NBER WORKING PAPER SERIES

# IS A DOLLAR A DOLLAR? HOW TRANSFER DESIGN SHAPES HOUSEHOLD SPENDING

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Working Paper 35698
http://www.nber.org/papers/w35698

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2026, Revised October 2026

We thank Jeffrey Campbell, Karen Dynan, Doug Elmendorf, Hilary Hoynes, Ezra Karger, Jonathan Parker, Jesse Rothstein, Michael Strain, seminar participants at Dartmouth, Princeton, UW-Madison, Indiana University, and Georgetown for helpful comments. Researchers' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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Is a Dollar a Dollar? How Transfer Design Shapes Household Spending
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NBER Working Paper No. 35698
September 2026, Revised October 2026
JEL No. D12, E21, H31, H53, I38


## ABSTRACT

Government transfers vary along two design dimensions that standard models predict should not matter: whether benefits are paid in cash or kind, and whether they arrive as one-time or recurring payments. We test to what extent these design choices affect household spending using sharp changes in four pandemic-era transfers to low-income families with children: one-time food vouchers, monthly food benefits, one-time cash payments, and monthly cash payments. Linking variation in benefit timing and amount to high-frequency household scanner data, we estimate spending responses in a harmonized difference-in-differences and event-study framework.

We find that households spend more out of in-kind benefits than out of cash transfers of similar value, and more out of recurring payments than out of one-time transfers in the short-run. Our estimates produce the first internally comparable set of short-run food-store MPCs across different transfer types ranging from 0.20 (one-time) and 0.43 (monthly) for in-kind benefits, versus 0.07 (one-time) and 0.22 (monthly) for cash. The patterns suggest that the form and timing of transfers systematically shape household spending in ways that are consistent with mental accounting, labeling, and forward-looking responses. More broadly, our results imply that transfer design—not just generosity and targeting—is a first-order policy lever for both social insurance and short-run demand stabilization.



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# 1 Introduction

Government transfer programs differ not only in eligibility criteria and generosity, but also in *how* benefits are delivered. A household can receive $600 as unrestricted cash or as a food voucher, as a single, lump-sum payment or in six monthly installments. In a standard model with forward-looking consumers, no binding liquidity constraints, and inframarginal in-kind benefits, none of these design choices should affect the amount or allocation of spending (Deaton, 1992; Browning and Lusardi, 1996). A dollar is a dollar. Yet governments routinely restrict the uses of transfers, label payments for particular purposes, and choose payment schedules that vary from one-time relief to monthly support. Whether these design choices affect spending is central to questions in public finance—because in-kind restrictions and monthly disbursement carry real administrative costs that are optimal only if they change behavior—and to macroeconomics, where marginal propensities to consume (MPCs) are a key input in models of fiscal transmission.

This paper studies how the form and frequency of transfers shape household spending. We analyze four large pandemic-era programs that produce a clean two-by-two comparison. Between 2020 and 2023, low-income U.S. families with school-age children received substantial resources in different forms through Pandemic EBT (P-EBT, one-time in-kind), the Supplemental Nutrition Assistance Program Emergency Allotment (SNAP EA, monthly in-kind), Economic Impact Payments (EIPs, one-time cash), and the temporarily expanded monthly Child Tax Credit (CTC, monthly cash). The four programs vary along both design dimensions—cash versus in-kind, and one-time versus recurring—while reaching overlapping populations of low-income households over a narrow window. This set-up allows us to compare cash with in-kind transfers holding frequency fixed, and recurring with one-time transfers while holding form fixed, within a single sample, dataset, and empirical framework.

We combine this policy variation with high-frequency household spending data from the NielsenIQ Consumer Panel, which records daily purchases including prices, products, dates of purchase, and store types for a longitudinal panel of households. Our analysis focuses

on low-income households with school-aged children, the group potentially receiving all four transfer types. For P-EBT and SNAP EA, we identify spending responses from cross-state variation in the timing of benefits, using not-yet-treated households as controls and reporting cohort-by-cohort estimates as a robustness check. For the EIP and CTC, we compare eligible households in the payment period to comparable households in the same calendar weeks of 2019. Because take-up is not observed at the household level, our regression coefficients are intention-to-treat effects; our headline MPCs additionally adjust for program-specific administrative take-up rates and trip underreporting.

We find that both the frequency and form of benefits substantially impact spending responses. Our estimated marginal propensities to consume at food stores after adjusting for underreporting of shopping trips for in-kind payments are 0.20 (P-EBT, one-time) and 0.43 (SNAP EA, monthly), and for cash are 0.07 (EIP, one-time) and 0.22 (CTC, monthly). Unadjusted MPCs are one-half these magnitudes.

Two patterns stand out. First, holding frequency fixed, the in-kind MPCs are roughly three times cash MPCs for one-time transfers (0.20 vs. 0.07) and nearly twice as large (1.9 times) for monthly transfers (0.43 vs. 0.22). Second, holding form fixed, monthly MPCs are roughly two to three times the one-time MPCs (0.43 vs. 0.20 for in-kind; 0.22 vs. 0.07 for cash). Restricting the outcome to food products only—excluding non-food items sold at food stores such as soap, paper products, and personal-care items—attenuates these numbers, with food-product MPCs of about 13-17% for in-kind benefits and 3-11% for cash. Neither pattern is consistent with full fungibility.

Turning to the composition of spending, transfer design affects the amount households spend at food stores, with monthly in-kind benefits increasing their purchases of both food and non-food items. That is, for monthly in-kind benefits (SNAP EA), the increase in total food-store spending is substantially larger than the increase in food-product spending, indicating that a substantial share of the SNAP EA response shows up in non-food purchases at food stores. This is inconsistent with a pure mental-accounting story in which dollars labeled "food" flow exclusively to food, and instead points to SNAP EA relaxing the budget

constraint on food so that freed-up cash flows to complementary in-store purchases. At the same time, we find little evidence that transfer design changes the food product mix: households do not systematically shift toward or away from perishables, bulk purchases, or "temptation" categories such as alcohol, tobacco, sweets and soda.

Four sets of analyses support the main identification strategy. First, event-study estimates show spending rising promptly after P-EBT, EIP, and CTC payments, with no evidence of differential pre-trends; SNAP EA spending is elevated in months when benefits are available and drops when states discontinue the program. The CTC event study exhibits a "sawtooth" pattern in which spending rises in the week of payment, remains elevated for two weeks, falls in the third week, then rises again with the next month's payment. This pattern suggests that households anticipate benefit replenishment. Second, spending responses are largest among the households most likely to be liquidity constrained: low-income families with children. Third, placebo comparisons for groups ineligible for child-targeted benefits show no evidence of spurious effects. Several robustness checks are consistent with the baseline estimates. We estimate an alternative SNAP EA impact from a benefit formula change that increased payments by $12 on average, and find that spending results are the same as those estimated from the $400 in monthly benefits in the pooled sample estimate. Our EIP1 estimate using 2019 as the control period is the same as from an alternative estimate using 2022, and pre-pandemic (2019) MPCs from refundable tax-credit payment are indistinguishable from the 2020 EIP1 estimates, suggesting that the small cash MPC we recover is not an artifact of pandemic-era conditions.

These findings contribute to several literatures. First, an extensive theoretical literature considers when in-kind transfers may dominate cash on targeting, paternalism, political-economy, and pecuniary-externality grounds (Nichols and Zeckhauser, 1982; Currie and Gahvari, 2008; Chorniy et al., 2025), alongside a growing empirical literature testing whether households treat food benefits as fungible with cash (Hoynes and Schanzenbach, 2009; Hastings and Shapiro, 2018). We build on this evidence and extend it in three ways: first, by comparing multiple in-kind and cash programs holding sample, empirical strategy, and

outcome definitions fixed; second, by systematically documenting *where* the extra in-kind spending occurs within food stores; and third, by showing that payment frequency is a distinct design margin.

Second, a parallel literature estimates household consumption responses to transitory income shocks, with recent findings emphasizing that households spend a meaningful share of predictable or anticipated income changes (Aladangady et al., 2023; Kueng, 2018; Ganong et al., 2024). Pandemic-era MPCs have been estimated by Parker et al. (2022); Baker et al. (2023); Song (2022) and Chetty et al. (2024) among others. A related strand highlights that MPC estimates can be sensitive to measurement and design choices (Boehm et al., 2025). For example, Orchard et al. (2025) and Orchard et al. (2026) show that estimated responses to earlier tax rebates are sensitive to the treatment of dynamics and to how consumption categories are aggregated. Several features of our setting are helpful for reconciling these findings. Our outcomes are precisely measured using household scanner reports instead of self-reported purchases; second, for P-EBT and SNAP EA, we use not-yet-treated groups in the same calendar year as controls to account for broader macroeconomic fluctuations; and third, we estimate MPCs at food stores, which is less sensitive to purchases of durable goods than a total-consumption MPC. Section 5.2 documents which portion of the food-store response is food and non-food, and which share of likely spending is not captured in the NielsenIQ data.

Finally, the paper informs the design of social insurance and anti-poverty programs (Bitler and Hoynes, 2016; Parker et al., 2022). During economic downturns and emergencies, policy-makers weigh broad cash payments against targeted recurring support and in-kind assistance. Our results imply that these choices affect not only *who* receives aid, but also *how quickly* and *where* the transfers are spent. In-kind and monthly benefits generate larger short-run responses at food stores, while cash and one-time benefits deliver broader flexibility and, we infer, higher rates of saving, debt repayment, or spending on categories outside of the NielsenIQ dataset such as rent, utilities, and durable goods. Our results are consistent with households treating recurring transfers as part of regular disposable resources, and treating

lump-sum payments as more available for saving, debt repayment, or spending outside of food stores. They also suggest an interpretation of forward-looking replenishment behavior in which the marginal use of a dollar depends on whether the household expects another dollar to arrive next month.

The remainder of the paper proceeds as follows. Section 2 describes the four pandemic-era transfer programs and the sources of policy variation we use to identify spending responses. Section 3 describes the NielsenIQ Consumer Panel, our analysis sample, and the trip under-reporting adjustment. Section 4 outlines the empirical approach. Section 5 presents the main results, including MPC estimates by transfer type and the composition of the spending response. Section 6 presents event-study estimates and examines threats to identification, including placebo tests and the treatment of staggered timing. Section 7 examines heterogeneity by income and household composition. Section 8 concludes with implications for household spending models and for the design of stabilization and anti-poverty policy.

# 2 Identification Strategy and Policy Variation

We study four pandemic-era transfers that vary along two design dimensions: whether benefits are paid in cash or as in-kind grocery benefits, and whether they arrive as a one-time lump sum or as monthly recurring payments. All four programs reached low-income families with school-age children, the population we use for our primary comparisons. Section 7 extends the analysis to other groups. We describe the policies in more detail below.

## 2.1 One-time, In-kind Payments: Pandemic EBT (P-EBT)

Due to widespread school closures during the COVID-19 pandemic, many children lost access to free or reduced-price school meals. The P-EBT program provided grocery vouchers for the value of the missed school meals to students who were eligible to receive free- or reduced-price school meals. These benefits could then be redeemed to purchase food at retailers that accepted SNAP benefits. The initial disbursement was primarily paid in a lump sum during summer 2020, worth $5.70 per student per day of school missed in spring

2020.[1] Because school closures were nearly universal in spring 2020, there was relatively little variation in payment amounts within or across states; payments averaged about $300 per student ($638 per household in our analysis sample).

The timing of P-EBT benefit receipt varied across states because participation required USDA approval of a state-submitted implementation plan. A few states made payments in April 2020, most in May or June, and some as late as fall 2020 (Figure A1).[2] Payments were automatically loaded onto SNAP participants' existing EBT cards. We identify the impacts of P-EBT payments from cross-state variation in the timing of disbursement, and we impute the benefit per child using state-level USDA reports on the amount issued and number of children served for the 2019-20 school year.

## 2.2 Monthly, In-kind Payments: SNAP Emergency Allotments (SNAP EA)

SNAP provides benefits that can be used to purchase most grocery items at most food stores. Benefits are paid monthly on electronic benefit transfer (EBT) cards that look and function like debit cards. Under normal circumstances, SNAP benefit levels are calculated with a formula similar to a negative income tax: households with no net income receive a "guarantee" equal to the maximum benefit, and as net income increases, benefits are reduced at a 30% rate.

In March 2020, states were given the option to enact temporary "Emergency Allotment" (SNAP EA) payments that increased benefits for all SNAP participants to the maximum benefit for their household size. All states took this option by April 2020. SNAP EAs were later amended so that starting between March and June 2021 (depending on the state) all participating households received at least $95 in SNAP EA payments.

Unlike regular SNAP, which has little cross-state or cross-time variation in benefit levels, SNAP EA produced sharp state-by-month variation as states terminated the emergency allotments at different times between June 2021 and March 2023, shown in Figure A1. We

[1] Approximately 84% of students lived in a state that made a single payment for the 2019-20 school year; 16% lived in a state that made multiple, smaller payments in the summer of 2020 (Bauer et al., 2024).

[2] See Section 4 for sample-window details.

use this cross-state variation stemming from the termination of increased monthly benefits to identify the impacts of additional in-kind monthly transfers.

SNAP EA payment amounts vary by a household's monthly net income—a complicated function of total income minus several deductions, including a portion of earned income, child care expenses, and some housing payments. Since the NielsenIQ data do not include sufficient information to precisely calculate SNAP EA payment amounts, we impute this information from SNAP Quality Control administrative data by calculating average SNAP EA payment for households with children by household size and income bin and assigning these SNAP EA amounts to households in our analysis sample. Although the "experiment" used to identify the impact is a reduction in the monthly benefit, to ease interpretation and comparison with the other policies we reverse the sign so the coefficient can be interpreted as the impact of a benefit increase. SNAP EA benefits averaged $400 per month in our sample, and their termination reduced average SNAP benefits for these households by 42%.

## 2.3 One-time, Cash Payments: Economic Impact Payments (EIP)

In each recession since 2001, families have received lump-sum "stimulus" payments in a policy effort to support incomes and stabilize aggregate demand. During the COVID-19 pandemic, three stimulus payments, called Economic Impact Payments (EIPs), were issued. The first, in April 2020, paid $1,200 to each adult and $500 per child to families earning less than $112,500 (heads of households) or $150,000 (married couples). The IRS automatically disbursed payments based on prior-year tax returns, and take-up was high by the end of April 2020 (Government Accountability Office, 2020; IRS, 2020).

The first EIP was large, unexpected, and perceived as one-time since subsequent payments were not discussed until months later, providing an optimal setting to examine expenditure responses to one-time cash transfers. Our identification for the EIP comes by comparing outcomes for families with children observed between March and May 2020 with similar families observed between March and May 2019, with payment amounts varying by the number of children and adults in the household, similar to the approach in Chetty et al. (2024).

### 2.4 Monthly, Cash Payments: Expanded Child Tax Credit (CTC)

The federal Child Tax Credit (CTC) normally provides an annual, partially refundable tax credit when families file their federal income taxes. The credit was temporarily changed for the 2021 tax year. First, it was made fully refundable so that low-income families received the full credit if they had little or no earned income. Second, the maximum credit was increased by roughly 50-80% depending on child age. Third, instead of operating as an annual tax credit, between July and December 2021, the IRS made monthly payments of $250 per child ($300 per child younger than 6) to households based on income and children the previous year.

Similar to the EIP analysis, we identify the impacts of the monthly cash transfers provided through the refundable advance CTC by comparing outcomes for households with children observed between April and November 2021 with similar households observed between April and November 2019, with payment amounts varying by the number and ages of children in the household.[3] Average benefits in our sample were $556 per month.

## 3 Data

We use household spending data from the NielsenIQ Consumer Panel, a longitudinal panel dataset in which participating households scan barcodes for all products purchased for personal, in-home use across all retail outlets. For each shopping trip, we observe the products purchased, their prices, the date, and the (de-identified) store. Households report demographic information annually, including the number and year of birth of household members and annual income (binned). We restrict the sample to households with at least one school-aged child (age 6-18 as of December 31).

Our primary outcome is total weekly spending at food stores as reported on scanned receipts, defined to include grocery, discount, and club stores as well as smaller specialty retailers such as convenience stores, bakeries, and butchers.[4] Restaurant spending (includ-

[3] We do not compare to the second half of 2020 because that timeframe is potentially contaminated by other COVID-19 relief payments.

[4] In our sample, 55% of food spending at food stores occurs at grocery stores, 35% at discount stores, 7% at club stores, and 3% at other types of food stores (bakeries, butchers, etc.). Store types not included in

ing fast food and delis) is excluded from the primary outcome and is reported separately. Using product-level scans, we disaggregate food-store spending into food products (grouped into perishables—dairy, deli, packaged meat, and fresh produce—and non-perishables—dry grocery and frozen foods) and non-food products. We report two additional subcategories: "sweets and soda" (candy, cookies, ice cream, frozen desserts, pudding, carbonated beverages and sugar/sweeteners) and "alcohol and tobacco."[5] All dollar values are inflation-adjusted by the monthly CPI for food at home and are reported in December 2022 dollars.

The NielsenIQ Consumer Panel captures product-level detail and daily timing with the same measurement framework across all four transfer programs we study, which enables straightforward comparisons across programs. Two features of the data require additional treatment. First, data are only available on the trips that panelists report. Einav et al. (2010) benchmark the NielsenIQ (then known as Nielsen Homescan) against retail records and estimate that about 53% of trips go unreported, while conditional on recording a trip households scan nearly all products. To account for missing trips, we adjust our headline MPCs by a factor of 2.13 ($= 1/(1-0.53)$). Importantly, this adjustment scales the estimated food-store spending response for underreporting but does not affect the relative comparisons across programs. Unadjusted (as-reported) responses are reported alongside adjusted MPCs in Section 5.[6]

Second, we reduce measurement error due to intermittent reporting by imposing two additional screens on reporting quality by requiring at least one grocery purchase every month of the calendar year, which removes households with inconsistent reporting, and dropping households whose reported monthly food-store or food-product spending exceeds their monthly income plus estimated SNAP benefits, which removes households with implausible spending. We additionally restrict the sample to "magnet" households, who record

food stores are stores such as apparel, beauty supply, computer, dollar stores, home furnishings, hardware, shoes, sporting goods and toy stores.

[5] Alcohol and tobacco purchases are not included in food products.

[6] An alternative adjustment for underreporting in the NielsenIQ data can be estimated by comparing spending on food products in our NielsenIQ sample to spending on food products on a similar sample calculated from the Consumer Expenditure Survey diary survey (Table A14). Using the pooled estimate that omits 2020, the implied adjustment factor is 1.5; including all years gives an adjustment factor of 1.4.

all products purchased including items without UPC codes.

The common sampling frame and data structure improves comparability across programs—the central contribution of this paper. Cross-program comparisons nonetheless require that reporting error does not differ systematically across program samples or in response to treatment. Since these adjustments affect spending *levels*, we report levels and adjustments separately.

