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Causes and Consequences of the Calorie Crunch

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Abstract

Monthly welfare programs such as the Supplementary Nutrition Assistance Program (SNAP) produce consistent cycles of expenditure and consumption amongst recipients. Food insecurity and negative behavioral outcomes track these cycles. This paper leverages new data from the USDA, the FoodAPS survey, and to answer a variety of questions related to these phenomena: Are consumption and expenditure cycles correlated? Who bears the burden of food shortages at the end of each benefit month? Does diet quality track food expenditure? I find robust expenditure and consumption cycles in the FoodAPS data, but contrary to popular belief, they are only weakly correlated. The youngest children are spared from cyclical food shortages, but school-aged children experience them when they are out of school. Universal participation of the sample in school meal programs while in school (and the complete lack of participation in summer meal programs) suggests that these programs may mitigate a great deal of children's food insecurity. Diet quality declines over the course of the month, compounding the impact of fewer meals on health. Food access issues cannot explain the identified cycles. We interpret these findings as evidence consistent with a consumption-driven calorie crunch in which the expenditure cycle is a response to the previous month's consumption deprivation.

Executive summary

Many researchers have documented the fact that SNAP recipients experience expenditure and consumption cycles. When benefits arrive there is a large spike in grocery expenditures and calories consumed. Over the remainder of the month, expenditure and consumption consistently decline. Reports of food insecurity follow these cycles. Crime and school misbehavior also track these cycles, encouraging research into their causes, consequences, and potential solutions.

This paper leverages a new data source, the USDA's FoodAPS Survey, to examine a variety of issues related to expenditure and consumption cycles. Most notably, these are the first data to offer simultaneous expenditure and consumption diaries. Often, researchers assume expenditure and consumption cycles to be a single phenomena, however this has gone untested until now. Additionally, the FoodAPS measures consumption at the meal level, making this the first paper to measure consumption cycles in terms of missed meals.

We find evidence of large and significant cycles in both expenditure and consumption in the FoodAPS data. Expenditure decays by roughly 4.6% per day over the course of the benefit month. Consumption falls by roughly 0.7 daily meals from the first day to the last day of the benefit month, and this measurement is robust to a new technique that uses the non-SNAP households in the FoodAPS as a control group. However, the correlation between expenditure and consumption cycles is much weaker than expected.

Children do not experience consumption cycles as severely as adults (or in many cases, at all). This is most consistently true for children under five years old, indicating that parents shelter the most vulnerable for shortfall. However, school-aged children do experience consumption cycles when school is out of session. This suggests that school meal programs may play a vital role in limiting cyclicality in food insecurity, given the near universal participation of the children in SNAP households. Primary school students appear to be the most affected by school breaks.

Because the meal consumption measures do not capture the contents of meals, a decrease in meal frequency could theoretically be ameliorated by an increase in meal quality, however this does not appear to be the case. Diet quality decreases over the course of the benefit month, according to self-reports, measurements of protein-to-carbohydrate ratios, and a variety of other measures.

It is commonly suggested that poor local food availability could be the root cause of expenditure cycles, which in turn cause consumption cycles. Using the geographic data in the FoodAPS, we find that travel time to the grocery store is not predictive of a more severe expenditure cycle.

This paper is designed to advance our understanding of the calorie crunch using the new FoodAPS data. The results suggest that summer meal programs for children could fill an important gap in food sufficiency at the end of the benefit month and the access-based explanations of these phenomena are perhaps less plausible than consumption-based explanations like self-control and bargaining failures.

Introduction

In a cross section of households receiving food benefits from the Supplementary Nutrition Assistance Program (SNAP) in 2011 and 2012, roughly 61% were food insecure, 31% were very food insecure and 25% of households had food-insecure children (Mabli *et al.*2013). While there is substantial work devoted to estimating the impact of program participation on nutritional and health outcomes, much less is dedicated to understanding what determines food insecurity within the program.[1] The literature on within-month expenditure and consumption cycles (the "calorie crunch") addresses this to some degree, but does not directly estimate the changing frequency of missed meals, one of the core consumption markers that defines food insecurity. This paper utilizes a new data source, the USDA's FoodAPS survey, to expand our understanding of the calorie crunch in a variety of ways. Most notably we measure consumption trends using changes in missed meals over the course of the month and demonstrate that its incidence within the household likely depends on the operation of school meal programs.

Consumer expenditure and consumption-smoothing failures that stem from benefit timing are typically studied to evaluate theory rather than because of their direct impact on well-being. Shapiro (2005), Hastings and Washington (2010) and Smith *et al.* (2016) use SNAP benefit receipt to examine present-biased discounting, firm price responses and income fungibility, respectively. This may be due in part to a structural calibration exercise in Shapiro (2005) that suggests very small welfare losses from the calorie crunch. Recent work on the behavioral consequences of benefit timing puts a spotlight back on the direct impact of cyclicality in food consumption. Foley (2011) shows that crime in areas with highly time-concentrated disbursements of welfare (including SNAP) increases over the benefit month. Seligman *et al.*

[1] See Bhattacharya and Currie (2001) and Hoynes and Schanzenbach (2009) on food insecurity. See Devaney and Moffitt (1991) on nutritional intake. See Currie and Cole (1991), Currie and Moretti (2008), Almond *et al.* (2011) and Kreider *et al.* (2012) on child health. See Hoynes *et al.* 2016 on long-run outcomes.

(2014) find that hypoglycemia hospital admissions are more common at the end of the month in low-income communities, and Gennetian *et al.* (2015) show that school disciplinary actions for middle and high-school students in SNAP households in Chicago increase by 51% from the first to the last week of the benefit month. Given what appear to be significant consequences of food-budget exhaustion, and the high rates of food insecurity within SNAP, we need a better understanding of what happens within households as resources run out and why.[2]

The FoodAPS survey from the USDA allows us to investigate a variety of features of the calorie crunch for this first time. First, we estimate the calorie crunch in terms of missed meals. This extends the benefit-timing literature to directly inform food insecurity. Second, we use the targeted sample of eligible and near-eligible non-participants in order to construct the most robust estimates of the calorie crunch to date. Using these individuals to difference out calendar-day expenditure and consumption means that other cyclical income sources that are roughly correlated with SNAP receipts and specific to a low-income population are controlled for. Third, we use simultaneous household expenditure and meal consumption logs to determine whether the failure to smooth consumption and expenditure are related phenomena. Given past work using expenditure (Hastings and Washington 2010, Castner and Henke 2011, Smith *et al.* 2016, Kuhn 2016) and consumption (Wilde and Ranney 2000, Shapiro 2005, Todd 2015), verifying this relationship is important. Fourth, we decompose the consumption impacts of benefit timing within households by age and gender. Are children spared the worst or do adults and school meal programs shelter them? Are mothers or fathers the ones who feel the impacts of food shortfall? Finally, we assess a common casual suggestion about the calorie crunch: that it is a symptom of poor food access.

[2] Food insecurity per se matters for reported health quality in both adults and children and for specific health outcomes (Gundersen and Kreider 2009, Gundersen and Ziliak 2015).

We find strong declines in both expenditure on food and consumption of food in the FoodAPS data. The meal consumption estimates, unique to this paper, indicate a loss of roughly 3 meals per benefit-month in our most conservative specification with estimates up to 12 meals per benefit-month in others. This estimate is per individual, and is relative to the counterfactual of constant meal consumption at the level established on the first day of the benefit month. Both expenditure and consumption estimates are robust to using eligible and near-eligible non-participants as a control group. Expenditure and consumption cycles are correlated within households, but only weakly. This is evidence that consumption cycles are the primitive phenomena, and they may sometimes feed back into expenditure declines, not the other way around. Indeed, we find no relationship between local food access and consumption or expenditure trends. Men and women experience similar consumption cycles, with dual-parent households doing better overall than single parents. We find that young children experience almost no calorie crunch in terms of missed meals. Primary school-aged children only experience a calorie when school is not in session, indicating that school meal programs play a valuable role in smoothing consumption. This is not true for older children.

Many of the 18 questions the USDA uses to evaluate food insecurity relate to missed meals (USDA 2015). For example, question 4 reads, "In the last 12 months, did you or other adults cut the size of your meals or skip meals because there wasn't enough money for food?" Question 9 reads, "In the last 12 months did you or other adults ever not eat for a whole day because there wasn't enough money for food?" And question 16 reads, "In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food?" By showing that the calorie crunch is a robust phenomenon by this measurement, we wish to emphasize that the in all likelihood, the food insecure SNAP households are also sometimes food secure SNAP households and vice versa. In fact, we find in the FoodAPS that the likelihood of being categorized as having "very low food security" is increasing over the course of the benefit month despite the retrospective framing of the food security questionnaire. Targeting insecurity associated with benefit timing means re-thinking disbursement timing and technique in addition to increasing benefit amounts (which Todd (2015) demonstrates is effective in mitigating the calorie crunch). Additionally, our results indicate that interventions targeting the point of consumption may be more effective that interventions targeting the point of sale.

The remainder of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the results and Section 4 concludes.

