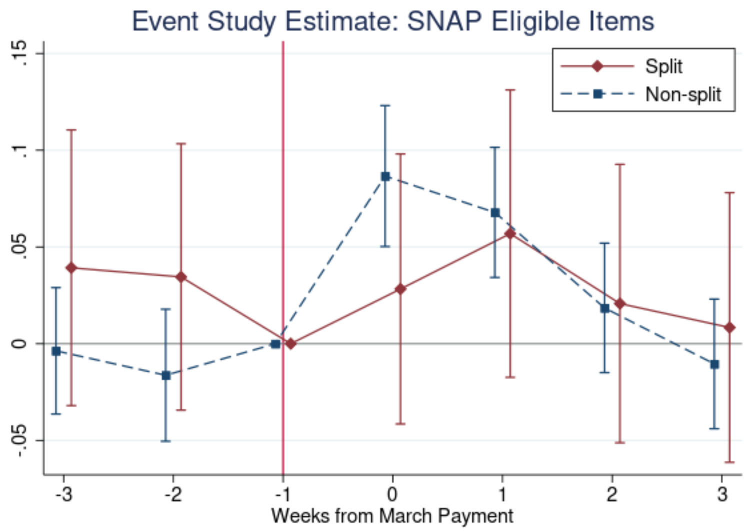


Panel C. Average Expenditures in 2019 By Payment Frequency



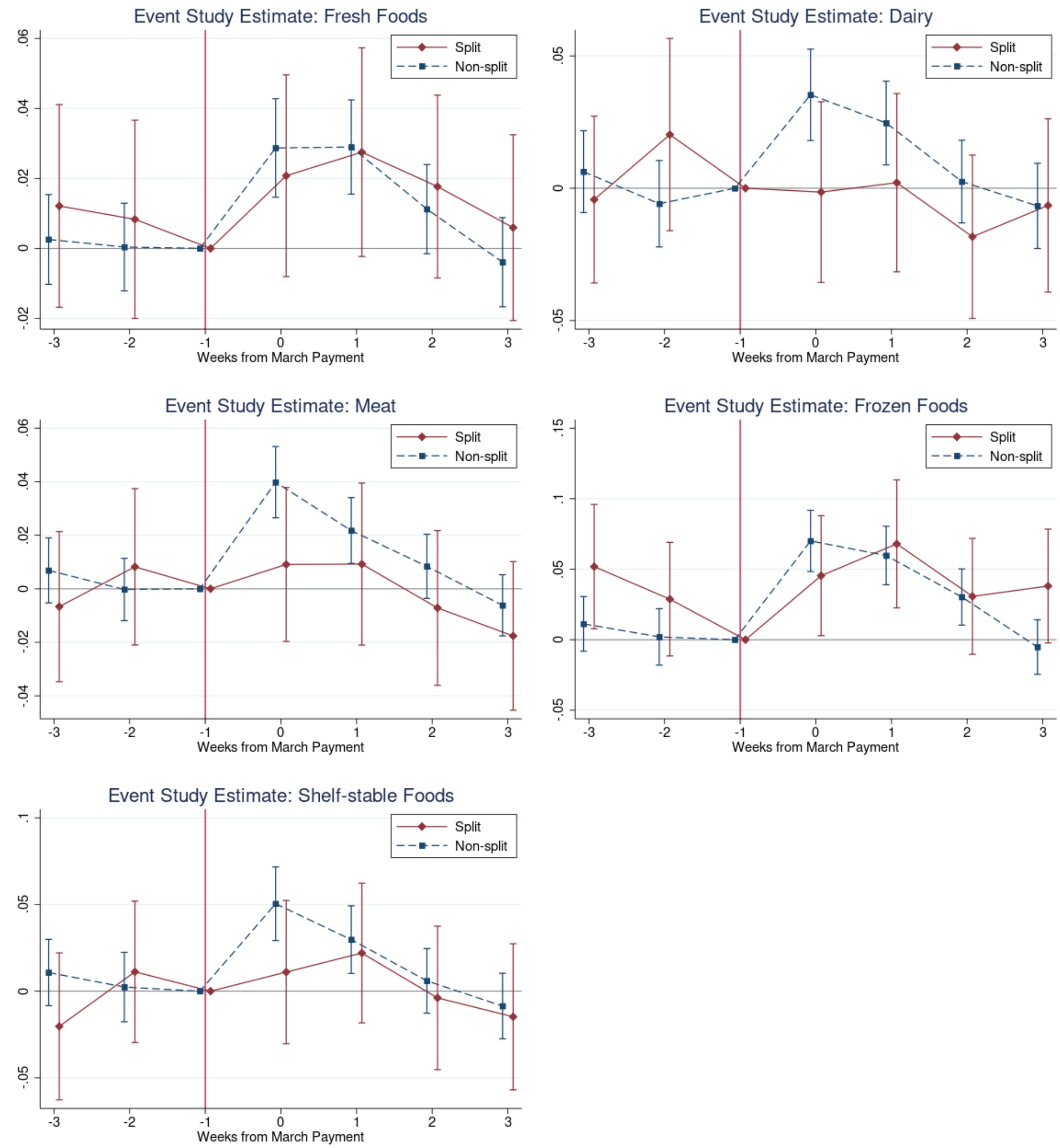
Note: These figures plot the average weekly expenditures on food eligible for SNAP benefits. Weeks are the seven-day periods counting from the 1st to the 28th day of each month. SNAP households are participants in the first quarter of 2018 and 2019. Non-participants are households that did not receive SNAP in the first quarter of both years. Panel A and Panel B plots average weekly spending by SNAP participation status in 2018 and 2019 respectively. Panel C shows the weekly expenditures pattern for SNAP households in 2019 by payment frequency.