The average household in our sample reports spending $870-$983 per month, about 75% ($651-$722) of it at food stores (Figure A2). These figures come from receipt-level totals and therefore include sales taxes and fees. Summing individual product-level scans instead yields food-store spending of $405-$547 per month, about 70% of the food-store totals measured at the receipt level, with the difference reflecting sales tax and any items not individually scanned. Of the product-level total, 61–74% is on food products and the remainder is on non-food items sold at food stores. Sample averages by program are shown in Table A1.

# 4 Empirical Approach

Our setting has two key advantages. First, we have precise information on benefit eligibility for multiple programs that have distinct design features and were issued over a relatively narrow time horizon. Second, detailed expenditure information is recorded at a daily level. We leverage this rich policy variation across households and over time in a difference-in-differences framework where we regress household-level spending on the estimated benefit amount received in the prior four weeks, controlling for demographics, state fixed effects, and time effects. Our most parsimonious approach takes the form:

$$y_{ist} = \beta Benefits_{ist} + X'_{ist}\theta + \delta_s + \phi_t + \varepsilon_{ist} \tag{1}$$

The treatment variable, $Benefits_{ist}$, measures the dollar value of benefits in hundreds of dollars that household $i$ living in state $s$ was eligible to receive in period $t \in \{w, m\}$. For P-EBT, the expanded CTC, and the first EIP, we know the first date of payment disbursal at a daily level and estimate its impact on expenditures at the weekly level ($t = w$), based on the

amount received in the previous 4 weeks. For SNAP EA payments, almost all states make SNAP payments throughout the month, with timing based on information not reported to NielsenIQ, such as Social Security Number or case number. Therefore, we only know the *month* in which households received SNAP EA and accordingly estimate expenditures at the monthly level ($t = m$). In order to ease interpretability, we aggregate all results to the monthly level, so that $\beta$ captures the monthly increase in spending at food stores for every $100 of benefits.

$\delta_s$ and $\phi_t$ are state and time fixed effects that account for time-invariant state policies affecting spending and benefit receipt and seasonal factors that may influence consumption, respectively. For programs with daily issuance information (P-EBT, CTC, and EIP), $\phi_t$ includes week-of-year and year fixed effects; for SNAP EA that relies on monthly variation, $\phi_t$ is month-by-year fixed effects.

$X_{ist}$ is a vector of control variables, including the head of household's age, gender, race/ethnicity, educational attainment, marital status, income, the number of children and adults in the household, the number of children under age 5 (as a proxy for WIC eligibility), the state unemployment rate, and the state's share of monthly SNAP payments disbursed during the reference period. We also control for state-specific policies adopted in response to the pandemic: an active stay-at-home order and mask mandate; restaurant closures; and Unemployment Insurance processing speed. Finally, we include controls for whether any of the other three programs we study were in effect in state $s$ during period $t$.

Because the P-EBT and SNAP EA treatment timing varies across states, we exclude states that were already treated prior to the beginning of our sample window, as well as state-weeks beyond the 4-week post-treatment window (P-EBT) and state-months beyond the 3-month post-treatment window (SNAP EA). This ensures that each estimate compares states that had recently disbursed funds with those that had not yet made payments in the case of P-EBT, and states that had terminated SNAP EA benefits compared to those who had not yet ended the program. In doing so, the comparison group consists of households living in not-yet treated, "clean" control states to avoid comparisons between newly treated

and previously treated states (Goodman-Bacon, 2021).

The timing of EIP and CTC benefits did not vary across states, so for these programs we cannot leverage cross-state comparisons. Instead, we construct control groups of households that meet the same sample restrictions (low-income and at least one school-aged child in the household) in 2019. We use 2019 as a comparison year because it is the most recent "typical" spending year prior to the COVID-19 pandemic, following an approach similar to Chetty et al. (2024). Thus, while the economic and demographic sampling criteria are the same across all programs we study, the sample windows vary with the timing of disbursements and the control groups. The sample windows are (Figure A1):

- P-EBT: April 15 – September 1, 2020 (control: not-yet-implemented states)
- SNAP EA: June 1, 2021 – June 30, 2023 (control: not-yet-terminated states)
- EIP: March 25 – May 19, 2020 (control: March 21 – May 15, 2019)
- CTC: April 14 – November 16, 2021 (control: April 11 – November 13, 2019)

All analyses use household weights from NielsenIQ. For programs that were implemented at the state level (P-EBT and SNAP EA) we cluster standard errors at the state level, while for those implemented nationally (EIP and CTC) we calculate HC1 robust standard errors.

We also extend Equation 1 to an event-study framework to examine how quickly families spend the benefits and the extent to which immediate effects fade over time. The event-study approach also helps assess the plausibility of the parallel trends identifying assumption. Specifically, we estimate the following equation:

$$y_{ist} = \sum_{k \neq -2} \beta_k \mathbb{1}\left[\tau_{st} = k\right] * \mathbb{1}\left[Year_t \neq 2019\right] + X'_{ist}\theta + \delta_s + \phi_t + \varepsilon_{ist} \tag{2}$$

where $\phi_t$ is the calendar week (P-EBT, EIP, and CTC) or month-year.[7] The event-time indicators, $\tau_{st}$, show changes in spending relative to 2 weeks or months before benefit receipt, respectively. Note also that these event studies measure benefit disbursement as a binary indicator, rather than the continuous measure of amount received used in the difference-in-

[7]Since the P-EBT analysis period spans April 15-September 1, 2020 and SNAP EA spans June 1, 2021-June 30, 2023, the $Year_t \neq 2019$ terms drop out.

difference estimates.

The approaches in Equations 1-2 are intention-to-treat (ITT) effects, as the NielsenIQ data do not include information on program receipt. For policymakers designing a new safety net program with non-compulsory participation, the ITT is a parameter of particular interest. In addition, we provide information on take-up rates below to provide an estimate for families that received each benefit (i.e., the treatment on the treated, TOT).

# 5 Results

## 5.1 Total Spending at Food Stores

We start by measuring how total spending at food stores (including food and non-food products) responds to each transfer in Table 1. Program benefits are scaled as the value in hundreds of dollars received over the past 4 weeks. Total monthly spending at food stores increases by approximately $7.39 with eligibility for each $100 in one-time, in-kind P-EBT benefits over the previous 4 weeks (panel a, column 1). P-EBT benefits averaged $638, implying that spending increased by about $47.15, or 6.5% of average monthly spending in the weeks after P-EBT was paid. We calculate a TOT estimate of a $9.47 increase in spending for every $100 in one-time, in-kind P-EBT benefits, based on evidence from Cunnyngham (2019) that 78% of income-eligible households participate in SNAP, and assuming the same rate for P-EBT (which was automatically paid to SNAP participants). After adjusting the TOT effect for underreporting of shopping trips in the NielsenIQ data, we obtain an MPC of 0.20 from one-time, in-kind P-EBT benefits.[8]

The intention-to-treat spending response is approximately twice as large for the in-kind benefits that are paid monthly: the ITT estimate for SNAP EA payments is $15.84 for every $100 of eligibility for SNAP EA payments (panel a, column 2).[9] When adjusting for program

[8] As described in Section 3, we scale the TOT by $\frac{1}{0.47} = 2.13$ under the estimate in Einav et al. (2010) that 47% of trips are recorded. If underreporting is consistent over the 2019-23 analysis period, this measurement error will not affect comparisons *across programs*. Cross-program comparisons would be biased if, for example, households are more likely to purchase the types of products that are typically not scanned (e.g., a granola bar that is eaten on the drive home) with cash rather than in-kind benefits or vice-versa. We do not believe this is a major concern but acknowledge that it is a potential limitation.

[9] Note that average monthly spending at food stores is lower among the SNAP EA sample than it is among the P-EBT sample ($651 vs. $722). This is driven by variation in timing of benefit receipt, as P-EBT payments were made when children were universally out of school, stay-at-home orders were in effect, and

take-up, the estimated TOT is $20.31 for every $100 in monthly in-kind SNAP EA benefits. The implied MPC is 0.43 for SNAP EA, given a $15.84 ITT response to $100 in benefits scaled by the take-up rate.

Changes in spending at food stores are smaller in response to cash payments than to in-kind transfers that are paid at the same frequency, as shown in panel b. The ITT estimate for the one-time EIP cash is $2.91, compared to $7.39 for one-time in-kind P-EBT, and the estimate for the monthly cash CTC is $8.61 compared to $15.84 for the monthly in-kind SNAP EA payments. That families spend less at food stores with cash than with grocery vouchers is consistent with previous work suggesting mental accounting in SNAP (Hastings and Shapiro, 2018).

Similar to in-kind transfers, households spend roughly three times the share of monthly cash payments compared with one-time cash transfers. These general patterns across programs persist after accounting for incomplete take-up: since estimated take-up of lump-sum cash EIPs was 92% (Clark et al., 2023), we obtain a TOT estimate of $3.16 additional spending at food stores for every $100 in transfers, and an MPC of 0.07. With a take-up of 83% for the monthly cash CTC (Congressional Research Service, 2022), the TOT estimate indicates that spending increases by $10.35 per $100 transfer, with an implied MPC of 0.22.[10] The P-EBT and EIP estimates are similar when household-level fixed effects are included, while SNAP EA attenuates and the CTC becomes substantially smaller and statistically insignificant (Table A2).

An advantage of this study is that we can compare spending responses across changes in four different types of transfers in a harmonized framework. We find that households increase spending at food stores more when they receive in-kind transfers that can only be used to purchase groceries than when they receive cash-based transfers of an equivalent value. In addition, within 4 weeks families spend a greater share from recurrent, monthly benefits

many people were working exclusively from home, while SNAP EAs were discontinued as late as March 2023 when schooling and the economy had largely returned to normal.

[10]Table A3 reports robustness to a less restrictive sample that includes households for which grocery spending is not more than 200% of income plus estimated SNAP benefits. Relative spending patterns are similar in this sample.

than transfers that are perceived to be one-time. The intent-to-treat responses translate into MPCs of 0.20 and 0.43 for one-time and monthly in-kind, and 0.07 and 0.22 for one-time and monthly cash—a roughly two-to-threefold difference by form and a two-to-threefold difference by frequency.[11] These patterns are consistent with both mental accounting and forward-looking behaviors.

## 5.2 Product- and Store-Level Spending Responses

One key difference between in-kind and cash transfers is that in-kind benefits can only be used to purchase food, and not other products that are sold at food stores. In the NielsenIQ data, product-level spending on food products, which relies on respondents scanning UPC codes or otherwise reporting products without UPCs, is approximately 35-60% as large as receipt-level total food spending across the four program samples.

When we compare how different programs affect spending on food products (Table 2, column 1), we generally find similar, albeit smaller, results to total spending at food stores in Table 1. The primary difference across the two measures is that spending on food products responds less to monthly in-kind SNAP EA than for one-time in-kind P-EBT. While each \$100 in SNAP EA results in \$15.84 more total spending at food stores, only about \$4.70 of this is spent on food products.[12] This complicates the mental accounting framework and suggests that while consumers spend more of the in-kind payments at grocery stores, they recognize that the benefits are fungible by purchasing more goods that cannot be bought directly with food vouchers. Interestingly, the ITT increase in spending on food products in response to monthly SNAP EA (\$4.70) is not much different than (and is not statistically significantly different from) the response to monthly cash CTC benefits (\$4.14), indicating that both monthly payments increase spending on the goods targeted by food vouchers by a similar amount. Overall, we estimate a marginal propensity to consume food items of

[11] Table A6 replicates the main specification using a two-week post-transfer window and finds spending responses concentrated in the first two weeks after payment for the one-time programs, with the CTC pattern smoothing out over the four-week window as expected under monthly replenishment. This is consistent with the event-study evidence in Section 6.1.

[12] The larger increase in spending on all goods compared with on targeted goods suggests that the pattern is being driven by inframarginal households. Sample sizes are insufficient to separately estimate responses among households for whom the SNAP restriction is binding.

13%-17% of both in-kind transfers (P-EBT and SNAP EA), 3% of one-time cash (EIP), and 11% of monthly cash (CTC).

We examine whether different transfers alter the composition of purchases by splitting food products into perishable and non-perishable goods. Each transfer generally increases households' spending on both types of goods by similar shares of mean spending. An exception is that one-time in-kind P-EBT benefits may increase purchases of non-perishable goods more than perishables (1.8% increase per $100 benefits, compared to 1.1%), which may reflect stocking up on stable food products with the sizable one-time in-kind transfer, while spending from the monthly SNAP EA is more concentrated among perishable items (2.2% increase per $100 in benefits, compared to 1.6% for non-perishable items). We find no evidence of increases in alcohol and tobacco consumption for any type of transfer, with estimated impacts that are small and not statistically significant.[13] We generally find no increase in purchase of sweets and sodas, except in response to monthly CTC payments where the estimate, while statistically significant, is small in magnitude.

Prior research has found that SNAP recipients shift toward bulk purchases and obtain better unit prices in the days after benefits arrive and liquidity constraints are least likely to be binding (Zaki and Todd, 2023; Wich and Harris-Lagoudakis, 2025). We test a related but distinct question: whether any of the four transfers changes the share of the household's food-store budget that goes to bulk-sized products, defined as items at or above the 80$^{\text{th}}$ percentile of the size distribution of their product type (column 6). About 25% of spending in our sample already goes to bulk-sized products, and we find no statistically significant change in that share in response to any of the four transfers.

Households can purchase food at a variety of stores, and program design may also influence where a household shops. Yet much of the existing work on grocery expenditures and income assistance programs is either limited to a single retailer or does not include information on store type. We next disaggregate the total (food plus non-food) spending response

[13] Chorniy et al. (2025) find that emergency department visits for drug and alcohol use increase after receipt of cash Supplemental Security Income (SSI) benefits, but not after SNAP receipt, suggesting some non-fungibility of benefits for the population receiving both programs.

across types of stores in Table 3. While SNAP EA and P-EBT are generally redeemable at a wide range of outlets including grocery, discount, and club stores, these transfers disproportionately increase spending at grocery stores, consistent with mental accounting. Cash transfers raise spending at discount stores and, for monthly cash, club stores.[14] Neither cash nor in-kind benefits increase spending at convenience stores, other food stores, or restaurants. (Restaurants are not included in other measures of spending at food stores.) This underscores the value of the more comprehensive NielsenIQ data that includes transactions from multiple retailers, as differences in estimated MPCs would be much larger if the analysis were restricted to grocery stores.

Changes in shopping behaviors also differ between one-time and monthly transfers and in-kind and cash benefits (Table A4). Households make slightly more shopping trips when they receive monthly in-kind benefits, but not when they receive other transfers.[15] They generally spend more per trip, though the increase for P-EBT is not statistically significant.

These patterns are robust to a range of alternative measures of monthly spending, as shown in Table A5. The first 4 columns compare receipt level vs product level expenditures at food stores and all stores. The dependent variable means change in predictable ways, with receipt- level spending greater than product-level spending, and spending at all stores greater than spending at the subset of food stores. The relative magnitudes of spending responses are consistent across spending measures, with larger increases in response to in-kind transfers than cash transfers of a similar frequency. A substantial amount of the increased SNAP EA spending is on non-food products at food stores (columns 9-12).

## 5.3 Relation to prior MPC estimates

Our MPC estimates are broadly in line with the existing literature and, taken together, reinforce several stylized facts about spending out of transfers. At the same time, the daily detailed expenditures from the NielsenIQ data and the fact that we observe multiple programs — cash and in-kind, lump-sum and monthly — allow us to compare patterns within a

[14] In general, Target and Wal-Mart are examples of discount stores. We provide these as examples and do not intend to suggest that these are or are not included in the NielsenIQ data.

[15] Though the coefficient in panel b column 1 is marginally statistically significant, it is very small in magnitude.

unified framework and along margins that earlier studies could not examine jointly. Figure 1 places our findings in the context of the broader literature.

#### 5.3.1 One-time cash: EIP

We begin by situating our cash-transfer estimates relative to prior work on stimulus payments and other cash transfers. Most closely related to our analysis, Parker et al. (2022) use Consumer Expenditure Survey interview data to estimate the MPC from the first pandemic-era EIP and find that households spent roughly 10% of their EIPs on nondurable goods and services in the three months after receipt. For comparability, when we estimate 3-month spending responses in the NielsenIQ data, we obtain an 18% MPC in Table A7 — slightly less than 3 times the 7% 1-month estimate in Table 1. Parker et al. (2022) further estimate an MPC of 4.2% for food spending, which is very similar to our MPC estimate for spending on food products over 3 months from the EIP in Table A7, column 3, despite substantial differences in data and outcome measurement.[16]

Parker et al. (2022) note that these COVID-era MPCs are smaller than the leading estimates for earlier stimulus payments: the 2001 and 2008 rebate literatures report nondurable MPCs in the range of 12%-40% in the quarter of receipt (Johnson et al., 2006; Parker et al., 2013). However, these earlier estimates are sensitive to how the consumption aggregate measure is defined. Orchard et al. (2026) show that when the 2001 rebate MPC is estimated using BEA consumption categories rather than the narrower nondurables aggregate in Johnson et al. (2006), the MPC on nondurable goods is about 0.06 and the MPC on total consumer expenditures is close to zero. Our EIP food MPC of 0.03 (0.07 at food stores) is comparable to their pre-COVID estimate. Further, as we show in Section 6.3, it is also indistinguishable from a pre-COVID (and non-recession) MPC estimated from refundable-tax-credit refunds in 2019. Taken together, our one-time-cash EIP estimates appear to reflect general features of the household response to lump-sum transfers rather than pandemic-specific dynamics.

[16] As discussed in Parker et al. (2022), their estimates (from self-reported consumption data) are substantially lower than estimates from studies of EIPs using transaction-level data. Karger and Rajan (2020) estimate that nearly half of the EIP is spent within a few weeks, while Baker et al. (2023) estimate that between one-quarter and one-third is.

### 5.3.2 Monthly cash: CTC

The monthly Child Tax Credit is a newer program with a smaller literature, but the emerging consensus is broadly consistent with our findings. Using the Consumer Expenditure Survey, Schild et al. (2023) find that CTC recipients increased spending on food, utilities, and children's essentials in the months payments were disbursed. Our monthly CTC food-store MPC of 0.22 (0.11 on food products) is broadly consistent with these prior estimates, with daily transaction data plausibly capturing short-run responses to monthly transfers more comprehensively than monthly survey recall. Ganong et al. (2024) examine consumption responses to a different monthly cash transfer (Unemployment Insurance) in the same pandemic period using detailed transaction information. They find MPCs at grocery stores ranging from 0.02 to 0.04, almost identical to our estimate of 0.02 when we limit spending to grocery stores (Table 3).

More broadly, spending responses to a range of other cash transfers that are paid on an annual basis, such as the EITC, Alaska Permanent Fund Dividend, and income tax refunds, tend to fall in the 0.02-0.17 range for food and food-adjacent categories (Kueng, 2018; Ganong et al., 2024; Aladangady et al., 2023; LaGuardia et al., 2025). Both our EIP food MPC (0.03) and our CTC food MPC (0.11) fall within this range, and the difference across estimates is generally consistent with differences in payment frequency we find.