Data and methods

The USDA's National Household Food Acquisition and Purchase Survey (FoodAPS) surveyed 4826 U.S. households between April 2012 and January 2013. 1581 households were SNAP participants, 1312 were eligible or near-eligible non-participants with incomes less than 185% of the poverty threshold and 1933 had incomes greater than 185% of the poverty threshold. Our primary analysis is restricted to households receiving SNAP benefits, but we also use the eligible and near-eligible non-participants as a control group in some specifications. Households reported their spending on all food items (both for at-home and away-from-home consumption) and meal consumption for a one-week period following an initial interview. The initial interview collected in-depth background information both at the household and individual levels. Geographic information relating home locations to store location is also included in the data.

Understanding survey timing is critical for our sample construction. The in-depth initial interview occurred before the households completed either their expenditure or meal diaries. We call the initial interview date day 0. Days 1 to 7 following the initial interview are diary days. On day 0, households reported the calendar date on which they last received SNAP benefits. A total of 1609 households reported a past SNAP receipt. There were no expenditures logged for 95 of those households. 123 did not match to any meal diaries and 44 households had blank meal diaries for all members. We keep only households for which we have matched expenditures and consumption. 133 of the matched households either reported or were confirmed to no longer be in the program. 80% of the remaining household-days require no adjustment based on last reported SNAP receipt: they fall within 30 days following the report and the reported disbursement occurred on a feasible day.[3] For households with missing last receipt reports and infeasible last receipt reports, we turn to administrative data that the USDA matched to households in the sample.[4] We only use disbursements on a feasible date that occurred no later than the first day of the diaries. This nets an additional 101 households. Finally, because rates of program churn are high (Mills *et al.* 2014), we observe considerable movement out of SNAP in the data and we identify benefit timing effects precisely based on the day of benefit receipt, we do not impute a more recent date of SNAP receipt that would contradict a household's report of their last benefit receipt. We impute days since receipt when it does not contradict a report.[5] This leaves us with a final sample of 1167 SNAP households with 8169 diary days and 25,571 diary-member, ranging from zero to 30 days since benefit receipt.

Following Shapiro (2005) and Kuhn (2016), we wish to estimate expenditure and consumption as a function of days since benefit receipt. Each state has its own SNAP disbursement schedule, with most states spreading it out over the beginning of the month. Figure

[3] No disbursements arrive on the 24th or later. Additionally, the 30-day requirement is adjusted down to a 29-day requirement when SNAP was last disbursed in a month with 30 days, a 28-day requirement for months with 29 days and a 27-day requirement for months with 28 days.

[4] This follows the USDA's approach or prioritizing reports over the administrative data due to match uncertainty.

[5] For example, imagine that a household reports a last benefit receipt of April 17th, 2012 during their initial interview on May 15th, 2012. May 16th, 2012, the first day of the diary, is 29 days since receipt. The second day of the diary is 30 days since receipt, which gets reset to 0 days since receipt since it does not contradict the report during the May 15 interview. In some consumption specifications, we will exclude these imputed benefit households. This is based on what appear to be very different consumption patterns from non-imputed benefit households, conditional on days since supposed receipt. See Section 3.2 for more detail.

1 shows the distributions of SNAP receipt calendar dates in our sample. There is a large spike on the first of the month followed by a steady flow over the next 10 days, with a gradual trail off from there. No state disburses SNAP after the 23rd of the month. Since disbursement rules based off last names, social security numbers and benefit ID numbers, there are no observable differences across households based on time of receipt (Kuhn 2016). However, given the bunching at the beginning of the month, it is generally true that SNAP receipt is correlated with other early-month occurrences like bills and income. For this reason, we use household and individual fixed-effects models in addition to OLS and similar approaches. Also, we take a novel approach in Section 3.1 by using the average expenditure of our sample of eligible and near-eligible non-participants to difference out the calendar-day expenditure of SNAP participants in the sample.

In general, our expenditure models will take the form

$$y_{h,t} = f(\alpha_h + \beta dss_{h,t} + X'_{h,t}\Gamma) + \epsilon_{h,t} \qquad (1)$$

where $y_{h,t}$ is household h's expenditure on food on diary day t, α_h is the intercept term, which may be restricted to be the same across all households depending on specification, $dss_{h,t}$ is the number of days since SNAP receipt for household h on diary day t, and $X_{h,t}$ is a vector of days-since-receipt control variables, including week of calendar month, a weekend indicator variable and a indicator variable for whether the household was called by a survey representative to confirm their recording of daily expenditures.[6] $f(\cdot)$ is usually the identity function, yielding a linear model, but we will use some other specifications as well, most notably Poisson regression.

Our consumption models are slightly different because the data are individual-specific. For individual i,

[6] These are also indexed by h because the mapping from t to days since SNAP depends on the household.

$$c_{i,h,t} = f(\alpha_i + \beta dss_{h,t} + X'_{h,t}\Gamma) + \epsilon_{i,h,t}$$

where $c_{i,h,t}$ is a measure of consumption for individual *i*, in household *h* on diary day *t*. Depending on specification, α_i may be restricted to be the same for all individuals, all individuals in household *h* or first-differenced out. We choose to first-difference the data for our individual fixed-effect specifications because serial correlation in the error term is likely. Standard errors are always clustered at the household level.

Expenditure data are collected at the item level and transaction levels in the FoodAPS. To construct daily household expenditure, we aggregate all food expenditures on a given diary day. This includes groceries for at home consumption and meals purchased away from home (unless specified otherwise). While SNAP funds cannot be used for many of these purchases, our goal is to capture total food expenditure and consumption regardless of budget source. Consumption data are collected at the individual level on each diary day. Breakfast, lunch, dinner and three potential snacks (am, pm and evening) can be reported as either consumed or not. We aggregate daily meal consumption by summing the breakfast, lunch and dinner indicators to avoid worrying about within-day across-meal substitution for any given meal. In the Appendix, we do present results for each meal individually, snack consumption and examining entire days without any consumption.

Results

We present the results in five sections. First, we present the estimates of expenditure cycles amongst SNAP recipients in the FoodAPS data. Second, we estimate consumption cycles and compare them within-household to the expenditure cycles. Third, we explore the incidence of food shortfall by age and gender. Fourth, we investigate whether the nature of consumption, in terms of nutritional quality, changes over the month in addition to quantity. Finally, we explore the relationship between local food access and expenditure and consumption trends.

Expenditure cycles

We find substantive and statistically significant expenditure cycles in the FoodAPS. Our primary specifications model the expenditure decline linearly, using OLS and a first-differenced fixed-effect approach in columns (1) and (2) of Table 1. We also present fixed-effect Poisson regression estimates in column (3) because expenditure decay over the full benefit months appears exponential (see Figure 2, Panel A). Linear models should work well when the day benefits arrive is removed and will be comparable to our preferred approach to the consumption data. Estimates without that day are in columns (4), (5) and (6). In Appendix Table A1, we consider a variety of alternative specifications, including a Tobit model for expenditures censored below at $0, a mean-differenced fixed-effect model, a standard Poisson model, as well as linear probability, first-differenced linear probability, Probit and conditional-Logit models of whether non-trivial expenses are recorded in Appendix Table A2. All of the estimates identify significant negative effect days since benefit receipt.

From the first to the last day of the benefit month in a 31-day cycle, average total food expenditures fall roughly from $94 to $19 (the median decreases from $44 to $3). The linear estimate of the per-day decline is $0.56 per day. Poisson regression, which should fit this sample better, indicates a decline of roughly 4.1% per-day. Much of the decline comes from the spike in spending on the day of receipt: average spending on the second day of the benefit month is roughly $38.[7] Removing that day cuts the magnitude of the linear estimate considerably, but a steady and significant decline of $0.23 per day remains. The assumption of linearity is more appropriate for this sample (see Figure 2, Panel B). Food for home consumption only follows a

[7] This is why the estimate of the daily decline differs so considerably from the slope of the line connecting the first data point in the benefit month to the last day in the benefit month. Removing the first 2 days of the month reconciles this.

similar path at lower levels (results in Appendix Table A3).

These effects of the benefit cycle operate on both the intensive and extensive margins, but the extensive margin effects are almost entirely concentrated in the first few days of the benefit month (see Figure 2, Panel C). 75% of households report non-trivial expenditures on the day that benefits arrive. This falls to 66% on the day after benefits arrive and 56% by the end of the month. This trend is more dramatic when we restrict attention to purchases for food-at-home (FAH): 62% shop on the day benefits arrive, 46% shop on the day after they arrive, and only 35% shop on the last day of the cycle. Non-trivial expenditures are defined as spending at least a dollar on food.

For robustness, we take a unique approach that utilizes non-SNAP households in the FoodAPS. We difference the expenditures of SNAP households from those of non-SNAP households on the same calendar day. For example, if a SNAP household reports $20 of expenditures on May 15, 2012, and the average expenditure among non-SNAP households on May 15, 2012 is $30, we replace the SNAP household's observation with -$10. We limit the non-SNAP households in this sample to those with income less than 185% of the federal poverty level.[8] Our estimates barely change with this procedure. Average SNAP household spending is about $74 greater than non-SNAP household spending on the day of receipt and about $5 less on day 30 of a 31-day cycle. The linear estimate of the downward trend in $0.55 per day in this specification with the full sample and $0.22 with day 1 removed. Full results are presented in Appendix Table A4. See Figure 2, Panel D for the full path of the difference over the benefit cycle. Given that food benefit cycles are not perfectly randomly distributed with respect to other income and benefit receipts (see Figure 1, which demonstrates that disbursements are more

[8] This reduces our sample size slightly, losing 4 SNAP households and 55 household-days on which we have no non-SNAP observations.

common near the beginning of the month), this procedure should increase confidence that the observed cycles are truly driven by the SNAP cycle.