Figure 5. Event Study: Daily Spending on SNAP Eligible Items



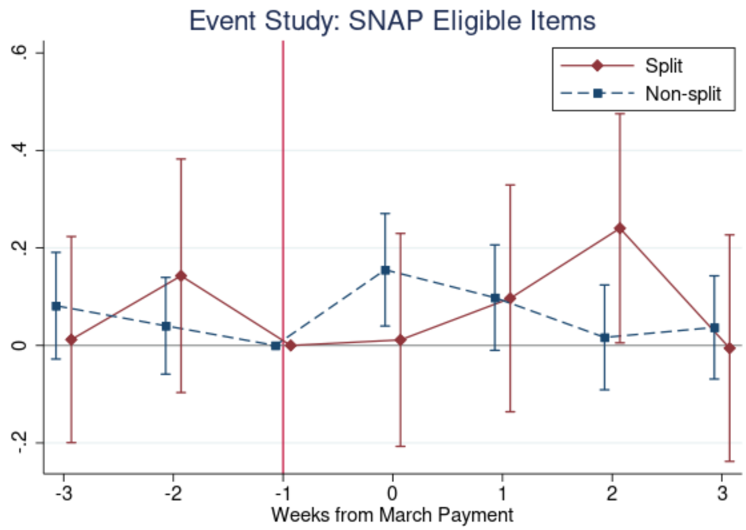
Note: The figure plots the estimates of the event study model evaluating the effect of March SNAP payment during the government shutdown. The coefficients are estimated a from random effect regression of daily food expenditures on the week indicators as well as a full set of control variables. The regressions control for household characteristics (age, marital status, education, race of the household head, and presence of children under age 18), number of SNAP authorized retailers, local TFP cost, weather effect (daily highest temperature and precipitation), time effect (day-of-week fixed effect, holiday effect), and unobserved household fixed effect. The figure also plots corresponding 95% confidence intervals using robust standard errors.