### 5.3.3 Monthly in-kind: SNAP EA

Since the SNAP EA payments changed benefit levels among SNAP recipients, the most analogous previous interventions are those that also change the intensive margin rather than program-participation variation. However, extensive-margin estimates are also informative for contextualizing spending responses to SNAP.

Hoynes and Schanzenbach (2009) provide an early extensive-margin estimate, exploiting the program's introduction; they estimate a food MPC out of SNAP benefits of 0.17-0.30, the lower end of which is close to our SNAP EA food-products estimate of 0.13. Hastings and Shapiro (2018) similarly study the extensive margin and find monthly food MPC of 0.5-0.6 among new recipients at a single retail chain. In contrast, our SNAP EA analysis focuses on

the intensive margin, leveraging policy-induced changes in benefit levels among households that are already enrolled in SNAP. In this respect, our results are conceptually closer to Beatty and Tuttle (2015) who use the temporary national increase in SNAP benefits during the Great Recession and find MPCs of 0.5-0.6, and to Bruich (2014) who finds a somewhat smaller intensive-margin MPC of 0.3. Our estimate of 0.43 for total food-store spending sits squarely within this intensive-margin range, and our lower food-product MPC (0.13) suggests that a meaningful share of the SNAP EA response goes to non-food items sold at food stores — a margin missed by studies restricted to grocery categories.

#### 5.3.4 One-time in-kind: P-EBT

Examples of one-time, in-kind programs are rare in recent decades, and no other existing study estimates a P-EBT MPC using scanner data. Insights from two literatures can help interpret the 0.20 P-EBT MPC we find. Bauer et al. (2024) use survey and administrative data to study P-EBT's effects on food-store spending, hardship, and health, and find that P-EBT redemption is rapid and concentrated on grocery purchases, a pattern consistent with the immediate, food-store-directed response we document. More generally, our P-EBT estimate is roughly three times our EIP estimate (0.20 vs. 0.07), consistent with the broader literature that in-kind food benefits generate larger short-run food-store spending than equivalent cash. That the P-EBT MPC is roughly half of the SNAP EA MPC (0.20 vs. 0.43) is a novel finding that isolates the frequency-of-delivery margin within a single benefit form and population. This comparison between SNAP EA and P-EBT is our clearest evidence that transfer frequency — not just the form of the transfer — shapes short-run spending responses.

## 6 Event Studies and Threats to Identification

Before turning to heterogeneity and mechanisms, we address identification challenges that arise in a design that pools four programs with different rollout structures. Our estimates would be biased if factors unrelated to the four transfer programs coincided with payment timing in ways that our controls do not absorb or if the difference-in-differences designs are poorly matched to the identifying variation. We address four such threats: coincident state-

level shocks, coincident calendar-time shocks, comparisons with staggered treatments, and differential pre-trends. We conclude this section with a series of falsification and internal validation checks that together provide strong evidence that the empirical design captures true program responses.

## 6.1 Event Studies

The pooled difference-in-differences estimates in Section 5 summarize the average spending response in the month after receiving benefits. To examine how the response unfolds over time, and to assess the parallel-trends assumption, we estimate event-study specifications as described in Equation 2. The event indicators trace out spending relative to two weeks (or two months in the case of SNAP EA) before benefits are received, with each pre- and post-treatment time period entered as a separate binary indicator. Because the event studies use binary indicators rather than the continuous dollar measures used in the difference-in-differences regressions, the coefficients are interpreted as the average change in spending in a given period around the event, not per $100 of benefits as in the DD specifications. Figure 2 reports event-study results for total spending at food stores for each of the four programs, and Figure A3 reports parallel results for spending on food products.

As shown in panel a, spending at food stores is flat in the four weeks prior to P-EBT receipt, and increases in the week that benefits are disbursed. Elevated spending persists for about four weeks post-payment and then attenuates, consistent with a one-time in-kind transfer being spent down relatively slowly. The results for spending on food products are qualitatively similar but smaller in magnitude, reflecting that some of the food-store impact flows to non-food purchases at food stores. The timing pattern is consistent with Bauer et al. (2024) who find that EBT redemptions increase promptly after benefit receipt and remain elevated for several weeks.

Panel b shows results for SNAP EA, the monthly recurring in-kind benefit. Recall that SNAP EA is identified using the termination of increased benefits, and is measured at the monthly (not weekly) frequency. For comparability to the other programs, we reverse the sign of the estimated effect so that estimates reflect the effect of benefit availability, rather

than benefit loss. Spending is stable in the pre-period and responds sharply and persistently to the change in SNAP EA benefits. The persistence in higher spending is what a recurring monthly benefit design predicts: households incorporate recurring benefits into monthly spending. Similar to the difference-in-differences findings, the results are smaller when limited to spending on food products only (Figure A3).

The one-time cash EIP generates a modest and persistent response, as shown in panel c. Spending at food stores increases in the week of disbursement and remains elevated for 6 weeks. Relatively little of the EIP goes to increased spending at food stores, which is consistent with the interpretation that households use one-time cash benefits for different types of spending (e.g. savings, debt repayment, durables).

Finally, the monthly recurring cash CTC produces a sawtooth pattern, with spending rising in week 0 when the first payment is made and remaining elevated for two weeks before dipping in week three then increasing again in week four when the next monthly payment arrives. A similar pattern repeats the following month, with higher spending in weeks 4-6 and a drop in week 7. This monthly pattern is consistent with forward-looking behavior when benefit replenishment is expected: households spend the CTC as it arrives because they anticipate another payment the following month.[17]

## 6.2 Coincident state-level shocks (P-EBT and SNAP EA)

Identification of the P-EBT and SNAP EA responses relies on state-by-week and state-by-month variation in program timing, with not-yet-treated households as controls. This design would be biased if states that implemented or terminated these programs experienced unrelated shocks at the same time that independently impact spending, such as changes in the labor market, other state policy changes, or differences in COVID severity. Our main results control for many such potential factors, including the unemployment rate, stay-at-home orders, UI processing speed, and the availability of other benefits. Yet it remains a possibility that unobserved time-varying factors contribute to these results.

[17]These findings are consistent with work by Parolin et al. (2023) that documents CTC reduced the probability that a household reported food hardship or was behind on housing rent payments.

We probe this concern in two ways. First, we assign placebo benefits to households that were not eligible for the programs and estimate the same difference-in-differences specification. If our estimates were driven by coincident state-level shocks instead of by the programs themselves, we would expect to see spending responses in the placebo groups. For P-EBT, all families with children are assigned benefits based on their state and number of school-age children. A small share (6-12%) of children from families with incomes above 200% of poverty actually do receive P-EBT benefits because they attend schools with universal free-meal provisions (Ruffini et al., 2025), so the estimated results are primarily driven by placebo estimates but include a small share of treated households. The estimates are not consistent with a positive, statistically significant impact as shown in columns 3, 5 and 6 of Table 4, panel a. Table 5 conducts a similar exercise among low-income childless households (see column 3) who were not eligible for this program that was designed to compensate for missing school meals among schoolchildren. Again, there is no measured spending response to this placebo test, providing further support for the identification strategy. For SNAP EA, households with incomes above 200% of the poverty line are rarely eligible for SNAP. We assign placebo benefits to them based on their state of residence and household composition. Spending responses are small and statistically insignificant (Table 4, panel b).

Second, we exploit the limited variation in benefit increases when the second SNAP EA measure was implemented between March and June 2021. The original SNAP EAs, introduced in March 2020, increased all households' monthly SNAP benefits to the maximum benefit level for their household size. As a result, those who typically received modest SNAP benefits (e.g., those with relatively higher incomes) saw substantial benefit increases, but the roughly 20% of those who were already receiving the maximum benefit received no additional funds. The SNAP EA payments were later expanded in 2021 so that all households received at least a $95 monthly benefit increase. In our analytic sample, the average benefit increase under this second expansion is only $12 per month, roughly 3% of the average SNAP EA payment of $400. Despite the lower dollar value, the implied spending response is $16.78 per $100 (Table A10, column 3), which although statistically imprecise, is very similar to

the pooled estimate of $15.84 in Table 1.

## 6.3 Coincident calendar-time shocks (EIP and CTC)

For the EIP and CTC, identification comes from comparing eligible households in the payment period to comparable households in the same calendar weeks of 2019 since nearly all benefits were issued to households in a very narrow timeframe. This design would be biased if 2020-2021 spending behavior differed from 2019 for reasons unrelated to the transfers—a reasonable concern to the extent that the pandemic itself changed shopping and consumption patterns in ways that correlate with the payment period.

We address this concern in four ways. First we re-estimate the EIP specification using 2022 instead of 2019 as the control period (Table A10, column 1). Because 2022 shares aspects of the pandemic-era shopping environment with 2020 but does not overlap with other EIP payments, this approach differences out pandemic-specific shocks that the 2019 comparison would leave in. The estimated spending impact is similar to the baseline.[18] Second, as an additional within-design comparison, we estimate a small and statistically insignificant response to the third EIP (Table A10, column 2). This provides a within-design placebo: if our estimation approach were mechanically producing positive spending responses from general pandemic-era spending patterns, we should see a response for the third EIP, but we do not.

Third, and most consequentially, we exploit the fact that refundable tax credits (EITC and CTC as delivered through the annual tax refund) are a long-standing analog to the EIP, in that low-income families receive a sizeable cash payment once per year at tax filing. Using variation in the timing and magnitude of these refund payments, we estimate spending responses to refundable tax credits in 2019 (fully pre-pandemic), 2021-23 (post-pandemic), and pooled across both periods. To estimate the amount of refundable tax credits each household in the NielsenIQ data was eligible to receive, we use TAXSIM to estimate the tax credits based on the household's income, number of children, and marital status. Variation

[18] We do not conduct a similar analysis for the CTC since April-November 2022 overlap with when most families received their tax refunds that included the second 6 months of the expanded CTC.

in receipt over time comes in part from differences in when refund payments were made, measured as monthly EITC outlays multiplied by the share of all income tax refunds issued in a given week as reported in the Department of Treasury's Monthly Treasury Statements, following LaGuardia et al. (2025). We then use this estimated share of EITC refunds issued each week to measure the expected transfer over the previous 4 weeks.

The estimates are essentially identical across periods, with monthly spending at food stores increasing by \$2.24-\$2.89 per \$100 in expected refundable tax credit benefits (Table A11). Notably, the estimate for the tax refund received in 2019 (pre-pandemic) is nearly identical to our main EIP estimate of \$2.91 per \$100, and this holds despite the refundable tax credit averaging \$7,273-\$8,258 versus \$4,373 for the first EIP. That the same one-time-cash MPC appears with a similar cash transfer fully received before the pandemic is inconsistent with the possibility that the low MPC for the first EIP is an artifact of pandemic conditions.

Finally, like the EIPs, the monthly refundable CTC was disbursed to all households on essentially the same date, so the identification comes from comparing weekly spending before and after onset of CTC payments in 2021 compared to a control group consisting of the same calendar weeks in 2019.[19] To probe whether other time-varying factors are driving the results, we estimate a placebo test among low-income households without children who were categorically ineligible for the credit. Placebo benefits are defined as the per-child CTC benefit multiplied by the number of household members. Among this placebo sample, there is no spending response (Table A13, panel d, column 3), bolstering confidence that our approach is not merely capturing other concurrent changes in spending over this period.

## 6.4 Comparisons across states in staggered difference-in-differences (P-EBT and SNAP EA)

Recent work has shown that when treatment is staggered across units (as it is for P-EBT and SNAP EA), two-way fixed-effects estimators can produce biased estimates by

[19] We do not show robustness to using a control group from 2022 like we did for EIPs because the enhanced CTC was paid in two parts: half was paid monthly in July-December 2021, and the other half was paid when the family received its income tax refund in the first quarter of 2022. This second lump sum was used to identify spending responses in Table A11, but would contaminate the DD control group for a CTC analysis comparing 2021 with 2022.

implicitly using already-treated units as controls for later-treated units (Goodman-Bacon, 2021). Orchard et al. (2025) argue that MPC estimates in the literature examining the 2008 rebates are meaningfully biased by this problem.

In our main analyses, we address this concern by dropping states after they receive treatment ("already-treated" units), thereby only using not-yet-treated households as controls. In this section, we further probe potential sensitivity to staggered treatments by estimating a separate difference-in-differences for each policy cohort. States ended SNAP EA payments over a long time window, ranging from August 2021 in the earliest states (FL, MT, NE, SD) to February 2023 for the states that did not opt to exit early. Yet the results for each cohort are similar in sign and magnitude to the baseline pooled estimate, indicating that the pooled estimate is not driven by a subset of cohorts (Table A8). The implementation timing of P-EBT is more compressed (April through September 2020), and cohort-by-cohort estimates are thus noisier individually, but are not significantly different from the pooled estimate (Table A9).

# 7 Heterogeneity in Spending Responses

Our analysis so far has focused on households with school-age children and incomes below roughly 130% of the federal poverty line, since these households were eligible for all four transfers. A natural question is whether spending responses differ across subgroups that were eligible for only some of the payments. In this section, we analyze heterogeneity in spending responses across income and demographic groups.

## 7.1 Heterogeneity by Income

One sample of interest is households who are less likely to face liquidity constraints, namely higher-income households. A meaningful share of such households with school-aged children also received some of the transfers we analyze, allowing us to estimate treatment effects directly. In other cases, few or no such households were eligible; there, assigning placebo benefit amounts provides a useful falsification test (Section 6). Across programs, we find a common pattern consistent with liquidity constraints: MPCs are generally largest

for the lowest-income families with children, while higher-income and placebo groups show smaller or no responses.

Table 4 reports estimates for total spending at food stores across alternative income groups, with column 1 reproducing the corresponding estimate from Table 1 for the primary sample. The broad pattern is that spending responses attenuate as income rises, although the source of this attenuation differs somewhat across programs. For P-EBT and SNAP EA, attenuation partly reflects declining eligibility rates at higher income levels. For the cash transfers, which extend further up the income distribution, attenuation is more likely to reflect weaker spending responses among households that are less likely to be liquidity constrained.

Panel a presents results for P-EBT, which paid benefits to some higher-income children who attended schools offering universal free meals. To capture this, expected P-EBT benefits are constructed as the number of school-age children in the household multiplied by the average benefit in the household's state. Likely eligibility rates among higher-income families are measured using county-level exposure to schoolwide free-meal schools based on data in Ruffini et al. (2025). In this sample, 86% of school-age children in households with incomes between 130% and 200% of poverty were likely eligible for P-EBT, and eligibility falls sharply above that range. The estimated effect for the 130%-200% group is somewhat smaller than in the primary-sample estimate in column 1 and not statistically different from zero. Estimates for higher-income groups are small or negative. Overall, as income increases and likely eligibility declines, the estimates become smaller and provide no evidence of increased spending in response to P-EBT timing.

Panel b reports results for SNAP EA. Under standard SNAP rules, families with gross incomes above 130% of poverty are generally not eligible for benefits, although "broad-based categorical eligibility" allows some higher-income families — typically with gross incomes below 200% of poverty — to participate. Among these higher-income participants, regular SNAP benefits are usually modest, so raising benefits to the maximum allotment mechanically generates larger benefit increases conditional on participation (Schanzenbach, 2019).

Families with incomes between 130% and 200% of poverty increase food-store spending in response to SNAP EA, but by less than the lowest-income group in both dollar and percentage terms. By contrast, households above 200% of poverty are essentially never eligible for SNAP; as described in Section 6, assigning them placebo benefits yields small and statistically insignificant estimates, supporting the interpretation of the main SNAP EA results as true program responses rather than concurrent state-level shocks.

Table A12 shows that the corresponding results for food products are broadly similar, but somewhat more muted. In particular, for the 130-200% group, SNAP EA increases total spending at food stores without generating a statistically significant increase in spending on food products alone. As in the primary sample, this pattern suggests that part of the SNAP EA response operates through non-food purchases at food stores rather than through food purchases alone.

Panels c and d turn to the cash transfers, EIP and CTC. Unlike the in-kind programs, these transfers were not tightly targeted to low-income households, so higher-income families with children were often still eligible. Here the central question is not whether higher-income households received the transfers, but whether they spent them differently. The estimates suggest that they did: spending responses are generally smaller for higher-income households, especially for the monthly CTC. For the EIP, food-store spending rises across income groups but tends to be attenuated at higher incomes. For the CTC, positive and statistically significant spending responses appear only in the lowest-income group, while estimates for the highest-income groups are negative and statistically significant. Taken together, these results reinforce that the spending response to cash transfers is strongest among lower-income households, consistent with more binding liquidity constraints among that group.

## 7.2 Heterogeneity by Household Composition

Eligibility for each program also varied across low-income households with different household compositions. In particular, low-income households without children could receive SNAP EA and EIP payments, while most low-income households with children younger

than school age were eligible for these benefits plus the CTC.[20] Table 5 reports results for total spending at food stores for these alternative low-income household types, with column 1 reproducing estimates for our primary sample of low-income households with school-age children.[21] Taken together, the results suggest that both liquidity and the presence of children shape how transfers are spent.

We begin by comparing households with school-age children to all low-income households with children, including those whose children are younger than school age (column 2). For P-EBT, the estimated spending response is attenuated in this broader group because younger children generally were not eligible for the program. By contrast, CTC benefits were larger for younger children, and the estimated spending response per $100 is nearly identical across columns 1 and 2 — about 1.2% in both cases. This pattern suggests that the presence of children matters for transfer responses, but that eligibility rules remain central for interpreting differences across household types.

We next turn to households without children. Because SNAP EA and EIP were not limited to families with children, these households provide a useful comparison group for understanding whether children increase spending responses or whether liquidity alone can account for the patterns in the main results. As shown in panel b, childless households increase total spending at food stores in response to SNAP EA, by about 1.5% for each additional $100 in benefits. This response is smaller than for households with children, but still economically meaningful, suggesting that liquidity matters even in the absence of children. At the same time, Table A13 shows no statistically significant increase in spending on food products alone for childless households. This pattern mirrors what we observed for households with children, and reinforces the earlier finding that benefits labeled "food" increase spending at food stores and are not confined to food products.

Panel c shows a similar comparison for the EIP. Low-income households without children increase food-store spending in response to the EIP, but by slightly less than households

[20]The primary exception was some households with children in immigrant families, who were excluded from the EIP if any member lacked a Social Security number.

[21]Table A13 shows results for food products.

with children do. This again suggests that part of the main EIP response reflects liquidity, while the larger response among families with children may reflect higher immediate spending needs. The remaining two programs, P-EBT and CTC, were targeted to families with children, so results for childless households are placebo tests, and show no increase in spending, supporting the interpretation that the main estimates are capturing true program responses rather than spurious correlations with benefit timing. The broad patterns suggest that transfer responses are shaped not only by liquidity, but also by household needs associated with raising children.

# 8 Conclusion

Dollars delivered through different transfer designs are not equivalent in practice. We use a common empirical framework, harmonized data, and identical outcome measures to compare spending responses across four large transfer programs that differ in form (in-kind or cash) and payment frequency (one-time or monthly). Our results indicate that one-time in-kind food benefits generate about triple the food-store MPC than one-time cash transfers of comparable value (0.20 vs. 0.07), and monthly in-kind benefits lead to food store spending responses that are roughly twice as large as monthly cash payments (0.43 vs. 0.22). Within each payment form, monthly delivery generates two to three times the food-store MPC of one-time delivery.