Consumption cycles

Consumption cycles as measured by meals are unique to this study; we have no benchmark for assessing the magnitude of the decline in likelihood of consuming a meal over the course of the month. It is important to remember that this is a coarse measure since we do not observe the contents of meals. Estimates with meal consumption measured at both the household and individual level are presented in Table 2. To model the outcome variable of the number of meals (breakfast, lunch or dinner) eaten by in individual in a day, we use an OLS specification and a first-differenced fixed-effect specification since a linear model should fit these data well (see Figure 3). We also utilize a Tobit model for censoring at 0 and 3 meals per-day. Since calories are relatively substitutable within a day, we prefer to study the sum of meal indicators rather than isolating any meal in particular. The coefficients represent the per-day decline in the number of meals eaten by an individual in columns (3)-(6), and in the case of the household-level estimates in columns (1)-(3), the decline in the average number of meals eaten by an individual within the household. Standard errors are clustered at the household level in all specifications.

There is a significant decline in number of meals eaten over the course of the month. The daily decline in number of meals eaten is an intuitive metric for interpreting the regression results, but they do not properly convey the big picture. The smallest estimate in Table 2, Panel A is a decline of 0.005 meals per day. This extrapolates to 0.15 fewer meals consumed on day 30 of a benefit month than day zero. Alternatively, this corresponds to about 2.33 fewer meals eaten over the course of the month than if consumption remained constant at its day 0 level. The largest estimate in Table 2, Panel A is a decline of 0.027 meals per day. This is about 0.81 fewer meals on day 30 than day 0 or roughly 12.56 fewer meals eaten over the course of the month. In Appendix Table A5 we break this decline up by meal, consider the likelihood of going an entire day without a meal, and snacks. The likelihoods of eating breakfast, lunch and dinner all fall significantly over the course of the month, with roughly similar magnitudes. The probability of going an entire day without a meal is significantly increasing over the month, and the number of snacks eaten per day declines significantly, with a magnitude similar to the decline in the number of meals eaten.

We also present estimates of the consumption trend with imputed data excluded. Specifically, observations that are assigned a days-since-receipt value based on a receipt of benefits over a month in the past are excluded from the estimates in Table 2, Panel B. For example, if a household taking the initial survey on May 15th reported last receiving food benefits on April 17th, we would have a direct observation of 29 days since benefit receipt on May 16th, the first diary day. We would then have 6 imputed observations of 0-5 days since benefit receipt from May 17th to May 22nd, assuming that benefits arrived on the same calendar day (as they should) each month. Despite verification of program participation in the sample, estimates of program churn (movement in and out of SNAP) are high: a 2011 study of SNAP participation in six states by Mills *et al.* showed that 17-28% of participating households had exited and re-entered SNAP in the last 4 months. Furthermore, Figure 3 demonstrates that reported consumption on days imputed at the beginning of the benefit month is very different than reported consumption on direct observations on the same days of the benefit month. The estimates using the non-imputed sample are larger in each specification than those using all data, but the magnitudes are not substantially different.

An advantage of having simultaneous expenditure and consumption reports from the same household is that we can ask whether two empirically-verified phenomena –expenditure cycles and consumption cycles— are related to one another as is commonly assumed. To do this, we estimate benefit-month trend coefficients for every household in the sample using both food expenditure and meal consumption and then estimate their correlation. Because the expenditure data is at the household level, we use meal consumption data aggregated to the household level as well. Given only seven observations per household, the estimates are noisy, and we present both trimmed and untrimmed estimates. Expenditure estimates are truncated at -$10 and $10/per day and consumption estimates are trimmed at -0.1 and 0.1 average meals per day. Results are in Table 3, with both trend variables standardized. As expected, there is an overall positive relationship between expenditure and consumption trends within households, however it is weak. Using either the whole sample or the trimmed sample, we find that a 1 standard deviation increase in the expenditure trend is correlated with about a 0.05 standard deviation increase in the consumption trend (p = 0.118 and p = 0.160, respectively). We also implement a specification that allows for a changing correlation between consumption and expenditure trends over the course of the month.[9] Oddly, the whole sample and trimmed sample yield opposing results. In the full sample, we find a positive and significant correlation that emerges at the end of the month: a one standard-deviation increase in the expenditure trend correlates with a one-tenth of a standard deviation increase in the consumption trend in week 4 of a benefit month (p = 0.006). In the trimmed sample, we find a positive a significant correlation at the beginning of the month --a one standard-deviation increase in the expenditure trend correlates with a 0.15 standard deviation increase in the consumption trend in week 1 of a benefit month (p = 0.021)—that decays to zero by week 4.

In summary, we strongly replicate the findings of prior literature on the failures to smooth expenditure and consumption over the SNAP benefit cycles. We find larger magnitudes

[9] We assign a household to a week of the month based on the first day of their seven-day diary.

of expenditure cycles than other work, although this varies depending on the specification. We are the first to identify consumption-smoothing failures as measured by missed meals and find strong and significant downward trends over the benefit month. This is consistent with Shapiro (2005) that identifies a decline in caloric intake. These two phenomena are correlated within households, but not as strongly as expected. Additionally, we leverage the targeted sampling of the FoodAPS to show that both types of trends are robust to being measured as calendar-day differences from the average non-SNAP household expenditure and consumption. Given that SNAP disbursements are not uniformly distributed with respect to other income sources, this is an important robustness check that has been missing from the literature.

Incidence of food shortfall within households

This section is devoted to decomposing the consumption findings from Section 3.2 within a household. Are children more vulnerable because they rely on others for meals or are the sheltered by well-meaning parents? Perhaps school meal programs protect kids directly. Are women in dual-adult households more vulnerable because they must bargain with a spouse? Kuhn (2015) finds that household composition determines, in part, the severity of the expenditure trend over the SNAP month. Households will more young children and dual-adults exhibit the strongest declines.[10] A proposed explanation for this finding is that the aggregation of preferences within the household and bargaining between decision makers can lead to dynamically inconsistent behavior (Jackson and Yariv 2014, Hertzberg 2012). Even if EBT has ameliorated some of the problems associated with food purchasing decisions (Kuhn 2015), the intra-household allocation of purchased food remains an important issue. The dynamics of this allocation over the benefit cycle have not been investigated.

[10] This is true prior to the implementation of EBT only. After the introduction of EBT, much of this heterogeneity is gone.

Age differences

We start by examining consumption cycles by age. Minors are split into three six-year age buckets. Indicators for each group are interacted with the days since benefit receipt variable. Table 4 shows the results of adding these interaction terms to regressions of the same form as columns (4) and (6) of Table 2. We also implement a household fixed-effects specification that allows within-household differences in trends to more directly contribute to our estimate of differential trends by age. First-differencing the data generates trend estimates from individual variation, and these trends are compared across age category with no regard to household; every adult is compared with equal weight to every child 0-5 years old, for example. The household fixed-effects allow within-household differences to inform the age parameters in the model such that a child's difference in trend from their parent matters more than a child's difference in trend from any random adult. Results are presented in Table 4 for both the full sample and non-imputed data only.

There are level differences in consumption favoring children, but more interestingly, we find that the decline in meal consumption is much less dramatic for the youngest children. While our estimate of the consumption trend for adults varies considerably across specifications, the interaction between the trend variable and an indicator for age < 6 is always positive and comparable to the negative coefficient on the trend itself. The sum of those coefficients is never significantly different than zero. There is some evidence that children 6-12 and 12-17 years-old experience less severe consumption declines, but this is sensitive to specification. In Appendix Tables A6, A7 and A8, we present results separately by meal, finding that breakfast consumption most closely mimics the pattern of results found for all meals pooled.

To generalize from our discrete age cutoffs, Figure 4 presents the average daily decline in the number of meals consumed as it varies by according to a 5th order polynomial in age. This is implemented using the OLS specification on the full sample. The graph is truncated at age 60, above which the standard errors increase considerably. We estimate a positive consumption trend for individuals 11 and under, significant at the 5% level for kids 8 and younger. The trend is negative for individuals older than 11, significant at the 5% level for those 15 and older. Figure 5 shows the evolution of the difference in average daily meal consumption from its level at the beginning of the benefit month. We group all kids under 12 and all individuals over 11 based on Figure 4. Furthermore, we smooth the data using a 5-period moving average before differencing it from the day 2 moving average value. Both groups experience upward trends in consumption over the first week of the month. Starting in the second week of the, consumption begins a prolonged decline for individuals 12 and older and remains steadily above its initial value for kids under 12. The fourth week of the month brings a steep decline for everyone, retuning young kids to about the level they started the month at and pushing older individuals down to 0.15 meals per day below that value.

We believe there are two primary mechanisms through which these age differences could operate: parental sheltering of kids and school meal provision. In the case of the first mechanism, we would expect to see adults in households without kids exhibiting less severe consumption declines. However, this comparison is confounded by selection into parenting. If parents tend to be more patient and effective budgeters than non-parents in the sample of SNAP participants, we would expect to see the opposite. Our estimate of the effect of days since benefit receipt on meal consumption for adults in households with no children is significantly larger in magnitude than for adults in households with kids (-0.004 meals per day for adults in households with kids and -0.012 meals per day for adults in households without kids, p = 0.060). This is consistent with parents being more patient than non-parents. When we re-estimate all the models in Table 4 with the sample limited to households with kids, we get slightly weaker estimates of the age-group interactions because of this change in the adult population. Overall, all we can say with respect to the sheltering hypothesis is that whatever sheltering may be occurring is not large enough to overwhelm selection effects.