Figure 6. Event Study: Daily Spending by Food Category



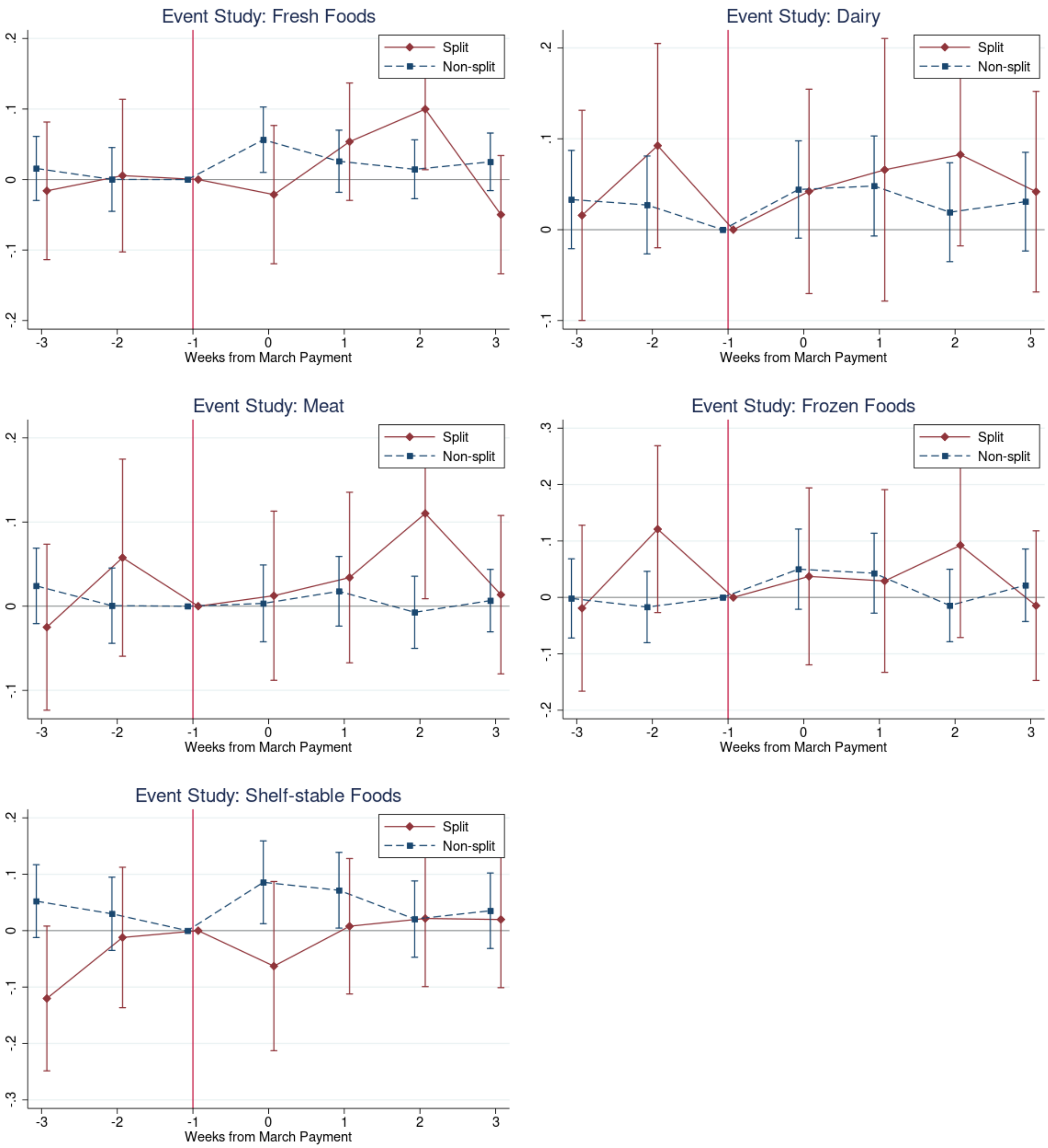
Note: The figure plots the estimates of the event study model evaluating the effect of March SNAP payment during the government shutdown. The coefficients are estimated a from random effect regression of daily food expenditures on the week indicators as well as a full set of control variables. The regressions control for household characteristics (age, marital status, education, race of the household head, and presence of children under age 18), number of SNAP authorized retailers, local TFP cost, weather effect (daily highest temperature and precipitation), time effect (day-of-week fixed effect, holiday effect), and unobserved household fixed effect. The figure also plots corresponding 95% confidence intervals using robust standard errors.

Figure 7. Dynamic Triple Difference: Change in Spending on SNAP Eligible Items



Note: The figure plots the estimates of the dynamic triple difference model evaluating the effect of March SNAP payment by payment frequency. The sample consists of households that participated in SNAP in 2019 but not 2018, as well as households that did not participates in 2018 or 2019. The coefficients are estimated from random effect regressions of daily food expenditures on the three-way interactions of week indicators, an indicator of year 2019, and an indicator of SNAP participation. The regressions control for household characteristics (age, marital status, education, race of the household head, and presence of children under age 18), number of SNAP authorized retailers, local TFP cost, weather effect (daily highest temperature and precipitation), time effect (day-of-week fixed effect, holiday effect), and unobserved household fixed effect. The figure also plots corresponding 95% confidence intervals using robust standard errors.