We interpret the two design effects as reflecting distinct behaviors. The frequency effect — monthly transfers generating substantially larger short-run food-store MPCs than one-time payments of comparable value — is understood as a forward-looking response to expected benefit replenishment. Under a standard buffer-stock intuition, a one-time cash transfer is a transitory income or wealth shock whose consumption effects may be spread over time. A monthly payment is instead treated as a recurring disposable resource that can be spent as it arrives because the next payment is anticipated. The P-EBT versus SNAP EA and EIP versus CTC comparisons are consistent with payment frequency influencing short-run spending. However, these programs differ in other respects, so the comparisons do not isolate the effect of changing payment frequency while holding the total transfer amount and policy

environment fixed. The payment form effect — that food-store MPCs are higher for in-kind than for cash transfers — is consistent with a labeling effect. Households treat a benefit labeled for "food" as belonging in the mental account for food purchases, even when the restriction is not economically binding. Indeed, many recipients of P-EBT or SNAP EA are inframarginal and thus could have absorbed the in-kind benefits into food purchases that would have happened anyway. The persistence of the in-kind effect in the comparison between SNAP EA and the CTC in Table 1 suggests the importance of this (non-binding) label.

Changes in the composition of spending further sharpen this labeling interpretation. All four programs induce additional spending at food stores, but the SNAP EA response includes a substantial increase in non-food spending at food stores. This pattern does not fully align with restrictions for products that can be purchased with in-kind benefits, and is more consistent with households treating in-kind benefits as food-*store* benefits instead of food-*product* benefits. We find little systematic evidence that transfer design changes the mix of food items purchased, which suggests that transfer design primarily affects how much households allocate to food-store spending rather than what they buy there.

Our results also address two recently raised concerns. Orchard et al. (2025) argue that MPC estimates from the 2008 rebate literature are biased by the inclusion of previously treated observations in staggered-treatment differences-in-differences estimates. Our identification strategy largely avoids this concern. Our P-EBT and SNAP EA estimates use not-yet-treated households as the control group, and we probe the robustness of our staggered-treatment approaches using cohort-by-cohort estimates. Our EIP and CTC estimates do not use a staggered-treatment approach, and instead exploit a single national treatment and compare it to same-calendar-week 2019 controls. In addition, we find similar MPC results using a fully pre-pandemic approach leveraging 2019 refundable tax credits. The similarity between the pre-pandemic MPC and the MPC estimated from the first EIP suggests that the low cash MPC is not an artifact of the pandemic.

A related contribution by Orchard et al. (2026) shows that MPC estimates from the

earlier rebate literature are sensitive to the specific categories used to construct the outcome spending variable. This is a useful reminder of the importance of measurement, and it is one reason we focus the analysis around a single, transparent outcome measured the same way for every household and every program. The quantity we estimate is spending at food stores, observed at daily frequency in the same NielsenIQ retailer set across all four programs. The consistency of the outcome and the population makes the four MPCs directly comparable: the differences we document between cash and in-kind, and between one-time and monthly, are not driven by differences in category definitions or populations across studies. We further decompose the food-store response into food and non-food purchases at food stores, to transparently show what portion of the response reflects grocery spending narrowly and what portion reflects the broader food-store market basket. We cannot translate our MPCs into total-consumption MPCs because important categories, including durables and many services, are not observed. We also cannot measure saving or debt repayment.

Our results have three policy implications. First, if the policy goal is to increase short-run food-store spending, in-kind benefits are more effective than the equivalent amount of cash. P-EBT and SNAP EA generate food-store MPCs roughly two to three times as large as the corresponding cash programs (EIP and CTC): about three times for one-time transfers and 1.9 times for monthly transfers. Second, when the policy goal is broader—smoothing consumption, offsetting negative income shocks, or providing insurance for expenditures such as rent, utilities, or medical bills—the case for cash may be stronger, but cannot be directly evaluated here since NielsenIQ does not observe categories like rent, utilities, and medical bills where cash flexibility likely matters most. The smaller food-store MPC of the EIP and CTC does not indicate that these programs were ineffective, but indicates that recipients spent a large share of the resources on categories not observed in the NielsenIQ data (or saved it). Complementary evidence on hardship, economic stability, health, and other outcomes is needed for a full welfare comparison. But policy makers choosing between cash and in-kind payments are choosing between different welfare margins, not between more and less effective transfer programs.

Third, frequency of delivery matters independently of the form of the benefit. A monthly program and a one-time payment of the same form and budgetary cost generate different short-run spending responses. This is directly relevant for designing countercyclical transfer programs: if the goal is to smooth consumption over a downturn, monthly benefits are preferable; in other cases a one-time lump sum may be more effective, especially in light of political economy considerations.

More broadly, our approach highlights both the value and limitations of high-frequency transaction data. By linking detailed NielsenIQ Consumer Panel data to sharp policy variation in timing and amount across multiple programs, states, and years, we estimate spending responses in a common empirical framework rather than inferring differences across programs from separate studies with different samples, time periods, and measurement conventions. At the same time, incomplete reporting of shopping trips means that our unadjusted observed-spending responses may understate actual food-store responses under stable underreporting, while the adjusted MPCs depend on the validity of the reporting-rate assumption. Further, the data do not allow us to observe how households spend these transfers outside the high-frequency nondurable sector captured well in the NielsenIQ data, including household savings, debt repayment, durables, and services. Linking scanner data to bank accounts or tax return data would allow these broader questions to be addressed.

Taken together, the evidence suggests a central lesson: dollars delivered through different benefits are not equivalent in practice. Spending responses depend on how the transfer is designed, labeled and delivered, with implications for welfare analysis and fiscal policy.

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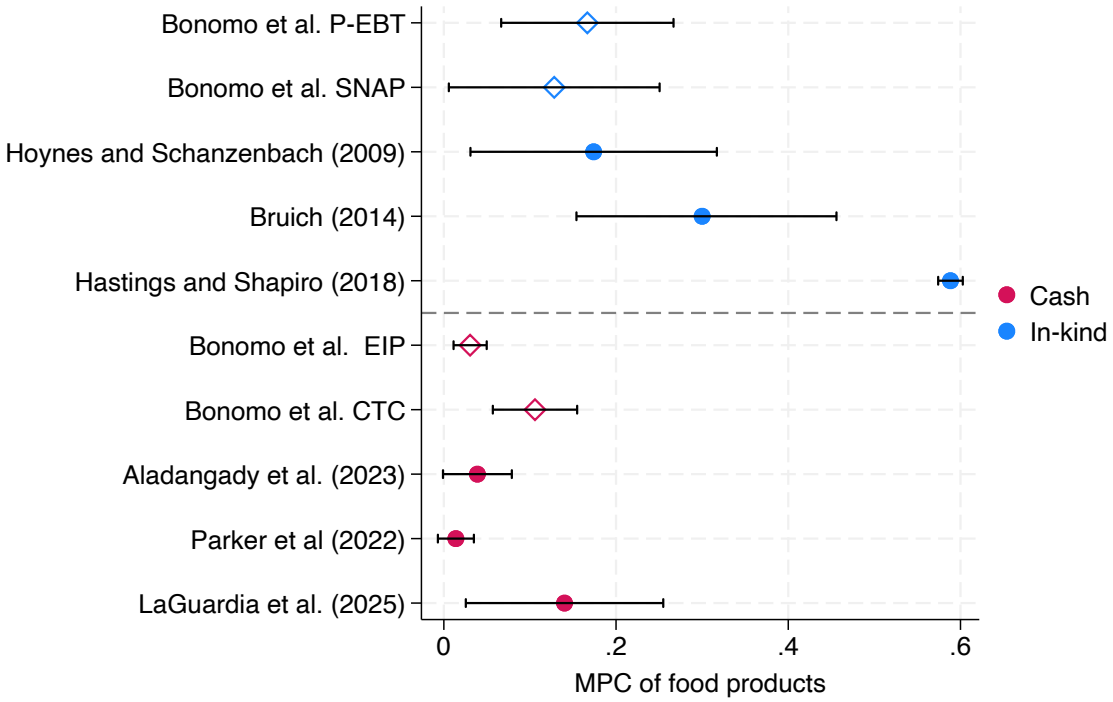
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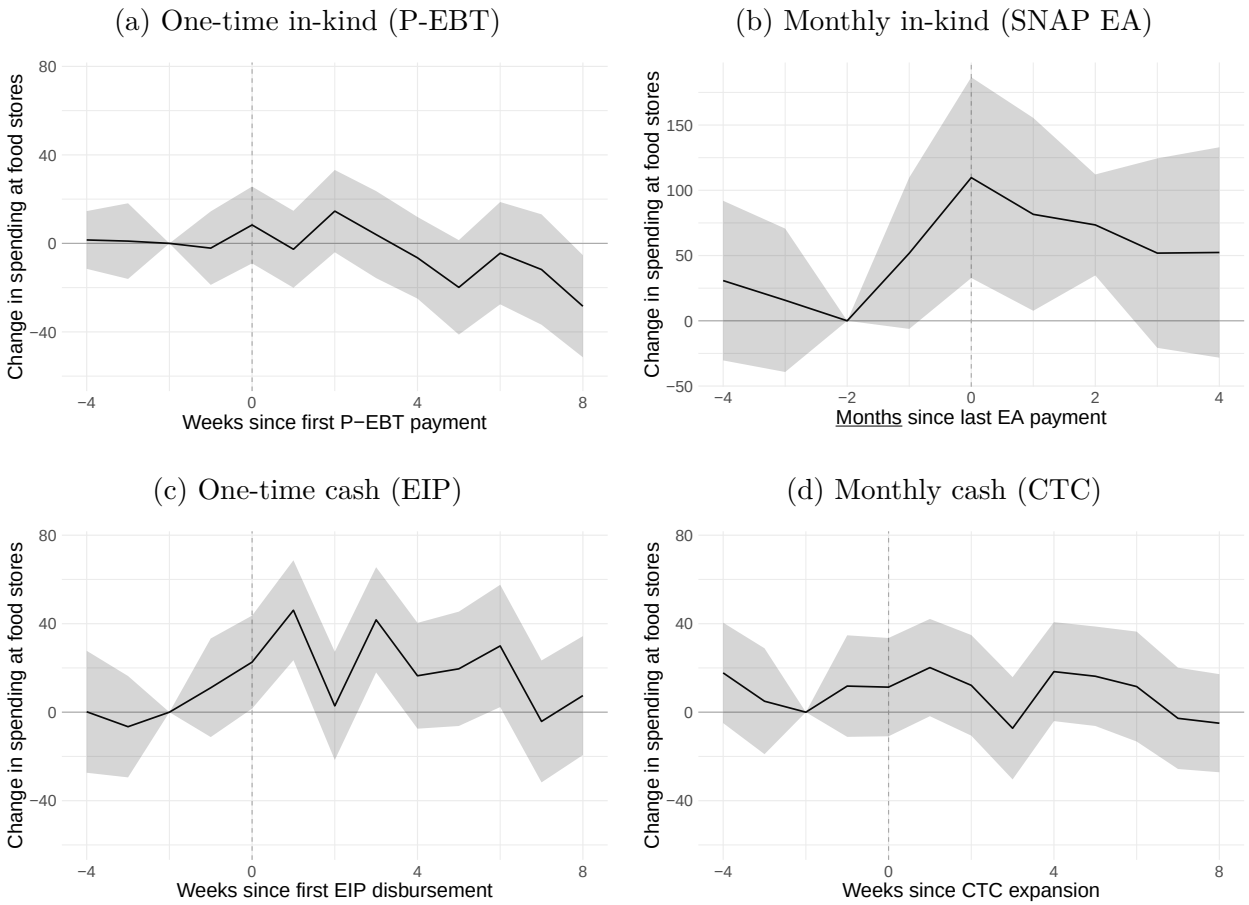
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Figure 1: Monthly food products marginal propensities to consume: Comparison to prior literature




*Notes:* Figure compares monthly marginal propensities to consume food products out of in-kind transfers (upper group, above the dashed horizontal line) and cash transfers (lower group). Hollow diamonds are estimates from this paper (P-EBT, SNAP EA, EIP, and the expanded CTC); filled circles are estimates from prior literature. Horizontal bars are 95 percent confidence intervals as reported in each original source. Quarterly estimates from Parker et al. (2022) divided by 3. See references for citations. Source: NielsenIQ Consumer Panel, 2019–2023 and prior literature.

Figure 2: Event study: Total spending at food stores




*Notes*: Figure plots estimates of the event-time coefficients $\beta_k$ from equation 2, where the outcome is total household spending at food stores. Event time $k = -2$ is the omitted period, so plotted estimates are changes in spending relative to 2 weeks (P-EBT, EIP, CTC) or months (SNAP EA) before the policy change. P-EBT, EIP, and CTC are estimated at the household-week level; SNAP EA is estimated at the household-month level. Sample, specification, and controls as in Table 1. Vertical line marks the first full period after transfer receipt (P-EBT, EIP, CTC) or benefit termination (SNAP EA). In panel (b), positive event time denotes the period after SNAP EA termination; estimated effects are multiplied by -1 to express the effect of benefit availability, rather than benefit loss. Shaded areas are 95 percent confidence intervals from standard errors clustered by state (P-EBT and SNAP EA) or heteroskedasticity-robust (EIP and CTC). Source: NielsenIQ Consumer Panel, 2019–2023.

Table 1: Total monthly spending at food stores and transfer receipt

| | (1) | (2) |
|---|---|---|
| | One-time payments | Monthly payments |
| Panel a: In-kind transfers | | |
| $100 transfers last 4 weeks (ITT) | 7.39 | 15.84 |
| | (3.50) | (4.36) |
| $100 transfers last 4 weeks (TOT) | 9.47 | 20.31 |
| Adjusted MPC (× 100) | 20.16 | 43.21 |
| N | 9956 | 18948 |
| DV mean | 721.71 | 650.68 |
| Avg transfer ($100s) | 6.38 | 4.00 |
| Benefit | P-EBT | SNAP EA |
| Panel b: Cash transfers | | |
| $100 transfers last 4 weeks (ITT) | 2.91 | 8.61 |
| | (0.71) | (2.10) |
| $100 transfers last 4 weeks (TOT) | 3.16 | 10.35 |
| Adjusted MPC (× 100) | 6.73 | 22.02 |
| N | 15432 | 58745 |
| DV mean | 680.49 | 707.44 |
| Avg transfer ($100s) | 43.73 | 5.56 |
| Benefit | EIP | CTC |

*Notes*: This table reports estimates of $\beta$, the coefficient on the transfer-amount from Equation 1, estimated separately for each program. The "one-time payments" column corresponds to P-EBT (Panel a) or EIP (Panel b), and the "monthly payment" column corresponds to SNAP EA (Panel a) or CTC (Panel b). Because SNAP EA is identified off benefit termination, its treatment variable is multiplied by -1 so that reported coefficients are the spending response to a $100 increase in benefits, under the assumption of symmetric responses to benefit gains and losses. Sample periods are P-EBT April 15-September 1, 2020, SNAP EA June 1, 2021-June 30, 2023, EIP the months of March-May in 2019 and 2020 and CTC the months of April-November in 2019 and 2021. Sample includes families with school-age children and household income no more than 130% of the federal poverty line in the previous year based on the midpoint of binned income, and that made at least one grocery purchase while spending no more than 100% of their income (including SNAP benefits) on groceries each month. Controls include state and week (or month for SNAP EA) fixed effects, household demographic controls (household size and income; head of household's age, gender, race/ethnicity, educational attainment, marital status; number of children; and number of adults), and state controls (unemployment rate, share of monthly SNAP benefits disbursed during the reference period, UI processing speed, pandemic-era stay-at-home and related policies). $ITT$ is the intent-to-treat estimate. $TOT = \frac{ITT}{p}$, where $p$ is the take-up rate among income-eligible households (0.78 for P-EBT and SNAP EA, 0.92 for EIP, 0.832 for CTC; sources in Section 5.1). Adjusted MPC $= \frac{TOT}{0.47}$, where 0.47 is the estimated share of shopping trips captured in the NielsenIQ panel (Einav et al., 2010). Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC (which use national event-time designs with no state variation in treatment timing). N is the number of household-period observations (household-week for P-EBT, EIP, and CTC, and household-month for SNAP EA). Source: NielsenIQ Consumer Panel, 2019–2023.