To investigate the role of school meal provision, we stratify our sample based on whether school is in session at the time of the meal diary. School meal provision cannot fully explain the differential trends by age that we see because the most persistent differences are for kids who are mostly too young for school. Figure 4 shows a significantly positive consumption trends for kids 10 and under, and while the effect is not consistent across specification, column (1) of Table 4 does show a sizeable differential trend for kids from 6 to 11, and columns (1) and (4) show differential trends for kids from 12 to 17. We do not use measures of school breakfast and lunch program participation, cost and frequency because they exhibit almost no variance within our sample of SNAP participants.[11] However, 36.3% of the school-aged children in our sample are on break from school, and participation in summer programs with meals is very low.

We classify an entire household as either in school or on break to allow adults' consumption trends to differ as well. This eliminates households without any school-aged children, meaning that our estimation sample for the youngest children is very different. The sample is split according to school status; we estimate our model on each sample and then test the equality coefficients across samples. Additionally, we re-construct the age groups to represent school types: not school age (< 5), primary school (4 < age < 11), middle school (10 < age < 14) and high school (13 < age < 18).[12] For this comparison to inform the impact of school in session kids' meal trends, it must be that other factors associated with being out of school are

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[11] 93.8% of children in our SNAP sample receive breakfast at school, 96.6% receive lunch at school, almost all for free.

[12] Because data on completed/upcoming grade is not recorded for students who are on break from school, we use this age classification rather than a direct observation of school type.

not driving differential consumption over the benefit month. Since the variation we use is almost entirely the comparison of summer to the rest of the year, this is a non-trivial concern. Changing weather patterns or seasonal work could affect the way people shop and eat. Results using the OLS specifications from columns (1) and (4) of Table 4 are presented in Table 5. Reassuringly, adult consumption trends are not more extreme when the kids are out of school. We find that primary school-age kids indeed experience a shift from doing better than adults when school is in to doing worse than adults when school is out. The OLS specifications in columns (1) and (2) show a statistically significant difference between the interaction terms associated with primary school across school status. The limited-sample estimates show a similar reversal, but the difference is not significant. We do not find evidence of differences by school status for middle school and high school students.

If school meal programs do explain the difference by school break status for primary school students, why aren't there effects for middle and high-school students? As kids get older, they may experience more social stigma associated with participating in meal programs. They may also prefer to use their free time before school and during the lunch break for other activities. The FoodAPS measures the number of days per week children get complete lunches and breakfasts at school in addition to whether their schools offer breakfast and lunch. While SNAP-participating children essentially all have access to these programs, there is some variation in the reported weekly usage. We regress lunch and breakfast program usage on indicators for middle and high school age, with primary school age as the omitted category. High-school students get 0.26 (S.E. = 0.124, p = 0.040) fewer lunches per week and 0.68 (S.E. = 0.179, $p < 0.001$) fewer breakfasts per week than primary school students. We do not find any differences for middle school students.

Gender differences

We follow our approach to age differences by interacting gender with the days since benefit receipt variable. Results are in Table 6. If women are disadvantaged in a household bargaining model that binds when resources are scarce, we should expect to see gender differences in consumption trends emerge when we limit the sample to households with multiple adults (in this case, defined specifically as a spouse or unmarried partner to the primary recipient). However, given the finding in the previous that are household-level differences associated with having kids that are likely due to selection, it is reasonable to believe that similar differences exist based on relationship status. Indeed, we find evidence that women in dual-adult households experience less severe consumption declines (comparing columns (1) and (4) of Table 6). Adding a household fixed effect or first-differencing (columns (2) vs. (5) and (3) vs. (6) of Table 6) mitigates this difference, indicating that dual-adult households do better overall. Differences across gender are limited to the first-differenced models in which we find evidence that men in dual-adult households experience more severe consumption declines.

If parental sheltering is responsible for some of the attenuated consumption decline for kids, there is scope for differential investment by child gender. However, specifications that feature interactions between gender and the child age groups used earlier reveal no consistent or significant evidence of differences in consumption trends by gender.

Consumption quality

Our measure of consumption captures the consequences of benefit cycles only when they amount to lost meals. Reductions in the amount and quality of food would mean that the consumption cycles are even more harmful than our estimates indicate. Given that the proportional decline in expenditure is much larger than consumption, we can say that the ratio of expenditure to number of meals consumes is also falling over the course of the month. However, this depends on the assumption that expenditures are converted into meals relatively quickly instead of slowly through the consumption of non-perishables. We obtain some direct evidence of changing diet using self-reported data from the initial survey on diet quality, the perceived costs of eating healthy and fruit/vegetable sufficiency. The likelihood of reporting very low adult food security increases by 4% over the course of the benefit month (p = 0.331). Self-reported own diet quality decreases by 0.12 standard deviations (p = 0.243) over the course of the benefit month. The likelihood of reporting sufficient fruit and vegetable consumption decreases by about 6% over the benefit month (p = 0.180).

Another way of assessing meal quality is to examine whether there are changes over the month in the types of food purchased for consumption at home. For example, more costly meats at the beginning of the month might be replaced by cheaper, less nutritious carbohydrates at the end of the month. Those carbohydrate foods are likely to be non-perishable and may be purchased at the beginning of the month as well. Therefore, we consider the time-path of the relationship between different food categories over the course of the month. Our first comparison is between protein and carbohydrates.[13] We feel that this comparison gets directly at the basis of a meal: chicken or pasta? This is measured by subtracting carbohydrate expenditures from protein expenditures on a given day and dividing by the total expenditures on food for home consumption on that day. Therefore, this is a measure of basket composition, conditional on grocery shopping. Shopping days with no reported expenditure on either protein or carbohydrate goods are excluded. We also consider substitution in accompanying foods: are fruits and vegetables at the beginning of the month replaced by snacks and sweets at the end of the month? Finally, we pool food categories into “good” (milk and dairy, protein, and fruits and vegetables) and “bad” (grains and snack and sweets) groups. We regress these measures on days since benefit receipt in specification akin to those in Table 4. Results are in Table 7.

[13] Specifically comparing items classified as “proteins” to “grains” as characterized by the USDA.

Purchases of protein goods as a fraction of total expenditures fall relative to carbohydrate purchases as a fraction of total expenditures over the course of the month, however the magnitude is small. On day zero, households that make a purchase of either food type spend about 17% more on protein goods. This falls to about 10% by the end of the benefit month. Estimates for the comparison between combined milk and dairy, protein and fruit and vegetable expenses, and combined carbohydrate and sweet and snack expenses are very similar. We do not observe a substitution over time between fruits and vegetables and sweets and snacks.

These broad categories don't fully capture the dynamic of a household adjusting its purchasing patterns to reflect a shrinking budget. We can leverage the detail of the FoodAPS to use the energy content and weight of the items purchased instead. With resources running out, we expect to see an increase in the calories per dollar of food purchased in order to obtain sufficient energy and an increase in grams per dollar purchased in order to satiate appetites. We find suggestive evidence of this. kCal per dollar spent on food is estimated to increase by roughly 20% over the course of the benefit month, from 409 kCal/$ to 492 kCal/$ ($p = 0.130$). Additionally, edible grams of food per dollar increases about 37% from 304 g/$ to 417 g/$ over the benefit month ($p = 0.001$).[14] These changes are likely linked to a shift away from protein towards carbohydrates over the course of the month.[15] Within carbohydrates, purchases shift away from food with dietary fiber content over the course of the month, towards food with a higher sugar content.[16]

Food access

A common suggestion is that the calorie crunch among benefit recipients might be a direct

[14] Therefore, the caloric density by weight is actually going down over the course of the month because the growth rate of g/$ exceeds that of kCal/$.
[15] The ratio of protein grams less carbohydrate grams to total grams purchased declines by 6% over the course of the month ($p = 0.205$). There do not appear to be substitutions towards or away from fats over the course of the month.
[16] The ratio of dietary fiber grams less sugar grams to total carbohydrate grams purchased declines by 9% over the course of the month ($p = 0.053$).

reflection of transactions costs in shopping. If SNAP participants are not located near grocery stores, then planning a large shopping trip to coincide with benefit arrival seems natural. Later in the month, a dwindling supply of stored food combined with poor local options for fresh food results in reduced consumption. If different types of households live nearby or far away from grocery stores, this could be responsible for the systematic differential severity in consumption declines found in this paper and Kuhn (2016). The FoodAPS has precise information on household-specific travel times to their primary grocery stores that can be used in conjunction with reported travel times. We use this information to explore the role that food access could play in our results.

All households report their travel time to their primary grocery store. For most households, the location of this store and the respondent's home address are used to calculate driving and waling travel times. The match between reported travel time and calculated travel time according to the reported transportation mode is good, although it is not perfect. While we use households reported travel times, because their perception of the time costs of shopping are what matters for their shopping decision, we drop reported times that are in the extremes of the distribution of mismatch between reported and calculated times.[17] The two-way travel times we use vary from 2 to 180 minutes.