Figure 8. Dynamic Triple Difference: Change in Daily Spending by Food Category



Note: The figure plots the estimates of the dynamic triple difference model evaluating the effect of March SNAP payment by payment frequency. The sample consists of households that participated in SNAP in 2019 but not 2018, as well as households that did not participates in 2018 or 2019. The coefficients are estimated from random effect regressions of daily food expenditures on the three-way interactions of week indicators, an indicator of year 2019, and an indicator of SNAP participation. The regressions control for household characteristics (age, marital status, education, race of the household head, and presence of children under age 18), number of SNAP authorized retailers, local TFP cost, weather effect (daily highest temperature and precipitation), time effect (day-of-week fixed effect, holiday effect), and unobserved household fixed effect. The figure also plots corresponding 95% confidence intervals using robust standard errors.

Table 1. State SNAP Disbursement Policies in 2019

State	Normal Issuance	Feb 19 Issuance	Mar 19 Issuance
Alabama	4 – 23	1/20/19	3/4/19
Alaska	1	1/20/19	3/4/19
Arizona	1 – 13	1/17/19 – 1/20/2019	3/1/19 – 3/6/19
Arkansas	4 – 13	1/17/19	3/4/19
California	1 – 10	1/16/19	3/1/19
Colorado	1 – 10	1/16/19 – 1/20/2019	3/1/19 – 3/10/19
Connecticut	1 – 3	1/20/19	3/1/19 – 3/3/19
Delaware	2 – 23	1/17/19	3/4/19
District of Columbia	1 – 10	1/16/19	2/26/19
Florida*	1 – 28	1/20/19	Half 3/1/19; Half normal
Georgia*	5, 7, 9, 11, 13, 15, 17, 19, 21, 23	1/14/19	Half 3/2/19; Half normal
Hawaii	1, 5	1/20/19	3/1/19 – 3/5/19
Idaho	1 – 10	1/20/19	3/1/19 – 3/10/19
Illinois	1, 3, 4, 5, 6, 7, 8, 9, 10, 13, 17, 20	1/20/19	3/1/19
Indiana*	5, 7, 9, 11, 13, 15, 17, 19, 21, 23	1/16/19	Half 2/22/19; Half normal
Iowa	1 – 10	1/17/19	3/1/19 – 3/10/19
Kansas	1 – 10	1/20/19	3/1/19
Kentucky	1, 3, 5, 7, 9, 11, 13, 15, 17, 19	1/20/19	3/1/19
Louisiana	1 – 14	1/16/19	3/1/19 – 3/2/19
Maine	10 – 14	1/17/19	3/3/19
Maryland	4 – 23	1/20/19	3/6/19
Massachusetts	1, 2, 4, 5, 7, 8, 10, 11, 13, 14	1/17/19 – 1/20/2019	3/1/19 – 3/4/19
Michigan	3, 5, 7, 9, 11, 13, 15, 17, 19, 21	1/19/19	3/3/19 – 3/5/19
Minnesota	4 – 13	1/20/19	3/4/19 – 3/6/19
Mississippi	4 – 21	1/20/19	3/4/19
Missouri	1 – 22	1/20/19	3/1/19 – 3/22/19
Montana	2 – 6	1/17/19	3/2/19
Nebraska	1 – 5	1/20/19	3/1/19
Nevada	1	1/20/19	3/1/19
New Hampshire	5	1/20/19	3/5/19
New Jersey	1 – 5	1/17/19	3/1/19
New Mexico	1 – 20	1/20/19	3/1/19
New York	1 – 9	1/17/19	3/1/19
North Carolina	3, 5, 7, 9, 11, 13, 15, 17, 19, 21	1/20/19	3/3/19
North Dakota	1	1/20/19	3/1/19
Ohio*	2, 4, 6, 8, 10, 12, 14, 16, 18, 20	1/16/19	Half 2/22/19; Half normal
Oklahoma	1, 5, 10	1/20/19	3/1/19
Oregon	1 – 9	1/18/19	3/1/19
Pennsylvania	First 10 weekdays	1/18/19	3/1/19 – 3/14/19
Rhode Island	1	1/20/19	3/1/19
South Carolina	1, 3, 5, 7, 9, 11, 13, 15, 17, 19	1/17/19	3/5/19
South Dakota	10	1/20/19	3/10/19
Tennessee	1 – 20	1/20/19	3/1/19 – 3/6/19
Texas	1, 3, 5, 6, 7, 9, 11, 12, 13, 15	1/20/19	3/1/19 – 3/10/19
Utah	5, 11, 15	1/20/19	3/5/19

Vermont	1	1/20/19	3/1/19
Virginia	1, 4, 7	1/17/19	3/1/19
Washington	1 – 10	1/20/19	3/2/19 – 3/11/19
West Virginia	1 – 9	1/20/19	3/1/19
Wisconsin	2, 3, 5, 6, 8, 9, 11, 12, 14, 15	1/20/19	3/1/19
Wyoming	1 – 4	1/16/19 – 1/19/2019	3/1/19 – 3/4/19

Note: SNAP issuance schedules are obtained from state government website.