Table 2: Monthly spending on food products by food type

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Food products | Perish-ables | Non-perishables | Alcohol + Tobacco | Sweets + Soda | % Bulk purchases |
| Panel a: One-time in-kind (P-EBT) | | | | | | |
| $100 transfers last 4 weeks (ITT) | 6.11 | 1.23 | 4.89 | 0.03 | 0.31 | -0.02 |
| | (1.87) | (0.65) | (1.31) | (0.40) | (0.47) | (0.08) |
| $100 transfers last 4 weeks (TOT) | 7.83 | 1.58 | 6.27 | 0.04 | 0.40 | -0.03 |
| Adjusted MPC (× 100) | 16.67 | 3.36 | 13.34 | 0.08 | 0.85 | |
| N | 9956 | 9956 | 9956 | 9956 | 9956 | 7789 |
| DV mean | 391.50 | 112.40 | 279.10 | 23.42 | 58.68 | 23.44 |
| Avg transfer ($100s) | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 |
| Panel b: Monthly in-kind (SNAP EA) | | | | | | |
| $100 transfers last 4 weeks (ITT) | 4.70 | 1.80 | 2.90 | 0.40 | 0.71 | -0.11 |
| | (2.29) | (0.87) | (1.50) | (0.60) | (0.45) | (0.16) |
| $100 transfers last 4 weeks (TOT) | 6.03 | 2.31 | 3.72 | 0.51 | 0.91 | -0.14 |
| Adjusted MPC (× 100) | 12.82 | 4.91 | 7.91 | 1.09 | 1.94 | |
| N | 18948 | 18948 | 18948 | 18948 | 18948 | 18487 |
| DV mean | 267.37 | 83.12 | 184.25 | 14.75 | 43.88 | 26.22 |
| Avg transfer ($100s) | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.01 |
| Panel c: One-time cash (EIP) | | | | | | |
| $100 transfers last 4 weeks (ITT) | 1.32 | 0.41 | 0.91 | 0.05 | 0.06 | 0.03 |
| | (0.42) | (0.13) | (0.31) | (0.07) | (0.09) | (0.02) |
| $100 transfers last 4 weeks (TOT) | 1.43 | 0.45 | 0.99 | 0.05 | 0.07 | 0.03 |
| Adjusted MPC (× 100) | 3.05 | 0.95 | 2.10 | 0.12 | 0.14 | |
| N | 15432 | 15432 | 15432 | 15432 | 15432 | 12192 |
| DV mean | 398.98 | 112.03 | 286.95 | 23.51 | 61.29 | 22.22 |
| Avg transfer ($100s) | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 44.05 |
| Panel d: Monthly cash (CTC) | | | | | | |
| $100 transfers last 4 weeks (ITT) | 4.14 | 0.95 | 3.18 | 0.18 | 0.73 | 0.04 |
| | (0.97) | (0.32) | (0.72) | (0.13) | (0.20) | (0.07) |
| $100 transfers last 4 weeks (TOT) | 4.98 | 1.14 | 3.82 | 0.22 | 0.88 | 0.05 |
| Adjusted MPC (× 100) | 10.59 | 2.43 | 8.13 | 0.46 | 1.87 | |
| N | 58745 | 58745 | 58745 | 58745 | 58745 | 44704 |
| DV mean | 247.35 | 73.73 | 173.62 | 13.15 | 40.10 | 25.12 |
| Avg transfer ($100s) | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.57 |

*Notes*: This table decomposes the total food-store spending response from Table 1 into spending on food products (column 1), perishables (bakery, meat, seafood, deli, dairy, produce, and miscellaneous fresh departments) (column 2), non-perishables (products in frozen or dry grocery good departments) (column 3), alcohol and tobacco (column 4), sweets and soda (column 5), and share of spending on bulk-size purchases, defined as items at or above the 80th percentile of the size distribution of their product type, defined for product modules with at least 50 UPCs (column 6). Sample, specification, and controls as in Table 1. Because bulk-share is a share-of-spending outcome, no MPC is reported for column 6. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

Table 3: Monthly spending by type of store

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Grocery stores | Discount stores | Club stores | Convenience stores | Other food stores | Restaurants | Online spending |
| Panel a: One-time in-kind (P-EBT) | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 6.05 | 2.17 | -1.48 | 0.31 | 0.34 | 0.26 | -0.79 |
| | (1.71) | (3.48) | (1.22) | (0.96) | (0.48) | (0.66) | (1.42) |
| $100 transfers last 4 weeks (TOT) | 7.76 | 2.78 | -1.90 | 0.40 | 0.44 | 0.33 | -1.01 |
| Adjusted MPC (× 100) | 16.50 | 5.92 | -4.04 | 0.85 | 0.93 | 0.71 | -2.15 |
| N | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 |
| DV mean | 276.48 | 299.86 | 72.51 | 60.06 | 12.79 | 39.23 | 45.50 |
| Avg P-EBT | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 |
| Panel b: Monthly in-kind (SNAP EA) | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 10.77 | 1.01 | 2.31 | 1.73 | 0.02 | -0.67 | -1.49 |
| | (2.69) | (2.70) | (1.63) | (1.12) | (0.40) | (0.88) | (1.13) |
| $100 transfers last 4 weeks (TOT) | 13.81 | 1.29 | 2.96 | 2.22 | 0.03 | -0.86 | -1.91 |
| Adjusted MPC (× 100) | 29.38 | 2.76 | 6.30 | 4.72 | 0.05 | -1.83 | -4.06 |
| N | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 |
| DV mean | 269.62 | 240.36 | 68.17 | 62.92 | 9.60 | 36.71 | 38.92 |
| Avg transfer ($100s) | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 |
| Panel c: One-time cash (EIP) | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 0.84 | 1.78 | 0.13 | 0.06 | 0.11 | 0.13 | 0.27 |
| | (0.41) | (0.49) | (0.25) | (0.20) | (0.07) | (0.09) | (0.23) |
| $100 transfers last 4 weeks (TOT) | 0.91 | 1.93 | 0.14 | 0.07 | 0.12 | 0.14 | 0.29 |
| Adjusted MPC (× 100) | 1.94 | 4.12 | 0.30 | 0.14 | 0.25 | 0.30 | 0.62 |
| N | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 |
| DV mean | 289.94 | 259.13 | 64.96 | 55.63 | 10.82 | 31.85 | 45.06 |
| Avg transfer ($100s) | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 |
| Panel d: Monthly cash (CTC) | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 0.82 | 5.13 | 2.36 | -0.06 | 0.36 | -0.15 | -0.47 |
| | (1.20) | (1.36) | (0.98) | (0.44) | (0.25) | (0.41) | (0.90) |
| $100 transfers last 4 weeks (TOT) | 0.99 | 6.17 | 2.84 | -0.07 | 0.43 | -0.18 | -0.56 |
| Adjusted MPC (× 100) | 2.10 | 13.12 | 6.04 | -0.15 | 0.92 | -0.38 | -1.20 |
| N | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 |
| DV mean | 276.03 | 289.19 | 74.00 | 57.63 | 10.58 | 48.13 | 46.61 |
| Avg transfer ($100s) | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 |

*Notes*: This table reports estimates of $\beta$ from Equation 1 where the outcome is household food-store spending at the indicated store type. Sample, specification, and controls as in Table 1. Because the NielsenIQ coverage adjustment is not measured on a store-by-store basis, reported MPCs are subject to the assumption that food spending is under-reported uniformly across store types. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

Table 4: Total monthly spending at food stores, alternative income cutoffs, households with school-aged children

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | <130% FPL | 130-200% FPL | 200-300% FPL | < 300% FPL | > 300% FPL | > 500% FPL |
| Panel a: One-time in-kind (P-EBT) | | | | | | |
| $100 transfers | 7.39 | 5.34 | -5.76 | 2.12 | 0.73 | -1.00 |
| last 4 weeks (ITT) | (3.50) | (4.03) | (2.11) | (2.42) | (2.16) | (3.02) |
| N | 9956 | 12763 | 17327 | 40046 | 45581 | 20455 |
| DV mean | 721.71 | 737.43 | 804.68 | 757.11 | 799.59 | 782.86 |
| Avg transfer ($100s) | 6.38 | 6.00 | 6.21 | 6.20 | 5.52 | 4.93 |
| Share eligible | 1.00 | 0.86 | 0.12 | 0.63 | 0.08 | 0.06 |
| Avg transfer if eligible ($100s) | 6.38 | 5.98 | 5.05 | 6.11 | 5.16 | 4.62 |
| % Δ (/$100) | 1.02% | 0.72% | -0.72% | 0.28% | 0.09% | -0.13% |
| Panel b: Monthly in-kind (SNAP EA) | | | | | | |
| $100 transfers | 15.84 | 7.19 | 1.73 | 4.24 | 2.25 | 4.57 |
| last 4 weeks (ITT) | (4.36) | (4.02) | (2.98) | (1.45) | (1.67) | (2.86) |
| N | 18948 | 22678 | 34184 | 75810 | 89277 | 40564 |
| DV mean | 650.68 | 691.07 | 723.68 | 691.56 | 732.93 | 730.69 |
| Avg transfer ($100s) | 4.00 | 7.09 | 8.01 | 6.48 | 7.43 | 6.83 |
| Share eligible | 1.00 | 0.57 | 0.00 | 0.47 | 0.00 | 0.00 |
| Avg transfer if eligible ($100s) | 4.00 | 7.05 | 9.33 | 4.98 | . | . |
| % Δ (/$100) | 2.43% | 1.04% | 0.24% | 0.61% | 0.31% | 0.63% |
| Panel c: One-time cash (EIP) | | | | | | |
| $100 transfers | 2.91 | 1.33 | 1.76 | 1.87 | 0.83 | 1.43 |
| last 4 weeks (ITT) | (0.71) | (0.61) | (0.63) | (0.38) | (0.39) | (0.59) |
| N | 15432 | 23336 | 30752 | 69104 | 84720 | 37792 |
| DV mean | 680.49 | 705.48 | 773.05 | 722.53 | 789.82 | 776.35 |
| Avg transfer ($100s) | 43.73 | 43.68 | 45.15 | 44.24 | 42.81 | 39.48 |
| Share eligible | 1.00 | 1.00 | 0.99 | 0.99 | 0.86 | 0.82 |
| Avg transfer if eligible ($100s) | 43.73 | 43.68 | 45.15 | 44.24 | 42.81 | 39.48 |
| % Δ (/$100) | 0.43% | 0.19% | 0.23% | 0.26% | 0.11% | 0.18% |
| Panel d: Monthly cash (CTC) | | | | | | |
| $100 transfers | 8.61 | 1.66 | 1.98 | 4.16 | -5.26 | -7.82 |
| last 4 weeks (ITT) | (2.10) | (1.98) | (1.82) | (1.14) | (1.19) | (1.98) |
| N | 58745 | 87978 | 118265 | 263376 | 313379 | 138446 |
| DV mean | 707.44 | 727.22 | 760.57 | 733.47 | 758.41 | 751.73 |
| Avg transfer ($100s) | 5.56 | 5.17 | 5.26 | 5.33 | 4.30 | 3.49 |
| Share eligible | 0.94 | 0.92 | 0.90 | 0.92 | 0.44 | 0.29 |
| Avg transfer if eligible ($100s) | 5.94 | 5.65 | 5.81 | 5.80 | 4.45 | 3.51 |
| % Δ (/$100) | 1.22% | 0.23% | 0.26% | 0.57% | -0.69% | -1.04% |

*Notes*: This table reports estimates of $\beta$ from Equation 1 estimated on alternative samples of household income relative to the federal poverty line (FPL) among households with school-aged children. Sample, specification, and controls as in Table 1, except for the income restriction. "Share eligible" is the fraction of the subsample estimated to be eligible, using program eligibility rules. "Avg transfer if eligible" is the average cumulative transfer amount received by eligible households in the subsample, in hundreds of dollars. %Δ(/$100) is the implied percent change in household food-store spending per $100 of transfer, computed as ITT divided by the subsample DV mean, expressed per $100. "Avg transfer if eligible" is shown "." for programs where no households are eligible (placebo tests). Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

Table 5: Total monthly spending at food stores, different types of low-income households

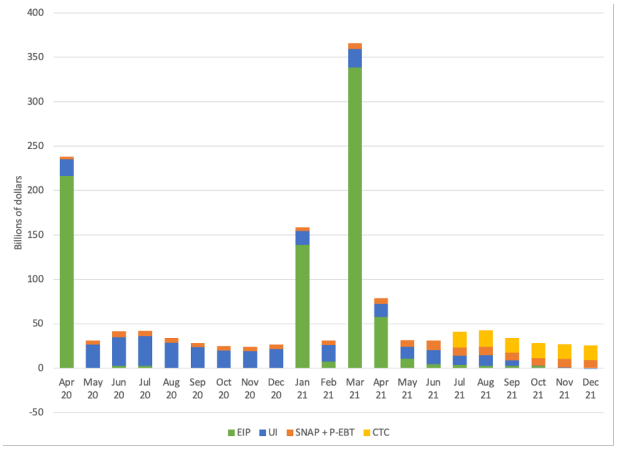
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | HH w/ school-aged children | HH w/ any children | HH w/o children | All HH |
| Panel a: One-time in-kind (P-EBT) | | | | |
| $100 transfers | 7.39 | 5.25 | -1.16 | 6.11 |
| last 4 weeks (ITT) | (3.50) | (4.05) | (1.56) | (3.71) |
| N | 9956 | 10932 | 22212 | 33144 |
| DV mean | 721.71 | 704.12 | 491.54 | 577.57 |
| Avg transfer ($100s) | 6.38 | 5.78 | 6.10 | 2.26 |
| Share eligible | 1.00 | 0.89 | 0.00 | 0.36 |
| Avg transfer if eligible ($100s) | 6.38 | 6.38 | . | 6.38 |
| % Δ (/$100) | 1.02% | 0.75% | -0.24% | 1.06% |
| Panel b: Monthly in-kind (SNAP EA) | | | | |
| $100 transfers | 15.84 | 14.53 | 8.28 | 12.61 |
| last 4 weeks (ITT) | (4.36) | (3.85) | (4.12) | (3.92) |
| N | 18948 | 20336 | 23871 | 44207 |
| DV mean | 650.68 | 643.60 | 556.26 | 607.68 |
| Avg transfer ($100s) | 4.00 | 3.96 | 2.72 | 3.41 |
| Share eligible | 1.00 | 1.00 | 1.00 | 1.00 |
| Avg transfer if eligible ($100s) | 4.00 | 3.96 | 2.72 | 3.41 |
| % Δ (/$100) | 2.43% | 2.26% | 1.49% | 2.08% |
| Panel c: One-time cash (EIP) | | | | |
| $100 transfers | 2.91 | 2.82 | 1.59 | 2.32 |
| last 4 weeks (ITT) | (0.71) | (0.68) | (0.51) | (0.40) |
| N | 15432 | 17080 | 36272 | 53352 |
| DV mean | 680.49 | 677.11 | 467.14 | 549.82 |
| Avg transfer ($100s) | 43.73 | 43.33 | 25.02 | 32.23 |
| Share eligible | 1.00 | 1.00 | 1.00 | 1.00 |
| Avg transfer if eligible ($100s) | 43.73 | 43.33 | 25.02 | 32.23 |
| % Δ (/$100) | 0.43% | 0.42% | 0.34% | 0.42% |
| Panel d: Monthly cash (CTC) | | | | |
| $100 transfers | 8.61 | 8.66 | -0.34 | 7.36 |
| last 4 weeks (ITT) | (2.10) | (2.04) | (1.21) | (1.47) |
| N | 58745 | 64728 | 133362 | 198090 |
| DV mean | 707.44 | 696.33 | 451.86 | 551.98 |
| Avg transfer ($100s) | 5.56 | 5.47 | 5.10 | 2.24 |
| Share eligible | 0.94 | 0.94 | 0.00 | 0.39 |
| Avg transfer if eligible ($100s) | 5.94 | 5.80 | . | 5.80 |
| % Δ (/$100) | 1.22% | 1.24% | -0.08% | 1.33% |

*Notes*: This table reports estimates of $\beta$ from Equation 1 estimated on subsamples defined by household composition measured annually. All columns limited to households with incomes no more than 130% of the federal poverty line. Column 1 includes our baseline sample, low-income households with school-age children. Column 2 includes households with children of any age. Column 3 is limited to childless households. Column 4 is all low-income households pooled. For households without children (column 3), imputed child-only benefits (CTC and P-EBT) are constructed from per-child benefit amounts and household size; the resulting "Avg transfer if eligible" is shown "." for programs where no households are eligible. Sample, specification, and controls as in Table 1, except for the demographic restriction. All other terms defined in Table 4. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