First, we verify that households with higher travel times shop less and spend more when they shop. We limit our expenditure sample here to food for at-home consumption and continue to define shopping as an indicator for whether at least $1 was spent on food for at-home consumption. In Table 8, column (1), we show that travel time does correlate negatively with shopping likelihood. A 10-minute increase in round trip travel time relates to a 1% reduction in the

[17] Specifically, we calculated the difference between the reported and calculated times and drop observations that are lower than the 5th percentile or higher than the 95th percentile of the difference distribution.

likelihood of grocery shopping. Column (2) demonstrates that expenditures are higher –roughly $1.74 for every 10 minutes of travel. Increasing the shopping threshold increases the size of the coefficients in both columns (1) and (2), with both being statistically significant. Thus, our basic predications for how travel time should interact with shopping pan out.

If travel time were a primary driver of the changes in shopping and expenditures over the course of the month, we would expect to see the gap in shopping between nearby and far away household expand over the course of the benefit month. At the end of the benefit month, distant households should be less likely to shop (at least relative to the baseline likelihood gap at the beginning of the month, which could be positive, negative or zero). In other words, when we add days since receipts and its interaction with travel time to the regressions from Table 8, column (1), we should negative coefficients on the interaction term. We do not find strong evidence in favor of this hypothesis. The coefficient on the interaction term in column (3) is a tightly estimated zero, indicating that there is a level gap in shopping likelihood associated with distance but that it isn't changing over the benefit cycle. Food access is not driving shopping patterns that lead to the calorie crunch. Figure 6 shows the shopping trends over the month based on round trip sample time. The data is roughly divided into equal thirds with groups of 10 minutes or less, 10-20 minutes and 20 minutes or more. The data are noisy, but the 20 minutes or more group is below the two closer groups consistently, but there are no clear time trends in the relationship across groups.

In Section 3.2, we established that while expenditure and consumption trends are correlated within households, they are not highly correlated. We thus estimate the direct relationship between travel time and consumption. Using both OLS and first-differenced individual fixed effects models, there is no time changing relationship between travel time and meal consumption. The OLS specification shows no level relationship either. Based on these findings, we think it is unlikely that food access is a primary cause of either the calorie crunch or its differential incidence across households.

Discussion and conclusion

The FoodAPS offers our first look at simultaneous expenditure and consumption profiles for SNAP households. We replicate previous research with our measures of expenditure, and provide the first results measured in terms of missed meals, which have direct implications for food security classification. Also, we show that quality of diet decreases over the benefit month; people eat fewer meals that consist of more carbohydrates and less protein. While households exhibit strong downward trends in both consumption and expenditure throughout the benefit month, these behaviors are only loosely correlated. This finding should prompt a more careful examination of how consumption decisions are made within the home, whereas the bulk of current policy interest focuses on intervention at the point of sale. For instance, long travel time to the primary grocery store, a commonly proposed explanation for poor purchasing and consumption habits, has no relationship to dynamic outcomes. On the other hand, when we examine within-household incidence of declines in consumption, we find that age is an important determinant of missed meals at the end of the month. The youngest children are sheltered from the calorie crunch regardless of school status, but primary-school age children are sheltered only when school is in session.

SNAP, the National School Lunch Program (NSLP) and the School Breakfast Program (SBP) have all been shown to positively impact children's health. We have already discussed the literature linking SNAP to health outcomes. Gleason and Suitor (2003) show that the NSLP improves nutritional intake, but also increases dietary fat consumption and indeed, Schanzenbach (2009) links the NSLP to increased childhood obesity. Gundersen *et al.* (2012) estimate an overall positive impact on health. Bhattacharya *et al.* (2006) show improvements in nutritional intake and overall diet quality for SBP participants and Dotter (2013) demonstrates that universally-free breakfast programs have lasting impacts on academic achievement. Given our results, we suspect that some of the positive impacts of these programs may operate through the mitigation of cyclical food insecurity associated with the calorie crunch. While participation in school meal programs is essentially universal in our SNAP sample, this does not mean redemption of those meals is. Breakfast is the most commonly skipped meal: 67% of low-income children don't eat breakfast every day, with 19% of all children skipping breakfast on any given day (Moag-Stahlberg 2011, O'Neil *et al.* 2015). Interventions that increase usage of the SBP and NSLP could mitigate cyclical food insecurity associated with SNAP in addition to raising the level of consumption. Additionally, participation in summer break programs with meal provision is essentially nonexistent. Current efforts to expand summer meal programs for children may also help smooth consumption.

A puzzling aspect of our results is that there appear to be very little impact of school meal programs for middle or high-school children. This could mean that our interpretation of the difference in calorie crunch by school status is incorrect. Or, it could indicate that older children underutilize these programs. We expect that stigma associated with these programs would increase with age. Mirtcheva and Powell (2009) show that as the eligibility rate of a school increases, NSLP usage increases. This is driven by behavior in high schools. Bhatia *et al.* (2011) remove paid lunch options at high and middle schools in San Francisco and find increased uptake of NSLP lunches that exceeded the number of students originally paying for lunch. Expanding usage of NSLP and SBP at these levels could reduce cyclical food insecurity and potentially alleviate the associated behavioral problems identified by Gennetian *et al.* (2015).

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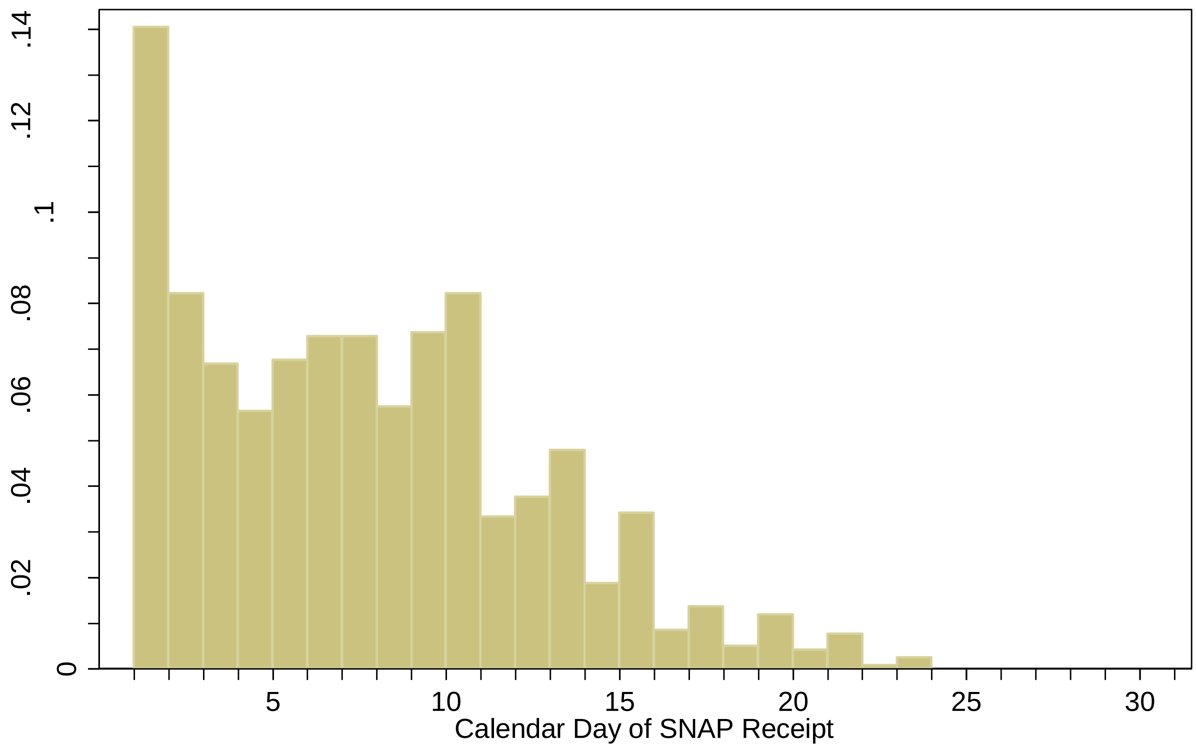