* indicates states that paid March benefit in two installments.

Table 2. Summary Statistics of Household Characteristics

Variable	Non-participants		Participants both years		Participants 2018 only		Participants 2019 only	
Household size	2.11	(1.09)	2.05*	(1.34)	2.43*	(1.47)	2.35*	(1.37)
Income below $40k	0.27	(0.44)	0.86*	(0.35)	0.68*	(0.47)	0.68*	(0.47)
Married	0.60	(0.49)	0.27*	(0.44)	0.42*	(0.49)	0.36*	(0.48)
Presence of children	0.14	(0.34)	0.18*	(0.38)	0.24*	(0.43)	0.21*	(0.41)
Head age > 50	0.82	(0.39)	0.78*	(0.41)	0.70*	(0.46)	0.69*	(0.46)
Head Employed	0.64	(0.48)	0.35*	(0.48)	0.64	(0.48)	0.48*	(0.50)
College Degree	0.56	(0.50)	0.29*	(0.46)	0.40*	(0.49)	0.32*	(0.47)
White	0.85	(0.36)	0.79*	(0.41)	0.72*	(0.45)	0.77*	(0.42)
Black	0.08	(0.27)	0.14*	(0.35)	0.21*	(0.41)	0.14*	(0.35)
Asian	0.03	(0.18)	0.02*	(0.13)	0.02*	(0.13)	0.02*	(0.13)
Hispanic Origin	0.05	(0.22)	0.06	(0.23)	0.06	(0.25)	0.08*	(0.28)
Observations	20,696		1,166		278		364	

Note: This table summarizes demographic characteristics of the households in the Nielsen Homescan Panel with matched self-reported SNAP participation status. Households are categorized into groups by their participation in SNAP in the first quarter of 2018 and 2019. Marital status, age, employment, education, and race are based on the information of the household head. The first column under each category reports the mean values and the second column reports the standard deviation.
* Indicates significant difference from column (1) at the 5% level.

Table 3. Summary Statistics of Household Weekly Purchase Pattern

Weekly Expenditures ($)	Non-participants		Participants both years		Participants 2018 only		Participants 2019 only	
Shopping days	2.18	(1.09)	2.13*	(1.16)	2.28*	(1.19)	2.13	(1.22)
Total	114.55	(70.43)	101.73*	(74.34)	110.55	(70.56)	107.05*	(89.12)
SNAP Eligible	57.79	(34.81)	52.96*	(34.71)	57.07	(37.76)	54.93	(44.66)
Fresh Produce	6.13	(6.87)	3.85*	(5.00)	4.60*	(5.44)	4.09*	(5.01)
Meat	3.40	(3.60)	3.12*	(3.32)	3.92*	(5.38)	3.45*	(3.86)
Dairy	7.41	(5.69)	6.22*	(5.17)	6.90*	(5.97)	6.54*	(5.61)
Frozen foods	11.66	(9.56)	11.03*	(9.70)	12.06	(10.74)	11.40	(11.02)
Shelf-stable	9.10	(8.71)	9.64*	(7.12)	9.41	(8.54)	9.78	(7.32)
Observations	20,696		1,166		278		364	

Note: This table summarizes weekly grocery expenditures of the households in the Nielsen Homescan Panel with matched self-reported SNAP participation status. Households are categorized into groups by their participation in SNAP in the first quarter of 2018 and 2019. The first column under each category reports the mean values and the second column reports the standard deviation.
* Indicates significant difference from column (1) at the 5% level.