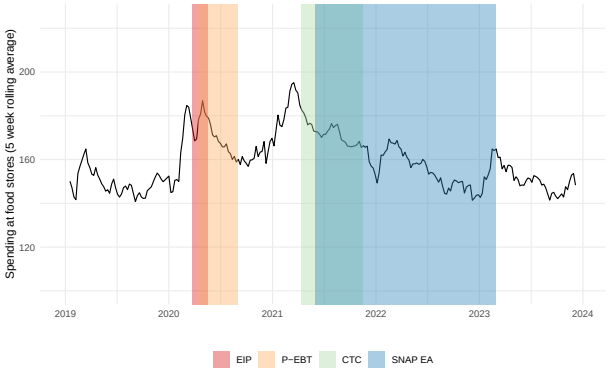
# 9 Appendix

Appendix Figure A1: Transfer payment timing

(a) Federal spending, select programs

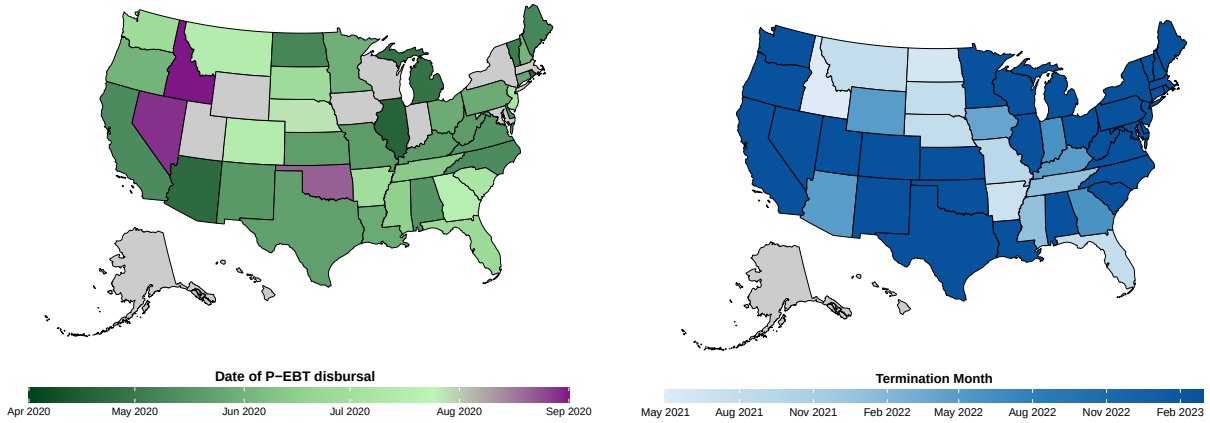



(b) Spending at food stores by program analysis period



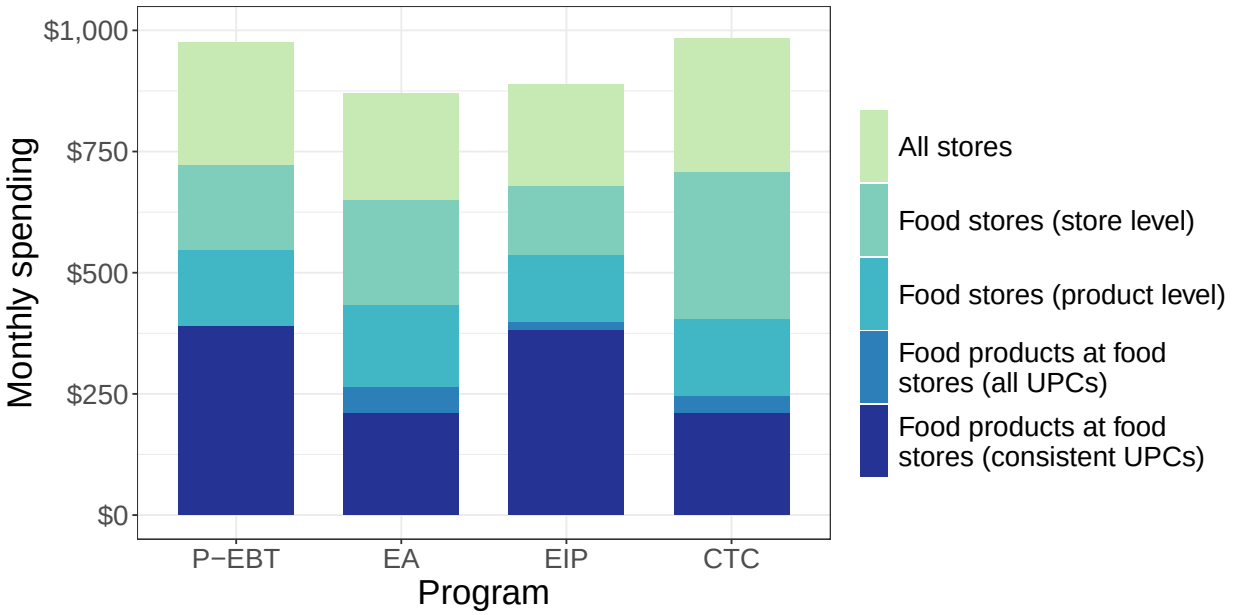

(c) Cross-state variation in P-EBT payments

(d) Cross-state variation in SNAP EA payments



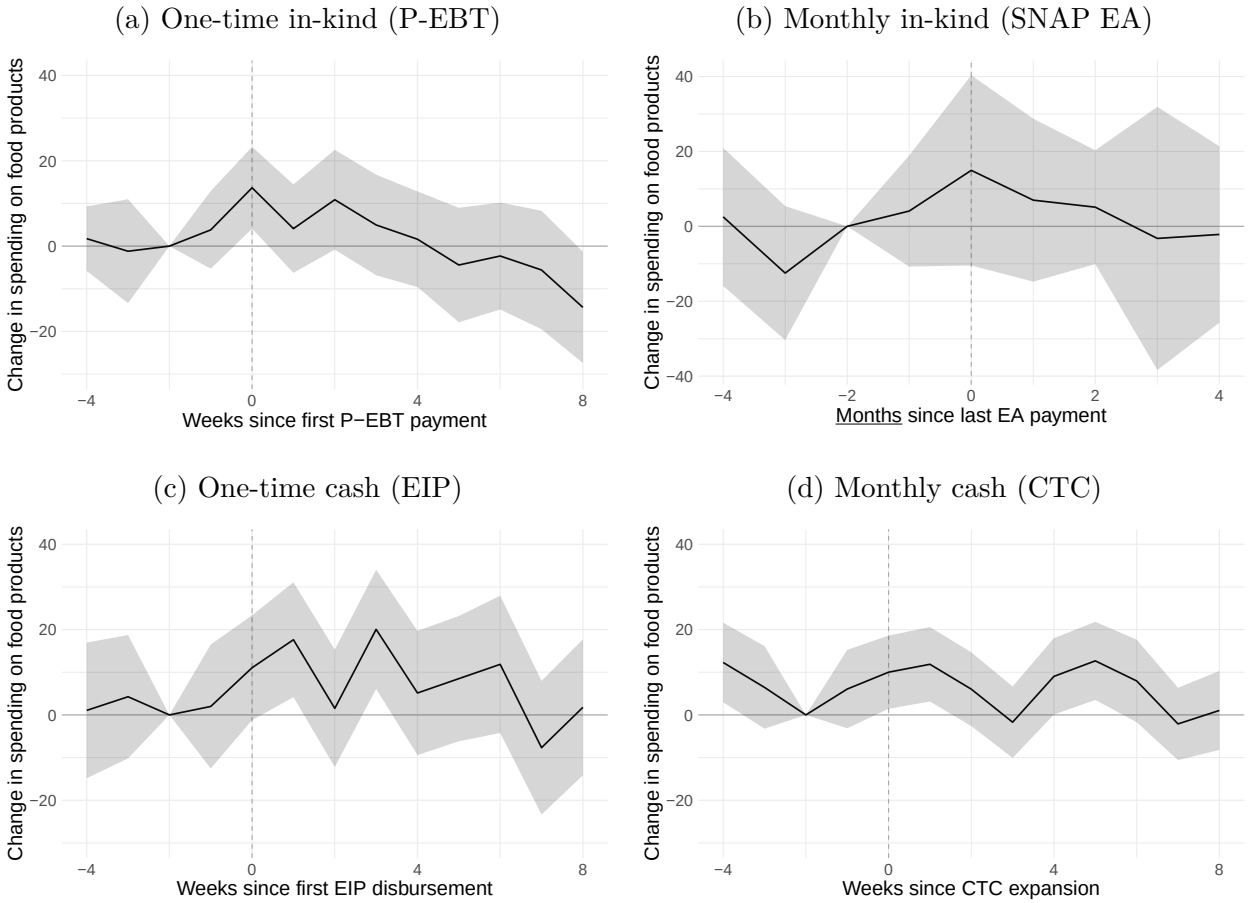

*Notes*: Panel a shows monthly timing of spending on EIP, enhanced UI, additional SNAP and P-EBT, and CTC from April 2020- December 2021 from monthly Treasury Statements, Panel b shows a 5-week rolling average of total spending at food stores among households with school-aged children and incomes no higher than 130% of the poverty threshold in the NielsenIQ data. Panels c and d show state-level variation in program administration used for identification. Panel c shows the week of first P-EBT issuance by state, from (Bauer et al., 2024); panel d shows the month of SNAP emergency allotment termination by state compiled by Schanzenbach (2023). Gray states indicate states excluded from the sample due to conflicting reports of issuance dates (P-EBT) or no coverage in the NielsenIQ data (Alaska and Hawaii). Sources: Monthly Treasury Statements 2020-2021, USDA FNS records, NielsenIQ Consumer Panel, 2019–2023, Bauer et al. (2024).

Appendix Figure A2: NielsenIQ spending coverage




*Notes*: Figure shows monthly spending in our analysis sample for each program's study period. "All stores" and "food stores" captures all purchases at all (food) stores based on receipt scans. "Food stores" spending is our primary dependent variable. "Product level" at food stores is the sum of all reported items and does not include taxes, fees, or unreported goods. "Food products at food stores" includes the subset of products that are food and beverages, and is the dependent variable in Table 2 column 1. "Consistent UPCs" include only spending on food products that appear at least once in the NielsenIQ data in each year of the analysis period, and are reported in Table A5. Source: NielsenIQ Consumer Panel, 2019–2023.

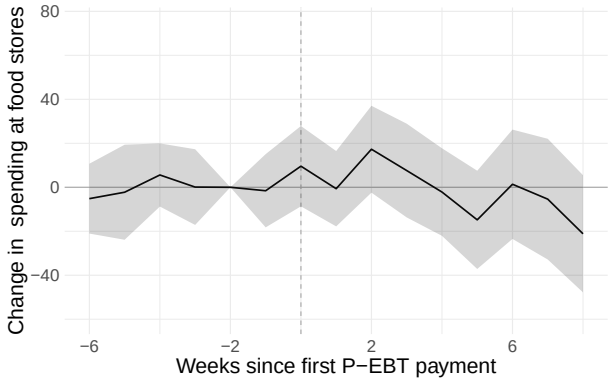
Appendix Figure A3: Event study: Spending on food products



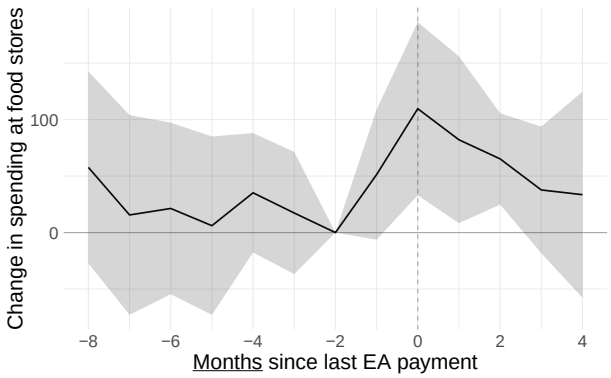

*Notes*: Figure plots estimates of the event-time coefficients $\beta_k$ from equation 2 with the outcome as spending on food products. Event time $k = -2$ is the omitted period. Sample and specification as in Figure 2. Shaded areas are 95 percent confidence intervals from standard errors clustered by state (P-EBT and SNAP EA) or heteroskedasticity-robust (EIP and CTC). Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Figure A4: Event study, longer pre-period: Total spending at food stores

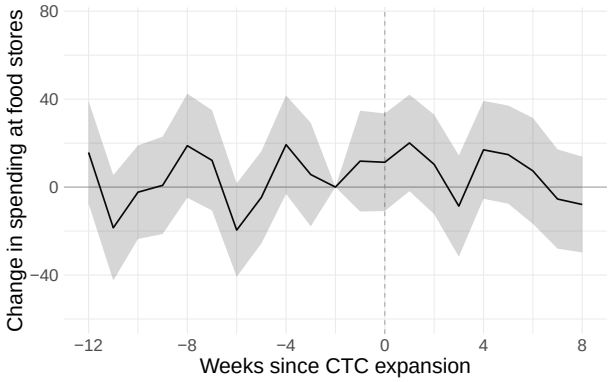
(a) One-time in-kind (P-EBT)




(b) Monthly in-kind (SNAP EA)




(c) Monthly cash (CTC)




*Notes*: Figure plots estimates of the event-time coefficients $\beta_k$ from equation 2 with the outcome total spending at food stores. Event time $k = -2$ is the omitted period. Sample, specification, and estimator as in Figure 2. Shaded areas are 95 percent confidence intervals from standard errors clustered by state (P-EBT and SNAP EA) or heteroskedasticity-robust (EIP and CTC). Source: NielsenIQ Consumer Panel, 2019–2023.

## Appendix Table A1: Summary statistics

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-time in-kind | | Monthly in-kind | | One-time cash | | | | Monthly cash | | | |
| | (P-EBT) | | (SNAP EA) | | (EIP) | | | | (CTC) | | | |
| | | | | | 2019 | | 2020 | | 2019 | | 2021 | |
| | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| **Outcomes of interest (monthly)** | | | | | | | | | | | | |
| Total spending at food stores | 721.71 | 768.04 | 650.68 | 438.57 | 626.93 | 670.54 | 680.49 | 735.75 | 593.52 | 654.75 | 707.44 | 731.90 |
| Spending on food products | 391.50 | 437.47 | 267.37 | 211.89 | 353.86 | 414.03 | 398.98 | 452.24 | 332.47 | 405.61 | 247.35 | 288.56 |
| Number of trips | 9.20 | 8.02 | 9.22 | 6.52 | 9.69 | 8.69 | 9.03 | 8.06 | 9.38 | 8.43 | 9.28 | 8.11 |
| Spending/trip | 91.89 | 85.17 | 85.55 | 60.62 | 76.31 | 69.4 | 88.71 | 85.03 | 74.34 | 69.15 | 90.04 | 81.79 |
| Perishable spend | 112.40 | 141.80 | 83.12 | 74.35 | 102.35 | 133.79 | 112.03 | 145.01 | 98.47 | 136.26 | 73.73 | 96.00 |
| Non-perishable spend | 279.10 | 324.79 | 184.25 | 152.85 | 251.51 | 309.32 | 286.95 | 336.54 | 234.00 | 298.27 | 173.62 | 216.89 |
| **Benefit amount** | | | | | | | | | | | | |
| Transfer amount | 638.12 | 384.69 | 400.21 | 230.53 | 0.00 | 0.00 | 4372.93 | 1402.88 | 0.00 | 0.00 | 555.87 | 333.04 |
| **Demographics** | | | | | | | | | | | | |
| Married | 0.550 | 0.498 | 0.497 | 0.500 | 0.526 | 0.499 | 0.513 | 0.500 | 0.526 | 0.499 | 0.499 | 0.500 |
| < HS | 0.055 | 0.228 | 0.041 | 0.197 | 0.045 | 0.207 | 0.047 | 0.212 | 0.045 | 0.207 | 0.039 | 0.195 |
| HS diploma | 0.329 | 0.470 | 0.355 | 0.479 | 0.352 | 0.478 | 0.340 | 0.474 | 0.352 | 0.478 | 0.355 | 0.478 |
| Some college | 0.401 | 0.490 | 0.382 | 0.486 | 0.393 | 0.488 | 0.404 | 0.491 | 0.393 | 0.488 | 0.376 | 0.484 |
| College degree + | 0.216 | 0.411 | 0.222 | 0.415 | 0.210 | 0.407 | 0.209 | 0.407 | 0.210 | 0.407 | 0.230 | 0.421 |
| Black | 0.166 | 0.372 | 0.163 | 0.369 | 0.169 | 0.375 | 0.154 | 0.361 | 0.169 | 0.375 | 0.159 | 0.366 |
| Hispanic | 0.211 | 0.408 | 0.217 | 0.412 | 0.182 | 0.386 | 0.218 | 0.413 | 0.182 | 0.386 | 0.201 | 0.401 |
| White | 0.558 | 0.497 | 0.552 | 0.497 | 0.595 | 0.491 | 0.568 | 0.495 | 0.595 | 0.491 | 0.571 | 0.495 |
| Other race | 0.065 | 0.247 | 0.068 | 0.251 | 0.054 | 0.227 | 0.060 | 0.237 | 0.054 | 0.227 | 0.068 | 0.252 |
| 2 heads of household | 0.547 | 0.498 | 0.470 | 0.499 | 0.486 | 0.500 | 0.493 | 0.500 | 0.486 | 0.500 | 0.464 | 0.499 |
| Female head only | 0.416 | 0.493 | 0.470 | 0.499 | 0.454 | 0.498 | 0.458 | 0.498 | 0.454 | 0.498 | 0.484 | 0.500 |
| Male head only | 0.037 | 0.189 | 0.060 | 0.238 | 0.060 | 0.237 | 0.050 | 0.217 | 0.060 | 0.237 | 0.052 | 0.222 |
| Age of HoH | 43.8 | 10.7 | 45.0 | 11.1 | 44.7 | 11.0 | 44.1 | 10.9 | 44.7 | 11.0 | 44.9 | 11.0 |
| # adults | 2.18 | 0.86 | 2.26 | 1.01 | 2.19 | 0.97 | 2.18 | 0.92 | 2.19 | 0.97 | 2.22 | 0.93 |
| # children | 2.12 | 1.11 | 2.07 | 1.06 | 2.21 | 1.15 | 2.10 | 1.09 | 2.21 | 1.15 | 2.10 | 1.04 |
| # children under 5 | 0.23 | 0.46 | 0.20 | 0.48 | 0.23 | 0.47 | 0.22 | 0.46 | 0.23 | 0.47 | 0.22 | 0.51 |
| HH income | 27138 | 19509 | 26637 | 18261 | 21144 | 9845 | 27278 | 19346 | 21144 | 9845 | 24084 | 9972 |
| **COVID policies and other benefits** | | | | | | | | | | | | |
| Stay-at-home active | 0.503 | 0.500 | 0.000 | 0.000 | 0.000 | 0.000 | 0.770 | 0.421 | 0.000 | 0.000 | 0.000 | 0.000 |
| Restaurant closure active | 0.569 | 0.495 | 0.000 | 0.000 | 0.000 | 0.000 | 0.914 | 0.281 | 0.000 | 0.000 | 0.005 | 0.071 |
| Mask mandate active | 0.070 | 0.255 | 0.152 | 0.359 | 0.000 | 0.000 | 0.008 | 0.092 | 0.000 | 0.000 | 0.497 | 0.500 |
| Any P-EBT disbursement | | | 0.586 | 0.493 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.742 | 0.437 |
| SNAP EAs active | 1.000 | 0.000 | | | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.991 | 0.093 |
| Unemployment rate | 0.126 | 0.048 | 0.013 | 0.008 | 0.011 | 0.006 | 0.090 | 0.052 | 0.010 | 0.005 | 0.023 | 0.010 |
| UI processed wi/ 1 wk | 0.343 | 0.232 | 0.365 | 0.191 | 0.545 | 0.179 | 0.461 | 0.277 | 0.558 | 0.180 | 0.336 | 0.208 |
| UI processed 1-2 wks | 0.622 | 0.211 | 0.583 | 0.181 | 0.815 | 0.114 | 0.813 | 0.148 | 0.829 | 0.108 | 0.564 | 0.167 |
| UI processed < 10 wks | 0.969 | 0.078 | 0.838 | 0.143 | 0.984 | 0.018 | 0.998 | 0.003 | 0.988 | 0.014 | 0.866 | 0.088 |
| # HH | 873 | | 1479 | | 910 | | 1019 | | 910 | | 985 | |

*Notes*: This table reports pre-period summary statistics for the estimation samples used in Table 1. Demographics are measured at household entry into the NielsenIQ panel and updated annually thereafter. Sample periods are P-EBT April 15-September 1, 2020, SNAP EA June 1, 2021-June 30, 2023, EIP the months of March-May in 2019 and 2020 and CTC the months of April-November in 2019 and 2021. Household income is observed in the binned categories reported by NielsenIQ. N is the number of unique households. Sample restrictions as in Table 1. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A2: Total monthly spending at food stores and transfer receipt, household fixed effects

| | (1) | (2) |
|---|---|---|
| | One-time payments | Monthly payments |
| Panel a: In-kind transfers | | |
| $100 transfers last 4 weeks (ITT) | 7.07 | 11.85 |
| | (3.20) | (2.18) |
| $100 transfers last 4 weeks (TOT) | 9.06 | 15.19 |
| Adjusted MPC (× 100) | 19.29 | 32.32 |
| N | 9956 | 18948 |
| DV mean | 721.71 | 650.68 |
| Avg transfer ($100s) | 6.38 | 4.00 |
| Benefit | P-EBT | SNAP EA |
| Panel b: Cash transfers | | |
| $100 transfers last 4 weeks (ITT) | 2.77 | 1.13 |
| | (0.67) | (2.33) |
| $100 transfers last 4 weeks (TOT) | 3.01 | 1.36 |
| Adjusted MPC (× 100) | 6.41 | 2.89 |
| N | 15432 | 58745 |
| DV mean | 680.49 | 707.44 |
| Avg transfer ($100s) | 43.73 | 5.56 |
| Benefit | EIP | CTC |

*Notes*: This table reports estimates of $\beta$ from Equation 1 estimated separately for each program, with the addition of household fixed effects. The "one-time payment" column corresponds to P-EBT (Panel a) or EIP (Panel b), and the "monthly payment" column corresponds to SNAP EA (Panel a) or CTC (Panel b). Because SNAP EA is identified off benefit termination, its treatment variable is multiplied by -1 so that reported coefficients are the spending response to a $100 increase in benefits, under the assumption of symmetric responses to benefit gains and losses. Sample periods are P-EBT April 15-September 1, 2020, SNAP EA June 1, 2021-June 30, 2023, EIP the months of March-May in 2019 and 2020 and CTC the months of April-November in 2019 and 2021. Sample includes families with school-age children and household income no more than 130% of the federal poverty line in the previous year based on the midpoint of binned income, and that made at least one grocery purchase while spending no more than 100% of their income (including SNAP benefits) on groceries each month. Controls include state and week (or month for SNAP EA) fixed effects, household demographic controls (household size and income; head of household's age, gender, race/ethnicity, educational attainment, marital status; number of children; and number of adults), and state controls (unemployment rate, share of monthly SNAP benefits disbursed during the reference period, UI processing speed, pandemic-era stay-at-home and related policies). $ITT$ is the intent-to-treat estimate. $TOT = \frac{ITT}{p}$, where $p$ is the take-up rate among income-eligible households (0.78 for P-EBT and SNAP EA, 0.92 for EIP, 0.832 for CTC; sources in Section 5.1). Implied MPC $= \frac{TOT}{0.47} * 0.01$, where 0.47 is the estimated share of shopping trips captured in the NielsenIQ panel (Einav et al., 2010). DV mean is the mean of the dependent variable, and Avg transfer ($100s) is the average transfer, in the estimation sample. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC (which use national event-time designs with no state variation in treatment timing) N is the number of household-period observations (household-week for P-EBT, EIP, and CTC, and household-month for SNAP EA). Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A3: Monthly total spending at food stores, spend no more than 200% income on food

| | (1) | (2) |
|---|---|---|
| | One-time payments | Monthly payments |
| Panel a: In-kind transfers | | |
| $100 transfers last 4 weeks (ITT) | 4.43 | 12.63 |
| | (3.38) | (5.08) |
| $100 transfers last 4 weeks (TOT) | 5.68 | 16.19 |
| Adjusted MPC (× 100) | 12.08 | 34.45 |
| N | 10819 | 21266 |
| DV mean | 785.42 | 708.99 |
| Avg transfer ($100s) | 6.31 | 3.70 |
| Benefit | P-EBT | SNAP EA |
| Panel b: Cash transfers | | |
| $100 transfers last 4 weeks (ITT) | 3.30 | 7.42 |
| | (0.75) | (2.19) |
| $100 transfers last 4 weeks (TOT) | 3.59 | 8.92 |
| Adjusted MPC (× 100) | 7.63 | 18.98 |
| N | 16816 | 65472 |
| DV mean | 728.43 | 765.81 |
| Avg transfer ($100s) | 43.17 | 5.44 |
| Benefit | EIP | CTC |