Figure 1: Distribution of Benefit Receipt in Sample

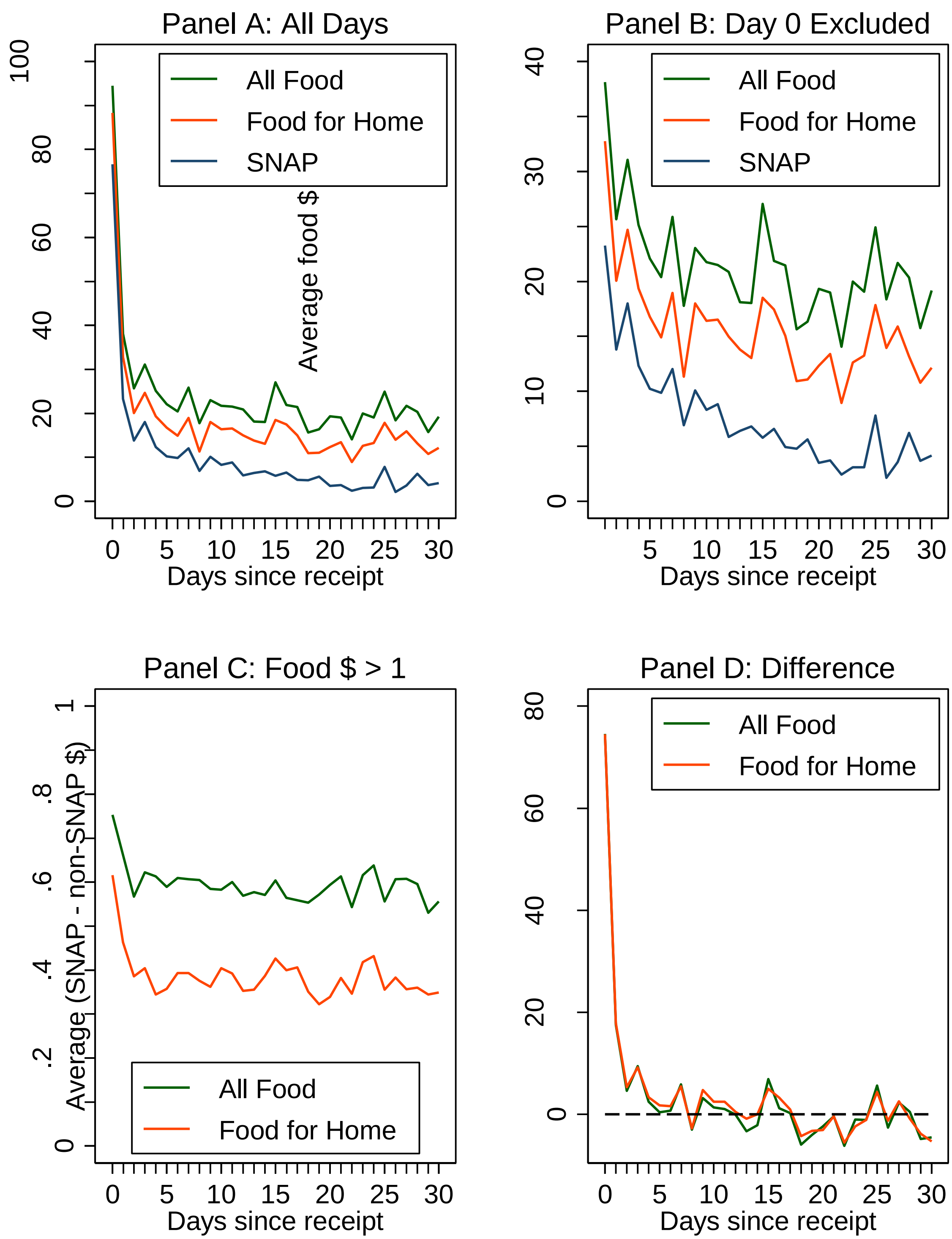

Figure 2: Expenditure Trends over the Benefit Month

Table 1: Estimates of Household Expenditure Trend						
Date range:	All			Days since receipt > 0		
Model:	OLS	FD	FE Poisson	OLS	FD	FE Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.555*** (0.067)	-3.819*** (0.386)	-0.041*** (0.006)	-0.231*** (0.058)	-2.343*** (0.332)	-0.018*** (0.006)
Constant	31.570 (1.538)			23.952 (1.327)		
Clusters	1167	1167	961	1167	1167	920
N	8169	6784	6585	7914	6559	6241

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Columns (2) and (5) feature fewer observations than columns (1) and (4) due to first-differencing. Columns (3) and (6) feature fewer observations than columns (1) and (4) because households with no variation in the dependent variable are dropped. Moving from columns (1), (2) and (3) to (4), (5) and (6) results in the loss of observations due to the exclusion of the day of benefit receipt from the sample.

Table 2: Estimates of Meal Consumption Trend at Household and Individual Levels						
Unit of Analysis:	Household			Individual		
Model:	OLS	Tobit	FD	OLS	Tobit	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Data						
Days since receipt	-0.006*** (0.002)	-0.009*** (0.003)	-0.025*** (0.004)	-0.005*** (0.002)	-0.012*** (0.004)	-0.022*** (0.004)
Constant	2.249 (0.040)	2.441 (0.056)		2.310 (0.041)	3.079 (0.096)	
Clusters	1167	1167	1167	1167	1167	1167
N	8169	8169	6784	25,571	25,571	21,225
Panel B: Non-imputed Data Only						
Days since receipt	-0.010*** (0.003)	-0.015*** (0.004)	-0.027*** (0.004)	-0.009*** (0.003)	-0.022*** (0.006)	-0.023*** (0.004)
Constant	2.347 (0.056)	2.589 (0.083)		2.411 (0.055)	3.327 (0.132)	
Clusters	1088	1088	1044	1088	1088	1044
N	6819	6819	5731	21,119	21,119	17,738

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. The number of meals in a day can range from 0 to 3 for an individual: breakfast, lunch and dinner. Averaged within a household, the meals variable is defined continuously between 0 and 3. Columns (3) and (6) have fewer observations than the other models at the same analysis unit because of the first differencing.

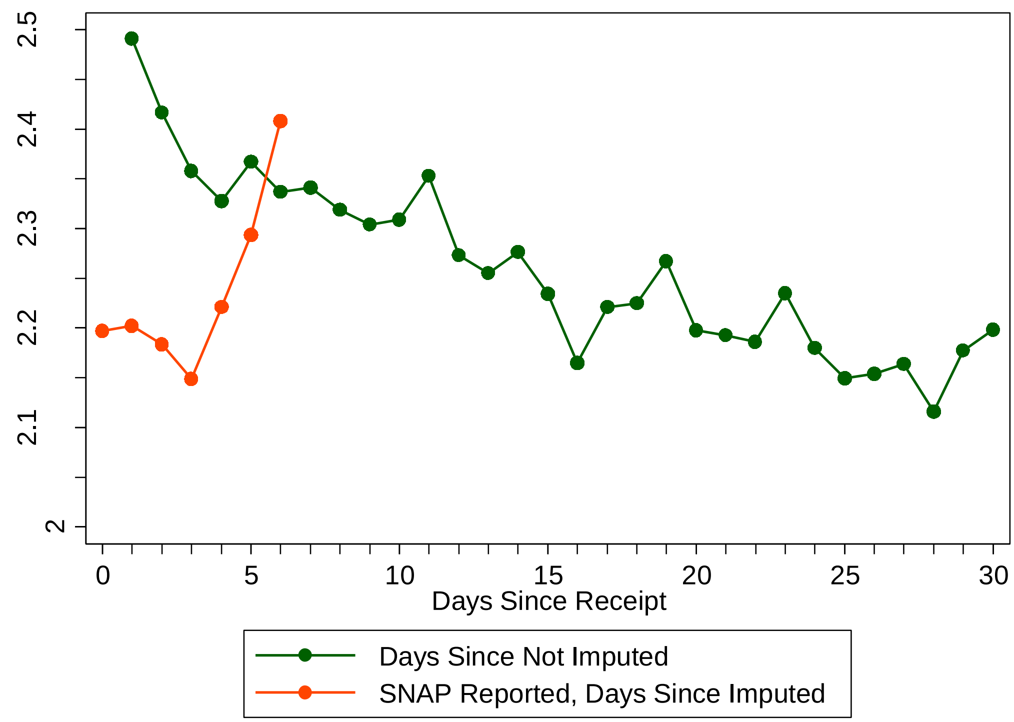

Figure 3: Consumption Trends over the Benefit Month

Table 3: Intra-Household Correlation between Expenditure and Consumption Trend Estimates				
Dep. Var.:	Household Meal Consumption Trend			
Estimates:	All	Trimmed	All	Trimmed
	(1)	(2)	(3)	(4)
Household Expenditure Trend	0.046 (0.029)	0.054 (0.039)	-0.048 (0.048)	0.155** (0.067)
Week of Month			-0.034 (0.024)	0.025 (0.031)
Household Expenditure Trend X Week of Month			0.051** (0.021)	-0.060* (0.033)
N	1167	615	1167	615

**: $p < 0.05$, *: $p < 0.10$.

Table 4: Number of Daily Meals Consumption Trend by Age Group						
Sample:	All			Non-Imputed Data Only		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.007*** (0.002)	-0.001 (0.001)	-0.022*** (0.004)	-0.012*** (0.003)	-0.002 (0.002)	-0.024*** (0.005)
Age < 6	0.441*** (0.061)	0.377*** (0.048)		0.402*** (0.088)	0.357*** (0.065)	
Days since receipt X age < 6	0.007** (0.003)	0.005* (0.002)	0.012 (0.008)	0.010** (0.005)	0.006* (0.003)	0.018** (0.009)
5 < age < 12	0.336*** (0.069)	0.365*** (0.048)		0.379*** (0.090)	0.402*** (0.068)	
Days since receipt X 5 < age < 12	0.007* (0.004)	0.001 (0.003)	0.003 (0.008)	0.006 (0.005)	-0.001 (0.004)	0.004 (0.009)
11 < age < 18	0.064 (0.081)	0.202*** (0.051)		-0.070 (0.132)	0.168** (0.075)	
Days since receipt X 11 < age < 18	0.009** (0.004)	0.001 (0.003)	-0.013 (0.010)	0.016** (0.007)	0.003 (0.004)	-0.015 (0.012)
Constant	2.199 (0.041)			2.311 (0.056)		
Clusters	1167	1167	1167	1088	1088	1044
N	25,571	25,571	21,225	21,119	21,119	17,738

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. The number of meals in a day can range from 0 to 3 for an individual: breakfast, lunch and dinner. Columns (3) and (6) have fewer observations than the other models in the same sample because of the first differencing.