Table 4. Summary Statistics of Local Retailers and Food Prices

Variable	Non-participants		Participants both years		Participants 2018 only		Participants 2019 only	
All Retailers	20.54	(16.17)	24.74*	(19.96)	24.73*	(1.47)	23.07*	(19.30)
Convenience Stores	9.04	(7.93)	11.38*	(9.34)	11.22*	(9.13)	10.63*	(9.31)
Grocery Stores	1.72	(3.85)	2.79*	(6.03)	2.58*	(5.36)	2.47*	(5.32)
TFP Cost	85.53	(10.10)	85.94	(10.52)	85.60	(10.38)	85.41	(9.84)
Observations	20,696		1,166		278		364	

Note: This table summarizes the number of SNAP authorized retailers and local food prices at the zip code of the households in the Nielsen Homescan Panel. Households are categorized into groups by their participation in SNAP in the first quarter of 2018 and 2019. The first column under each category reports the mean values and the second column reports the standard deviation.
* indicates significant difference from column (1) at the 5% level.

Table 5. The Smoothness of the SNAP Spending Cycle

	Ln(Expenditures on SNAP Items)	
	(1)	(2)
	Twice-Monthly	Monthly
Week1*SNAP*Y2019	-0.109	0.124*
	(0.112)	(0.060)
Time Fixed Effect	√	√
Household Characteristics	√	√
Weather	√	√
Avg. Exp. In Ref. Weeks ($)	60.71	51.81
N	249,049	1,061,039

Note: This table presents estimation results of equation (3) where the dependent variables are logged expenditures on items eligible for SNAP benefits and the main independent variables are the interactions of a dummy for the year of disruption, a dummy for the first week in the benefit month, and a dummy for 2019-only SNAP participant. The sample consists of purchases during the four weeks after the March payment among households that only participated in 2019 and households that never participated in 2018 and 2019. All specifications are estimated using random effect GLS accounting for unobserved household fixed effect. All regressions control for the full set of control variables.
Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 6. The Effect of Twice-Monthly SNAP Payment

	(1) Ln(SNAP exp)	(2) Ln(SNAP exp)	(3) Ln(SNAP exp)	(4) Ln(SNAP exp)
Split vs. No Split	-0.198*	-0.195*	-0.195*	-0.196*
	(0.104)	(0.103)	(0.104)	(0.104)
Time Fixed Effect		√	√	√
Household Characteristics			√	√
Weather				√
Avg. Weekly Exp. in Week 1 ($)	54.88	54.88	54.88	54.88
Avg. Exp. Other weeks ($)	51.66	51.66	51.66	51.66
N	1,320,416	1,320,416	1,320,416	1,310,088

Note: This table contains the results obtained when the dependent variables are logged expenditures on items eligible for SNAP benefits and the main independent variables are the interactions of a dummy for the year of disruption, a dummy for the first week in the benefit month, a dummy for 2019-only SNAP participant, and a dummy for twice-monthly payment. The sample consists of purchases during the four weeks after the March payment among households that only participated in 2019 and households that never participated in 2018 and 2019. All specifications are estimated using random effect GLS accounting for unobserved household fixed effect. Columns (2)-(4) control for day-of-week fixed effects and holidays. Columns (3) and (4) additionally control for presence of children, marital status, age, education, and race of the household head, along with local retailers and food cost. Daily precipitation and temperature are added in the last column.

Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 7. The Effect of Twice-Monthly SNAP Payment, Decomposition by Food Categories

	(1) ln(Fresh)	(3) ln(Dairy)	(4) ln(Meat)	(2) ln(Frozen)	(5) ln(Stable)
Split vs. No Split	-0.103*	-0.043	-0.040	-0.010	-0.087
	(0.057)	(0.059)	(0.047)	(0.080)	(0.068)
Avg. Weekly Exp. Week 0 ($)	4.34	6.65	3.29	12.04	9.24
Avg. Exp. Other weeks ($)	4.13	6.30	3.08	10.78	8.82
N	1,310,088	1,310,088	1,310,088	1,310,088	1,310,088

Note: This table contains the results obtained when the dependent variables are logged expenditures on food categories eligible for SNAP benefits and the main independent variable is the interaction of a dummy for the year of disruption, a dummy for the first week of the benefit month, a dummy for 2019-only SNAP participants, and a dummy for twice-monthly payment. The sample consists of purchases during the four weeks after the March payment among households that only participated in 2019 and households that never participated in 2018 and 2019. All specifications are estimated using random effect GLS accounting for unobserved household fixed effect. All columns control for day-of-week fixed effects and holidays, and household characteristics including presence of children, marital status, age, education, and race of the household head, number of local SNAP retailers, the local food cost, as well as daily precipitation and temperature.
Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.