*Notes*: This table estimates the same specification as Table 1 but includes households that spend no more than 200% of their income (including SNAP benefits) on food. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A4: Monthly shopping patterns and transfer receipt

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Number of trips | | Spending per trip | |
| | One-time payments | Monthly payments | One-time payments | Monthly payments |
| Panel a: In-kind transfers | | | | |
| $100 transfers last 4 weeks (ITT) | 0.02 | 0.10 | 0.63 | 1.22 |
| | (0.03) | (0.05) | (0.48) | (0.65) |
| $100 transfers last 4 weeks (TOT) | 0.03 | 0.13 | 0.81 | 1.56 |
| N | 9956 | 18948 | 8381 | 18948 |
| DV mean | 9.20 | 9.22 | 91.89 | 85.55 |
| Avg transfer ($100s) | 6.38 | 4.00 | 6.38 | 4.00 |
| Benefit | P-EBT | SNAP EA | P-EBT | SNAP EA |
| Panel b: Cash transfers | | | | |
| $100 transfers last 4 weeks (ITT) | 0.02 | 0.03 | 0.20 | 0.72 |
| | (0.01) | (0.02) | (0.07) | (0.25) |
| $100 transfers last 4 weeks (TOT) | 0.02 | 0.04 | 0.22 | 0.87 |
| N | 15432 | 58745 | 12973 | 48991 |
| DV mean | 9.03 | 9.28 | 88.71 | 90.04 |
| Avg transfer ($100s) | 43.73 | 5.56 | 43.93 | 5.56 |
| Benefit | EIP | CTC | EIP | CTC |

*Notes*: This table reports estimates of $\beta$ from Equation 1 into an extensive margin (columns 1–2: number of shopping trips per household-month) and an intensive margin (columns 3–4: average spending per trip) response. Sample, treatment variable, and controls as in Table 1. The spending-per-trip columns drop household-weeks with zero trips for P-EBT, EIP, and CTC and household-months with zero trips for SNAP EA. TOT calculated as in Table 1. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

## Appendix Table A5: Monthly food and non-food spending, Various definitions

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **All products** | | | | **Food products** | | | | **Non-food products** | | | |
| | All stores, receipt | Food stores, receipt | All stores, product | Food stores, product | All stores, product | Food stores, product | All stores, clean UPCs | Food stores, clean UPCs | All stores, product | Food stores, product | All stores, clean UPCs | Food stores, clean UPCs |
| Panel a: One-time in-kind (P-EBT) | | | | | | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 6.97 | 7.39 | 8.13 | 7.27 | 6.56 | 6.11 | 6.56 | 6.11 | 1.57 | 1.16 | 1.57 | 1.16 |
| | (5.41) | (3.50) | (3.34) | (2.49) | (1.87) | (1.87) | (1.87) | (1.87) | (2.22) | (1.15) | (2.22) | (1.15) |
| $100 transfers last 4 weeks (TOT) | 8.94 | 9.47 | 10.42 | 9.32 | 8.41 | 7.83 | 8.41 | 7.83 | 2.01 | 1.49 | 2.01 | 1.49 |
| Adjusted MPC (× 100) | 19.01 | 20.16 | 22.18 | 19.83 | 17.89 | 16.67 | 17.89 | 16.67 | 4.28 | 3.16 | 4.28 | 3.16 |
| N | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 |
| DV mean | 974.54 | 721.71 | 686.71 | 547.47 | 460.33 | 391.50 | 460.33 | 391.50 | 226.38 | 155.97 | 226.38 | 155.97 |
| Avg transfer ($100s) | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 |
| Panel b: Monthly in-kind (SNAP EA) | | | | | | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 11.28 | 15.84 | 7.49 | 8.86 | 4.82 | 4.70 | 4.25 | 4.16 | 2.67 | 4.16 | 3.00 | 4.41 |
| | (5.42) | (4.36) | (3.38) | (3.02) | (2.33) | (2.29) | (1.79) | (1.80) | (1.93) | (1.25) | (1.84) | (1.08) |
| $100 transfers last 4 weeks (TOT) | 14.46 | 20.31 | 9.60 | 11.36 | 6.18 | 6.03 | 5.45 | 5.33 | 3.42 | 5.33 | 3.85 | 5.65 |
| Adjusted MPC (× 100) | 30.77 | 43.21 | 20.43 | 24.17 | 13.15 | 12.82 | 11.59 | 11.35 | 7.28 | 11.35 | 8.18 | 12.03 |
| N | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 |
| DV mean | 869.96 | 650.68 | 553.99 | 437.51 | 288.27 | 267.37 | 227.24 | 210.63 | 265.71 | 170.14 | 226.42 | 138.59 |
| Avg transfer ($100s) | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 |
| Panel c: One-time cash (EIP) | | | | | | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 3.63 | 2.91 | 2.59 | 2.04 | 1.39 | 1.32 | 1.33 | 1.25 | 1.20 | 0.72 | 0.88 | 0.52 |
| | (0.99) | (0.71) | (0.64) | (0.54) | (0.44) | (0.42) | (0.43) | (0.41) | (0.36) | (0.24) | (0.32) | (0.23) |
| $100 transfers last 4 weeks (TOT) | 3.95 | 3.16 | 2.82 | 2.22 | 1.51 | 1.43 | 1.45 | 1.36 | 1.30 | 0.78 | 0.96 | 0.57 |
| Adjusted MPC (× 100) | 8.40 | 6.73 | 5.99 | 4.72 | 3.21 | 3.05 | 3.08 | 2.89 | 2.78 | 1.67 | 2.04 | 1.20 |
| N | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 |
| DV mean | 889.33 | 680.49 | 665.22 | 536.73 | 468.53 | 398.98 | 449.33 | 382.40 | 196.68 | 137.74 | 181.58 | 126.33 |
| Avg transfer ($100s) | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 |
| Panel d: Monthly cash (CTC) | | | | | | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 8.45 | 8.61 | 4.53 | 5.34 | 5.27 | 4.14 | 3.89 | 3.12 | -0.73 | 1.20 | -1.33 | 0.80 |
| | (2.92) | (2.10) | (1.60) | (1.30) | (1.02) | (0.97) | (0.82) | (0.78) | (0.99) | (0.62) | (0.91) | (0.54) |
| $100 transfers last 4 weeks (TOT) | 10.16 | 10.35 | 5.44 | 6.42 | 6.33 | 4.98 | 4.68 | 3.75 | -0.88 | 1.44 | -1.60 | 0.96 |
| Adjusted MPC (× 100) | 21.61 | 22.02 | 11.58 | 13.66 | 13.48 | 10.59 | 9.95 | 7.98 | -1.87 | 3.07 | -3.40 | 2.05 |
| N | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 |
| DV mean | 983.36 | 707.44 | 538.15 | 404.84 | 267.18 | 247.35 | 226.90 | 210.66 | 270.96 | 157.49 | 240.53 | 134.69 |
| Avg transfer ($100s) | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 |

*Notes*: This table reports estimates of $\beta$ from Equation 1 with alternative outcome definitions by store scope (all stores vs. food stores only) and the level at which purchases are counted (receipt total including taxes and fees; product-level sum across all UPCs; or product-level sum restricted to "clean" UPCs that appear at least once in every sample year). Sample, specification, and controls as in Table 1. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

## Appendix Table A6: Monthly food spending, shorter timing

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total spend food stores | Food products | Number of trips | Spend/ trip | Grocery stores | Dis- count stores | Club stores | Con- venience stores | Other food stores | Rest- aurants | Perish- ables | Non- perish ables | Alcohol + Tobacco | Sweets + Soda | % Bulk purchases |
| Panel a: One-time in-kind (P-EBT) | | | | | | | | | | | | | | | |
| $100 transfers last 2 weeks (ITT) | 6.78 | 6.13 | 0.03 | 0.72 | 5.90 | 2.83 | -2.42 | 0.29 | 0.16 | -0.12 | 1.10 | 5.03 | -0.08 | 0.29 | -0.00 |
| | (3.50) | (2.19) | (0.04) | (0.65) | (1.94) | (3.74) | (1.22) | (1.04) | (0.52) | (0.53) | (0.79) | (1.49) | (0.24) | (0.41) | (0.10) |
| $100 transfers last 2 weeks (TOT) | 8.69 | 7.86 | 0.04 | 0.92 | 7.56 | 3.63 | -3.10 | 0.37 | 0.21 | -0.15 | 1.41 | 6.45 | -0.10 | 0.37 | 0.00 |
| Adjusted MPC (× 100) | 18.49 | 16.72 | 0.08 | 1.96 | 16.09 | 7.72 | -6.60 | 0.79 | 0.44 | -0.33 | 3.00 | 13.72 | -0.22 | 0.79 | |
| N | 8276 | 8276 | 8276 | 6991 | 8276 | 8276 | 8276 | 8276 | 8276 | 8276 | 8276 | 8276 | 8276 | 8276 | 6488 |
| DV mean | 721.71 | 391.50 | 9.20 | 91.89 | 276.48 | 299.86 | 72.51 | 60.06 | 12.79 | 39.23 | 112.40 | 279.10 | 23.42 | 58.68 | 23.44 |
| Avg transfer ($100s) | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 | 6.37 |
| Panel b: Monthly in-kind (SNAP EA) | | | | | | | | | | | | | | | |
| $100 transfers last 2 weeks (ITT) | | | | | | | | | | | | | | | |
| Panel c: One-time cash (EIP) | | | | | | | | | | | | | | | |
| $100 transfers last 2 weeks (ITT) | 3.04 | 1.48 | 0.02 | 0.15 | 0.67 | 1.85 | 0.46 | -0.13 | 0.19 | 0.14 | 0.44 | 1.04 | -0.01 | 0.00 | 0.04 |
| | (0.92) | (0.51) | (0.01) | (0.10) | (0.52) | (0.64) | (0.33) | (0.27) | (0.10) | (0.12) | (0.17) | (0.38) | (0.08) | (0.12) | (0.03) |
| $100 transfers last 2 weeks (TOT) | 3.30 | 1.61 | 0.02 | 0.16 | 0.73 | 2.01 | 0.50 | -0.14 | 0.21 | 0.15 | 0.48 | 1.13 | -0.01 | 0.00 | 0.04 |
| Adjusted MPC (× 100) | 7.03 | 3.42 | 0.05 | 0.35 | 1.55 | 4.28 | 1.06 | -0.30 | 0.44 | 0.32 | 1.02 | 2.41 | -0.02 | 0.00 | |
| N | 11574 | 11574 | 11574 | 9695 | 11574 | 11574 | 11574 | 11574 | 11574 | 11574 | 11574 | 11574 | 11574 | 11574 | 9117 |
| DV mean | 680.49 | 398.98 | 9.03 | 88.71 | 289.94 | 259.13 | 64.96 | 55.63 | 10.82 | 31.85 | 112.03 | 286.95 | 23.51 | 61.29 | 22.22 |
| Avg transfer ($100s) | 43.92 | 43.92 | 43.92 | 44.11 | 43.92 | 43.92 | 43.92 | 43.92 | 43.92 | 43.92 | 43.92 | 43.92 | 43.92 | 43.92 | 44.17 |
| Panel d: Monthly cash (CTC) | | | | | | | | | | | | | | | |
| $100 transfers last 2 weeks (ITT) | 7.51 | 3.98 | 0.03 | 0.45 | 1.93 | 3.78 | 0.64 | 0.38 | 0.78 | -0.46 | 0.97 | 3.01 | 0.11 | 1.04 | -0.06 |
| | (3.02) | (1.43) | (0.03) | (0.35) | (1.71) | (2.03) | (1.28) | (0.60) | (0.44) | (0.60) | (0.48) | (1.06) | (0.20) | (0.32) | (0.11) |
| $100 transfers last 2 weeks (TOT) | 9.03 | 4.78 | 0.04 | 0.54 | 2.32 | 4.54 | 0.77 | 0.46 | 0.94 | -0.55 | 1.17 | 3.62 | 0.13 | 1.25 | -0.07 |
| Adjusted MPC (× 100) | 19.21 | 10.18 | 0.08 | 1.15 | 4.94 | 9.67 | 1.64 | 0.97 | 1.99 | -1.18 | 2.48 | 7.70 | 0.28 | 2.66 | |
| N | 26530 | 26530 | 26530 | 22051 | 26530 | 26530 | 26530 | 26530 | 26530 | 26530 | 26530 | 26530 | 26530 | 26530 | 20105 |
| DV mean | 702.75 | 246.31 | 9.29 | 88.90 | 273.22 | 291.50 | 70.91 | 56.65 | 10.46 | 50.59 | 73.32 | 173.00 | 13.29 | 40.24 | 25.75 |
| Avg transfer ($100s) | 5.58 | 5.58 | 5.58 | 5.56 | 5.58 | 5.58 | 5.58 | 5.58 | 5.58 | 5.58 | 5.58 | 5.58 | 5.58 | 5.58 | 5.58 |

*Notes*: This table reports estimates of $\beta$ from Equation 1 with the main-text spending outcomes in Tables 1-2 using a two-week (rather than four-week) transfer window: the treatment variable is the amount of P-EBT, CTC, or the first EIP issued to households in the previous two weeks. Panel b (SNAP EA) is intentionally blank: SNAP benefits are typically disbursed throughout the month, so a two-week window is not well-defined for SNAP EA. Sample and controls as in Table 1, except that N drops in each panel because the two-week window removes more household-periods with the required lag structure. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A7: EIP MPC robustness: 1-month vs 3-month response window, total spending at food stores and on food products

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Spending at food stores | | Spending on food products | |
| | EIP 1 (1 month) | EIP1 (3 month) | EIP 1 (1 month) | EIP1 (3 month) |
| \$100 transfers last 4 weeks (ITT) | 2.91 | | 1.32 | |
| | (0.71) | | (0.42) | |
| \$100 transfers last 12 weeks (ITT) | | 7.98 | | 4.05 |
| | | (1.53) | | (0.93) |
| \$100 transfers last 4 weeks (TOT) | 3.16 | | 1.43 | |
| \$100 transfers last 12 weeks (TOT) | | 8.67 | | 4.40 |
| Adjusted MPC (× 100) | 6.73 | 18.46 | 3.05 | 9.37 |
| N | 15432 | 32793 | 15432 | 32793 |
| DV mean | 680.49 | 2041.47 | 398.98 | 1196.94 |
| Avg transfer (\$100s) | 43.73 | 43.57 | 43.73 | 43.57 |

*Notes*: This table reports estimates of $\beta$ from Equation 1 over two different response windows for the EIP: a one-month window (columns 1 and 3, our baseline specification) and a three-month window (columns 2 and 4, analogous to the timing in Parker et al. (2022)). Column 1 matches the main EIP specification in Table 1 Panel b column 1 and column 3 matches the EIP specification in Table 2 Panel c column 1. The treatment variable in columns 2 and 4 is the amount of the first EIP issued to households in the previous twelve weeks (equivalent to three four-week periods). Weekly spending estimates are then rescaled by a factor of either 4 (columns 1 and 3) or 12 (columns 2 and 4) to reflect the spending increase over the entire post-period; therefore estimates in columns 1 and 3 can be interpreted as effects on monthly spending while estimates in columns 2 and 4 reflect effects on quarterly spending. The outcome in columns 1 and 2 are total household spending at food stores, and the outcome in columns 3 and 4 is spending on food products. Sample, controls, and MPC construction as in Table 1. Robust standard errors in parentheses. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A8: Monthly in-kind robustness: Total spending at food stores, by SNAP EA cohort

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Overall | Aug 2021 | Sept 2021 | Jan 2022 | Apr 2022 | May 2022 | June 2022 | Feb 2023 |
| | All states | FL, MT, NE, SD | MO | MS, TN | IA | AZ, KY, WY | GA, IN | All other states |
| $100 transfers last 4 weeks (ITT) | 15.84 | 14.90 | 26.01 | 13.63 | 39.91 | 19.45 | 13.70 | 15.22 |
| | (4.36) | (4.63) | (5.08) | (5.90) | (19.37) | (4.95) | (4.74) | (8.27) |
| $100 transfers last 4 weeks (TOT) | 20.31 | 19.10 | 33.35 | 17.47 | 51.17 | 24.94 | 17.56 | 19.51 |
| Adjusted MPC (× 100) | 43.21 | 40.64 | 70.95 | 37.18 | 108.87 | 53.06 | 37.37 | 41.52 |
| N | 18948 | 5634 | 6160 | 9027 | 9303 | 10319 | 11523 | 15941 |
| DV mean | 650.68 | 690.91 | 689.17 | 679.02 | 664.99 | 662.99 | 655.51 | 643.38 |
| Average transfers ($100s) | 4.00 | 4.06 | 4.40 | 3.93 | 5.87 | 4.77 | 4.00 | 3.92 |

*Notes*: This table reports estimates of $\beta$ from Equation 1 separately for each SNAP EA termination cohort. Column 1 reports the pooled estimate across all cohorts (matching Table 1 Panel a column 2). Columns 2–8 restrict the treated sample to states that terminated SNAP EA payments in the indicated month, with all other states still receiving SNAP EA as the comparison. States terminating benefits prior to August 2021 (ID, ND, AR) are not included because they either terminate benefits before the beginning of our sample window or contribute no households to our sample. Sample and controls as in Table 1. Treatment variable is the amount of SNAP EA (×-1) issued in the previous four weeks. Robust standard errors clustered by state in parentheses. Columns 2–7 have between one and four treated clusters; standard-error interpretation in those columns should be treated with caution and asymptotic inference is not reliable in the usual sense. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A9: One-time in-kind robustness: Total spending at food stores, by P-EBT cohort