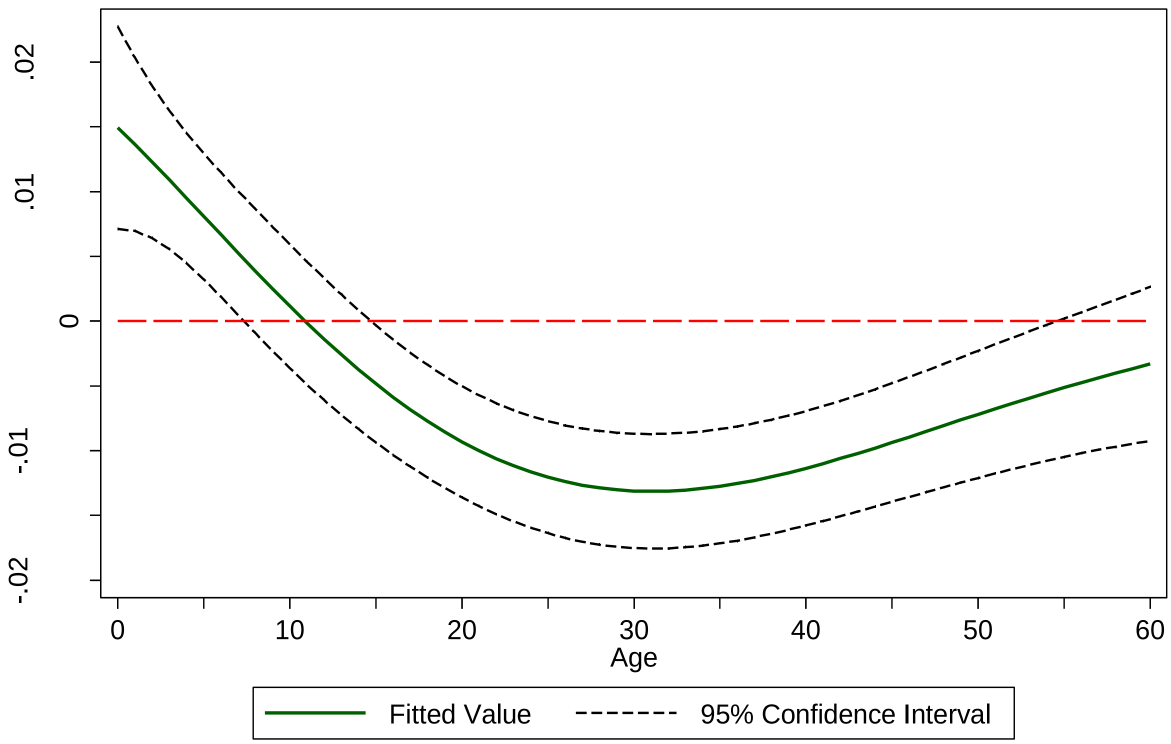

Figure 4: Consumption Trend by Age

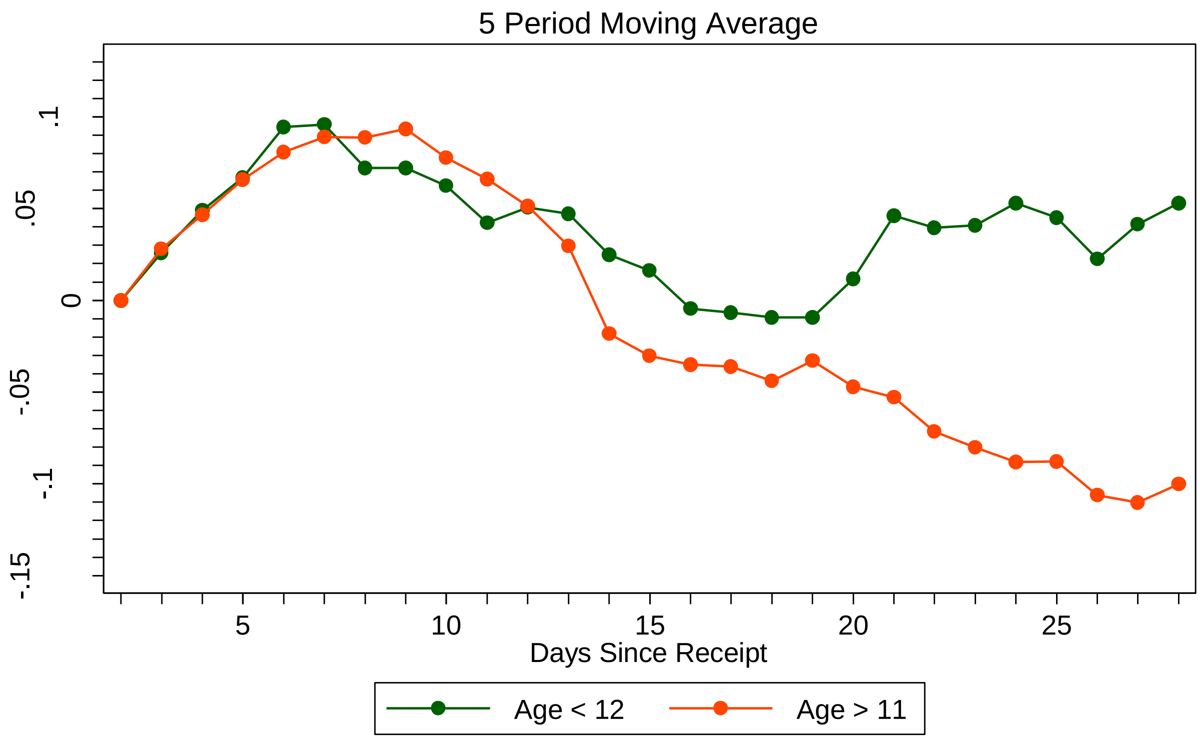

Figure 5: Smoothed Differences in Consumption from their Initial Value

Table 5: Difference in Consumption Trends by School Break Status				
Sample:	All		Non-Imputed Data Only	
School:	Open	Closed	Open	Closed
	(1)	(2)	(3)	(4)
Days since receipt	-0.004 (0.003)	-0.002 (0.004)	-0.007 (0.005)	-0.001 (0.006)
Difference:	-0.002 $\chi^2 = 0.22$ ($p = 0.637$)		-0.006 $\chi^2 = 0.56$ ($p = 0.455$)	
Days since receipt X not school-age	0.003 (0.005)	-0.001 (0.007)	0.003 (0.007)	-0.002 (0.009)
Difference:	0.004 $\chi^2 = 0.16$ ($p = 0.688$)		0.005 $\chi^2 = 0.22$ ($p = 0.637$)	
Days since receipt X primary school	0.007 (0.005)	-0.008 (0.007)	< 0.001 (0.006)	-0.013 (0.010)
Difference:	0.015* $\chi^2 = 3.04$ ($p = 0.081$)		0.013 $\chi^2 = 2.18$ ($p = 0.260$)	
Days since receipt X middle school	-0.002 (0.006)	-0.001 (0.010)	-0.001 (0.009)	0.011 (0.015)
Difference:	-0.001 $\chi^2 < 0.01$ ($p = 0.953$)		-0.012 $\chi^2 = 0.48$ ($p = 0.468$)	
Days since receipt X high school	0.009 (0.006)	0.009 (0.008)	0.014 (0.009)	0.017 (0.014)
Difference:	< 0.001 $\chi^2 < 0.01$ ($p = 0.996$)		-0.003 $\chi^2 = 0.03$ ($p = 0.862$)	
Constant	2.156 (0.071)	2.199 (0.089)	2.246 (0.098)	2.168 (0.125)
Clusters	529		487	
N	15,743		12,850	

*: $p < 0.10$. Level effects of school age are excluded for presentation. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month and a weekend indicator are included as controls in all specifications. The number of meals in a day can range from 0 to 3 for an individual: breakfast, lunch and dinner.

Table 6: Number of Daily Meals Consumption Trend by Gender						
Sample:	All Data			Dual-Adult HHs		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.007*** (0.002)	< 0.001 (0.001)	-0.016*** (0.005)	-0.003 (0.003)	0.001 (0.002)	-0.013** (0.006)
Male?	-0.042 (0.045)	0.009 (0.032)		-0.011 (0.046)	0.004 (0.040)	
Days since receipt X Male?	0.001 (0.002)	< 0.001 (0.002)	-0.014** (0.006)	-0.001 (0.002)	< 0.001 (0.002)	-0.016** (0.007)
Constant	2.203 (0.045)					
Clusters	1162	1162	1162	494	494	494
N	15,386	15,386	12,765	8358	8358	6933

***: $p < 0.01$, **: $p < 0.05$. Standard errors clustered by household are in parentheses beneath the estimates. All data are from adults. Week of month and a weekend indicator are included as controls in all specifications. The number of meals in a day can range from 0 to 3 for an individual: breakfast, lunch and dinner. First-differenced models have fewer observations both because of the differencing and because we exclude across benefit-month differences.