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Overall | Apr 19 - 25 | Apr 26 - May 2 | May 3 - 9 | May 10 - 16 | May 17 - 23 | May 24 - 30 | May 31 - June 13 | June 14 - 27 | June 28 - July 11 | July 12- 25 | July 26 - Aug 21 |
| | All states | AZ, IL, RI | DC, MI, VT | ME, ND | AL, CA, DE, NC, VA | KS, KY, MO, NM, TX, WV | CT, LA, MN, OH, PA | NH, OR, TN | FL, MS, WA | AR, NJ, SC, SD | CO, GA, MT | NE, OK |
| $100 transfers last 4 weeks (ITT) | 7.39 | 11.15 | 2.60 | 13.00 | -0.11 | 10.17 | 29.73 | 22.86 | -5.38 | 12.81 | 8.20 | 12.27 |
| | (3.50) | (7.88) | (15.56) | (10.50) | (6.76) | (7.57) | (7.04) | (11.64) | (5.46) | (6.99) | (5.11) | (9.11) |
| $100 transfers last 4 weeks (TOT) | 9.47 | 14.29 | 3.33 | 16.67 | -0.14 | 13.04 | 38.12 | 29.31 | -6.90 | 16.42 | 10.51 | 15.73 |
| Adjusted MPC (× 100) | 20.16 | 30.41 | 7.09 | 35.46 | -0.30 | 27.74 | 81.10 | 62.36 | -14.68 | 34.94 | 22.37 | 33.47 |
| N | 9956 | 3474 | 3163 | 2496 | 4174 | 4044 | 4009 | 2035 | 2266 | 1305 | 1746 | 831 |
| DV mean | 721.71 | 737.76 | 750.16 | 712.77 | 711.19 | 694.16 | 699.67 | 735.45 | 651.03 | 701.85 | 707.67 | 715.40 |
| Average transfers ($100s) | 6.38 | 6.45 | 4.92 | 7.82 | 8.05 | 5.17 | 6.38 | 7.01 | 5.93 | 5.90 | 5.41 | 5.50 |

*Notes*: This table reports estimates of $\beta$ from Equation 1 separately for each P-EBT issuance cohort. Column 1 reports the pooled estimate across all cohorts (matching Table 1 panel A column 1). Cohorts in columns 2-12 are defined as states that issued their P-EBT payments during a given calendar week through May (columns 2-7) or a 2-week period thereafter (columns 8-11). Columns 2–12 restrict the treated sample to states that issued P-EBT payments in the indicated month, with all other states not yet receiving P-EBT as the comparison. Sample and controls as in Table 1. Standard errors, in parentheses, clustered by state. Columns 2–12 have between two and six treated clusters; standard-error interpretation in those columns should be treated with caution and asymptotic inference is not reliable in the usual sense. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A10: Total spending at food stores robustness: Alternative EIP control groups, later EIPs, SNAP EA introduction

| | (1) | (2) | (3) |
|---|---|---|---|
| | EIP 1 (2022 control group) | EIP 3 (2019 control group) | SNAP EA turn-on |
| $100 transfers last 4 weeks (ITT) | 1.82 | 0.16 | 16.78 |
| | (0.70) | (0.41) | (30.21) |
| $100 transfers last 4 weeks (TOT) | 1.98 | 0.17 | 21.51 |
| Adjusted MPC (× 100) | 4.21 | 0.37 | 45.77 |
| N | 16400 | 15160 | 10236 |
| DV mean | 680.49 | 774.14 | 702.88 |
| Avg transfer ($100s) | 43.73 | 71.53 | 0.12 |

*Notes*: This table reports three robustness checks using the approach in Equation 1. Column 1 re-estimates the first EIP specification (Table 1 Panel b column 1) using families in 2022 rather than 2019 as the comparison group. Column 2 estimates the response to the third EIP (disbursed in early 2021) using 2019 as the control group. Column 3 estimates the response to the 2021 increase in SNAP EA payments (rather than their termination): treatment is the additional amount of the SNAP EA payment in the previous four weeks. Sample, specification, and controls as in Table 1, other than these sample window changes. Standard errors, in parentheses, are clustered by state for SNAP EA and are heteroskedasticity-robust for the EIP. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A11: Cash MPC robustness: Comparison to pre- and post-pandemic EITC

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | EITC (all years) | EITC (2019) | EITC (2021-2023) | EIP1 |
| $100 transfers last 4 weeks (ITT) | 2.39 | 2.89 | 2.24 | 2.91 |
| | (0.30) | (0.47) | (0.40) | (0.71) |
| $100 transfers last 4 weeks (TOT) | 2.57 | 3.11 | 2.41 | 3.16 |
| Adjusted MPC (× 100) | 5.47 | 6.61 | 5.12 | 6.73 |
| N | 95910 | 23184 | 72726 | 15432 |
| DV mean | 663.60 | 607.24 | 679.93 | 680.49 |
| Avg transfer ($100s) | 74.94 | 82.58 | 72.73 | 43.73 |

*Notes*: This table reports estimates of $\beta$ from Equation 1 to compare the first-EIP cash MPC to MPCs estimated for the Earned Income Tax Credit (EITC) and Child Tax Credit (CTC) in three sample windows. The treatment variable in columns 1-3 is the expected EITC + CTC amount received over the past four weeks, constructed by combining TAXSIM projections of each household's annual EITC + CTC (based on income, number of children, and marital status) with a weekly refund-timing profile derived from the Department of the Treasury's Monthly and Daily Treasury Statements as in LaGuardia et al. (2025). Column 1 pools all filing years of data (2019 and 2021–2023); column 2 restricts to pre-pandemic 2019; column 3 restricts to post-pandemic 2021–2023; column 4 reproduces the first-EIP estimate from Table 1 Panel b column 1 for comparison. To convert EITC ITT estimates to TOT estimates, we rescale by 0.93, the take up rate for annual CTC benefits (Castelin et al., 2024). We use the take-up rate for CTC rather than EITC, as nearly all households in our sample are eligible for both credits and CTC take-up is the maximum of the two. Sample, controls, and MPC calculation as in Table 1. Robust standard errors in parentheses. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A12: Monthly spending on food products, alternative income cutoffs, households with school-aged children

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | <130% FPL | 130-200% FPL | 200-300% FPL | < 300% FPL | > 300% FPL | > 500% FPL |
| Panel a: One-time in-kind (P-EBT) | | | | | | |
| $100 transfers | 6.11 | 2.52 | -2.42 | 2.10 | 0.82 | -0.85 |
| last 4 weeks (ITT) | (1.87) | (2.22) | (1.14) | (1.33) | (1.13) | (1.12) |
| N | 9956 | 12763 | 17327 | 40046 | 45581 | 20455 |
| DV mean | 391.50 | 410.46 | 439.99 | 415.20 | 448.91 | 435.34 |
| Avg transfer ($100s) | 6.38 | 6.00 | 6.21 | 6.20 | 5.52 | 4.93 |
| Share eligible | 1.00 | 0.86 | 0.12 | 0.63 | 0.08 | 0.06 |
| Avg transfer if eligible ($100s) | 6.38 | 5.98 | 5.05 | 6.11 | 5.16 | 4.62 |
| % Δ (/$100) | 1.56% | 0.61% | -0.55% | 0.51% | 0.18% | -0.20% |
| Panel b: Monthly in-kind (SNAP EA) | | | | | | |
| $100 transfers | 4.70 | 1.07 | -0.62 | 0.52 | 0.31 | 1.07 |
| last 4 weeks (ITT) | (2.29) | (1.44) | (1.55) | (0.77) | (0.86) | (1.06) |
| N | 18948 | 22678 | 34184 | 75810 | 89277 | 40564 |
| DV mean | 267.37 | 283.27 | 291.56 | 281.66 | 279.36 | 275.35 |
| Avg transfer ($100s) | 4.00 | 7.09 | 8.01 | 6.48 | 7.43 | 6.83 |
| Share eligible | 1.00 | 0.57 | 0.00 | 0.47 | 0.00 | 0.00 |
| Avg transfer if eligible ($100s) | 4.00 | 7.05 | 9.33 | 4.98 | . | . |
| % Δ (/$100) | 1.76% | 0.38% | -0.21% | 0.18% | 0.11% | 0.39% |
| Panel c: One-time cash (EIP) | | | | | | |
| $100 transfers | 1.32 | 0.24 | 0.55 | 0.63 | 0.36 | 0.34 |
| last 4 weeks (ITT) | (0.42) | (0.36) | (0.34) | (0.22) | (0.22) | (0.32) |
| N | 15432 | 23336 | 30752 | 69104 | 84720 | 37792 |
| DV mean | 398.98 | 414.83 | 443.30 | 420.29 | 468.30 | 461.92 |
| Avg transfer ($100s) | 43.73 | 43.68 | 45.15 | 44.24 | 42.81 | 39.48 |
| Share eligible | 1.00 | 1.00 | 0.99 | 0.99 | 0.86 | 0.82 |
| Avg transfer if eligible ($100s) | 43.73 | 43.68 | 45.15 | 44.24 | 42.81 | 39.48 |
| % Δ (/$100) | 0.33% | 0.06% | 0.12% | 0.15% | 0.08% | 0.07% |
| Panel d: Monthly cash (CTC) | | | | | | |
| $100 transfers | 4.14 | 0.76 | -1.39 | 0.95 | -2.81 | -3.30 |
| last 4 weeks (ITT) | (0.97) | (0.85) | (0.74) | (0.50) | (0.46) | (0.79) |
| N | 58745 | 87978 | 118265 | 263376 | 313379 | 138446 |
| DV mean | 247.35 | 242.58 | 258.86 | 250.22 | 244.89 | 238.96 |
| Avg transfer ($100s) | 5.56 | 5.17 | 5.26 | 5.33 | 4.30 | 3.49 |
| Share eligible | 0.94 | 0.92 | 0.90 | 0.92 | 0.44 | 0.29 |
| Avg transfer if eligible ($100s) | 5.94 | 5.65 | 5.81 | 5.80 | 4.45 | 3.51 |
| % Δ (/$100) | 1.67% | 0.31% | -0.54% | 0.38% | -1.15% | -1.38% |

*Notes*: This table repeats the specification in Table 4 with spending on food products (rather than total food-store spending) as the outcome. Sample, treatment variables, and controls as in Table 4. "Share eligible," "Avg transfer if eligible," and "% Δ ($100)" as defined in Table 4. "Avg transfer if eligible" is shown "." for programs where no households are eligible (placebo tests). Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A13: Monthly spending on food products, different types of low-income households

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | HH w/ school-aged children | HH w/ any children | HH w/o children | All HH |
| Panel a: One-time in-kind (P-EBT) | | | | |
| $100 transfers | 6.11 | 4.49 | -1.03 | 5.24 |
| last 4 weeks (ITT) | (1.87) | (2.28) | (0.88) | (1.95) |
| N | 9956 | 10932 | 22212 | 33144 |
| DV mean | 391.50 | 383.47 | 270.07 | 315.96 |
| Avg transfer ($100s) | 6.38 | 5.78 | 6.10 | 2.26 |
| Share eligible | 1.00 | 0.89 | 0.00 | 0.36 |
| Avg transfer if eligible ($100s) | 6.38 | 6.38 | . | 6.38 |
| % Δ (/$100) | 1.56% | 1.17% | -0.38% | 1.66% |
| Panel b: Monthly in-kind (SNAP EA) | | | | |
| $100 transfers | 4.70 | 3.53 | 2.29 | 2.24 |
| last 4 weeks (ITT) | (2.29) | (2.03) | (2.28) | (1.86) |
| N | 18948 | 20336 | 23871 | 44207 |
| DV mean | 267.37 | 263.53 | 221.69 | 246.32 |
| Avg transfer ($100s) | 4.00 | 3.96 | 2.72 | 3.41 |
| Share eligible | 1.00 | 1.00 | 1.00 | 1.00 |
| Avg transfer if eligible ($100s) | 4.00 | 3.96 | 2.72 | 3.41 |
| % Δ (/$100) | 1.76% | 1.34% | 1.03% | 0.91% |
| Panel c: One-time cash (EIP) | | | | |
| $100 transfers | 1.32 | 1.16 | 0.63 | 0.90 |
| last 4 weeks (ITT) | (0.42) | (0.40) | (0.30) | (0.23) |
| N | 15432 | 17080 | 36272 | 53352 |
| DV mean | 398.98 | 398.46 | 271.52 | 321.51 |
| Avg transfer ($100s) | 43.73 | 43.33 | 25.02 | 32.23 |
| Share eligible | 1.00 | 1.00 | 1.00 | 1.00 |
| Avg transfer if eligible ($100s) | 43.73 | 43.33 | 25.02 | 32.23 |
| % Δ (/$100) | 0.33% | 0.29% | 0.23% | 0.28% |
| Panel d: Monthly cash (CTC) | | | | |
| $100 transfers | 4.14 | 4.01 | -2.89 | 0.17 |
| last 4 weeks (ITT) | (0.97) | (0.94) | (0.51) | (0.66) |
| N | 58745 | 64728 | 133362 | 198090 |
| DV mean | 247.35 | 243.94 | 155.09 | 191.48 |
| Avg transfer ($100s) | 5.56 | 5.47 | 5.10 | 2.24 |
| Share eligible | 0.94 | 0.94 | 0.00 | 0.39 |
| Avg transfer if eligible ($100s) | 5.94 | 5.80 | . | 5.80 |
| % Δ (/$100) | 1.67% | 1.64% | -1.86% | 0.09% |

*Notes*: This table repeats the specification in Table 5 with spending on food products (rather than total food-store spending) as the outcome. For households without children (column 3), imputed child-only benefits (CTC and P-EBT) are constructed from per-child benefit amounts and household size; the resulting "Avg transfer if eligible" is shown as "." when no households in the subsample are eligible. Sample, treatment variables, and controls as in Table 5. "Share eligible," "Avg transfer if eligible," and "% Δ ($100)" as defined in Table 5. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.

Appendix Table A14: Comparison of Implied Monthly Spending: NielsenIQ vs. Consumer Expenditure Survey

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | NielsenIQ | | Consumer Expenditure Survey | | | |
| | Food products only | Food stores | Food products (Diary survey) | Nondurables (Interview survey) | Food coverage (%) | Nondurables coverage (%) |
| 2019 | 343 | 647 | 403 | 705 | 85% | 92% |
| 2020 | 378 | 717 | 421 | 724 | 90% | 99% |
| 2021 | 255 | 752 | 496 | 802 | 51% | 94% |
| 2022 | 285 | 671 | 411 | 732 | 69% | 92% |
| Pooled, all years | 315 | 697 | 433 | 742 | 73% | 94% |
| Pooled, omitting 2020 | 294 | 690 | 437 | 747 | 67% | 92% |

*Notes*: CEX sample is Consumer Units (CUs) approximating the NielsenIQ sample definition: at least one household member age 6–18, household income (inclusive of imputed SNAP benefits at or below 130 percent of the federal poverty line, and food-at-home spending at or below 100 percent of income). Data 2019Q1–2022Q4. CEX food-at-home spending is drawn from the CEX Diary Survey and restricted to each CU's first reporting week to mitigate second-week under-reporting. Weekly Diary values are annualized $\times 52$ and then divided by 12 for monthly dollars. Nondurable expenditures include food, alcohol, utilities, household operations, public transit, gas and motor oil, personal care , tobacco, miscellaneous goods, apparel, out-of-pocket health, reading, and education. Data drawn from the CEX Interview Survey and restricted to each CU's first reported interview to mitigate recall telescoping in later interviews. Interview quarterly aggregates are divided by 3 for monthly dollars. All dollar figures are in 2022 dollars, deflated by the annual average CPI for Food at Home. Means are weighted using the CEX final sampling weight scaled to the reference-period frequency. Source: NielsenIQ Consumer Panel, 2019–2023 and Consumer Expenditure Survey (CEX) 2019-2022.

Appendix Table A15: Monthly spending on food products by type of store

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Grocery stores | Discount stores | Club stores | Convenience stores | Other food stores | Rest-aurants | Online spending |
| Panel a: One-time in-kind (P-EBT) | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 5.68 | 1.54 | -0.96 | -0.12 | -0.03 | 0.03 | 0.38 |
| | (1.38) | (1.86) | (0.91) | (0.11) | (0.07) | (0.57) | (0.34) |
| $100 transfers last 4 weeks (TOT) | 7.28 | 1.97 | -1.23 | -0.15 | -0.04 | 0.04 | 0.49 |
| Adjusted MPC (× 100) | 15.49 | 4.20 | -2.62 | -0.33 | -0.08 | 0.08 | 1.04 |
| N | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 | 9956 |
| DV mean | 200.15 | 140.63 | 40.26 | 7.75 | 2.71 | 33.66 | 5.54 |
| Avg P-EBT | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 | 6.38 |
| Panel b: Monthly in-kind (SNAP EA) | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 5.92 | -1.86 | 0.54 | 0.08 | 0.01 | -0.45 | 0.20 |
| | (1.53) | (1.52) | (0.69) | (0.09) | (0.02) | (0.58) | (0.35) |
| $100 transfers last 4 weeks (TOT) | 7.59 | -2.38 | 0.69 | 0.10 | 0.01 | -0.58 | 0.26 |
| Adjusted MPC (× 100) | 16.15 | -5.07 | 1.47 | 0.22 | 0.03 | -1.23 | 0.55 |
| N | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 | 18948 |
| DV mean | 147.47 | 94.66 | 20.98 | 3.91 | 0.35 | 29.05 | 6.53 |
| Avg transfer ($100s) | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 | 4.00 |
| Panel c: One-time cash (EIP) | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 0.72 | 0.47 | 0.16 | -0.02 | -0.00 | 0.12 | 0.01 |
| | (0.32) | (0.26) | (0.15) | (0.04) | (0.03) | (0.08) | (0.05) |
| $100 transfers last 4 weeks (TOT) | 0.78 | 0.51 | 0.17 | -0.02 | 0.00 | 0.13 | 0.01 |
| Adjusted MPC (× 100) | 1.67 | 1.09 | 0.37 | -0.05 | 0.00 | 0.28 | 0.02 |
| N | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 | 15432 |
| DV mean | 212.13 | 134.33 | 36.93 | 11.94 | 3.66 | 27.77 | 8.42 |
| Avg transfer ($100s) | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 | 43.73 |
| Panel d: Monthly cash (CTC) | | | | | | | |
| $100 transfers last 4 weeks (ITT) | 1.26 | 2.46 | 0.39 | 0.06 | -0.03 | 0.01 | 0.37 |
| | (0.71) | (0.58) | (0.36) | (0.09) | (0.03) | (0.32) | (0.17) |
| $100 transfers last 4 weeks (TOT) | 1.51 | 2.96 | 0.47 | 0.07 | -0.04 | 0.01 | 0.44 |
| Adjusted MPC (× 100) | 3.22 | 6.29 | 1.00 | 0.15 | -0.08 | 0.03 | 0.95 |
| N | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 | 58745 |
| DV mean | 135.46 | 87.73 | 19.53 | 4.26 | 0.37 | 37.67 | 5.37 |
| Avg transfer ($100s) | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 |

*Notes*: This table repeats the specification in Table 3 with spending on food products (rather than total food-store spending) as the outcome. Sample, treatment variables, and controls as in Table 3. Because the NielsenIQ coverage adjustment is not measured on a store-by-store basis, reported MPCs are subject to the assumption that food spending is under-reported uniformly across store types. Standard errors, in parentheses, are clustered by state for P-EBT and SNAP EA and are heteroskedasticity-robust for EIP and CTC. Source: NielsenIQ Consumer Panel, 2019–2023.