Table 7: Expenditure Bundle Trends over the Benefit Month			
Food Comparison:	$\frac{\$Protein - \$Carb}{\$Total}$	$\frac{\$Fruit \& Vegetable - \$Snack \& Sweet}{\$Total}$	$\frac{\$Good - \$Bad}{\$Total}$
	(1)	(2)	(3)
Days since receipt	-0.002*** (0.001)	> -0.001 (0.001)	-0.002** (0.001)
Constant	0.168 (0.016)	-0.035 (0.017)	0.159 (0.019)
Clusters	950	968	1110
Observations	1775	1941	2977

***: $p < 0.01$, **: $p < 0.05$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Days without any expenditure on either category being compared are excluded, therefore the number of observations depends on how frequently the items in question were purchased.

Table 8: Travel Time, Grocery Shopping and Grocery Expenditures				
Dependent variable:	1(Exp. ≥ 1)	Exp. | Exp. ≥ 1	1(Exp. ≥ 1)	Exp. | Exp. ≥ 1
	(1)	(2)	(3)	(4)
Round trip travel time (minutes)	-0.001*** (< 0.001)	0.174* (0.098)	-0.002*** (0.001)	0.381 (0.257)
Days since receipt			-0.003*** (0.001)	-1.039*** (0.274)
Days since receipt X Round trip travel time (minutes)			< 0.001 (< 0.001)	-0.014 (0.014)
Constant	0.437 (0.016)	45.299 (3.696)	0.478 (0.020)	55.621 (5.532)
Clusters	941	893	941	893
N	6587	2406	6587	2406

***: $p < 0.01$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. The food expenditures are limited to purchases made for food at home because the travel time is calculated based on the distance to the respondent's primary grocery store. Reported travel time is used, but set to missing if it is an outlier in the distribution of mismatch between reported and calculated travel times (truncated at the 5th and 95th percentiles).

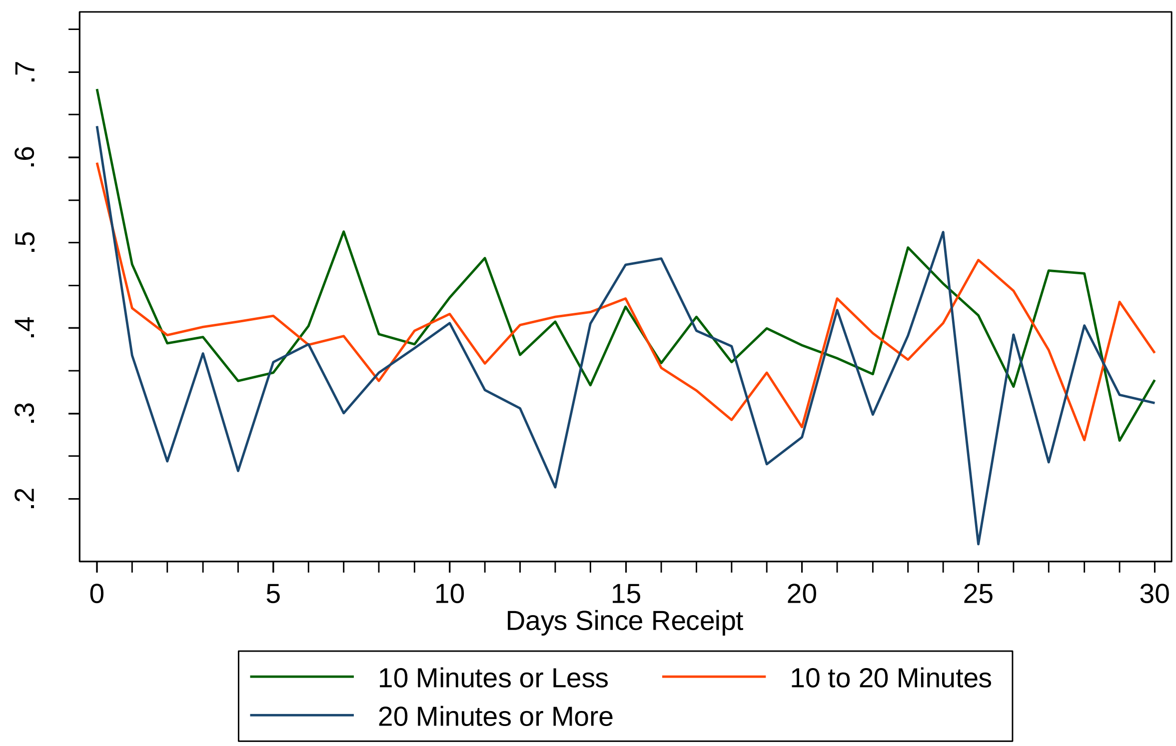

Figure 6: Round Trip Travel Time and Shopping Likelihood over the Benefit Month

Appendix

Table A1: Alternative Estimates of Household Expenditure Trend

Date range:	All			Days since receipt > 0		
Model:	Tobit	MD	Poisson	Tobit	MD	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.763*** (0.111)	-0.958*** (0.144)	-0.027*** (0.003)	-0.318*** (0.101)	-0.327*** (0.118)	-0.012*** (0.003)
Constant	13.561 (2.196)	36.678 (2.153)	3.530 (0.063)	5.818 (2.209)	25.727 (1.856)	3.207 (0.066)
Clusters	1167	1167	1167	1167	1167	1167
N	8169	8169	8169	7914	7914	7914

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Columns (4)-(6) feature fewer observations due to the excluded day of SNAP receipt.

Table A2: Extensive Margin Estimates of Household Shopping Trend

Model:	LPM	FD LPM	Probit	Household Conditional Logit
	(1)	(2)	(3)	(4)
Days since receipt	-0.002** (0.001)	-0.008*** (0.002)	-0.002** (0.001)	-0.004*** (0.001)
Constant	0.615 (0.017)		0.614 (0.017)	
Clusters	1167	1167	1167	1050
N	8169	7002	8169	7350

***: $p < 0.01$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Marginal effects are presented in columns (3) and (4). Column (2) features fewer observations because of the first-differencing. Column (4) features fewer observations because households without variation in the dependent variable are dropped.

Table A3: Estimates of Household Food at Home Expenditure Trend						
Date range:	All			Days since receipt > 0		
Model:	OLS	FD	FE Poisson	OLS	FD	FE Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.590*** (0.062)	-3.458*** (0.360)	-0.052*** (0.008)	-0.267*** (0.050)	-2.022*** (0.304)	-0.025*** (0.008)
Constant	26.290 (1.440)			18.688 (1.162)		
Clusters	1167	1167	835	1167	1167	787
N	8169	6784	5656	7914	6559	5277

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Columns (2) and (5) feature fewer observations than columns (1) and (4) due to first-differencing. Columns (3) and (6) feature fewer observations than columns (1) and (4) because households with no variation in the dependent variable are dropped. Moving from columns (1), (2) and (3) to (4), (5) and (6) results in the loss of observations due to the exclusion of the day of benefit receipt from the sample.

Table A4: Estimates of Household Expenditure Trend Measured as a Difference from the Expenditures of non-SNAP Households						
Date range:	All			Days since receipt > 0		
Dep. var:	Expenditures ($)		1(Exp. ≥ 1)	Expenditures ($)		1(Exp. ≥ 1)
Model:	OLS	FD	FD LPM	OLS	FD	FD LPM
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.555*** (0.069)	-3.864*** (0.394)	-0.038*** (0.004)	-0.223*** (0.060)	-2.365*** (0.340)	-0.034*** (0.004)
Constant	10.413 (1.582)			2.621 (1.380)		
Clusters	1167	1167	1167	1167	1167	1167
N	8154	6769	6769	7899	6544	6544

***: $p < 0.01$. Standard errors clustered by household are in parentheses beneath the estimates unless otherwise indicated. Week of month, a weekend indicator and an indicator for whether the diary day was a day on which the survey team called to check up on the respondent's expenditure logs are included as controls in all specifications. Columns (2), (3), (5) and (6) feature fewer observations than columns (1) and (4) due to first-differencing.

Table A5: Estimates of Meal Consumption Trend at Household and Individual Levels						
Unit of Analysis:	Household			Individual		
Model:	OLS	Tobit	FD	OLS	Probit	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Breakfast Only						
Days since receipt	-0.003*** (0.001)	-0.007*** (0.003)	-0.010*** (0.002)	-0.002** (0.001)	-0.002** (0.001)	-0.009*** (0.002)
Constant	0.655 (0.019)	0.898 (0.054)		0.682 (0.018)	0.682 (0.018)	
Panel B: Lunch Only						
Days since receipt	-0.001* (0.001)	-0.005* (0.003)	-0.006*** (0.002)	-0.002** (0.001)	-0.002** (0.001)	-0.005*** (0.002)
Constant	0.732 (0.017)	1.208 (0.063)		0.766 (0.018)	0.765 (0.017)	
Panel C: Dinner Only						
Days since receipt	-0.002** (0.001)	-0.009** (0.004)	-0.009*** (0.002)	-0.001 (0.001)	-0.001 (0.001)	-0.007*** (0.002)
Constant	0.862 (0.014)	2.109 (0.112)		0.861 (0.014)	0.861 (0.014)	
Panel D: Breakfast, Lunch, Dinner all Missed						
Days since receipt	0.001* (< 0.001)	0.013* (0.008)	0.011*** (0.001)	0.001 (< 0.001)	0.001 (< 0.001)	0.009*** (0.001)
Constant	0.047 (0.010)	-2.884 (0.308)		0.046 (0.009)	0.047 (0.008)	
Panel E: Snacks (any)						
Days since receipt	-0.002*** (< 0.001)	-0.013*** (0.004)	-0.014*** (0.002)	-0.001** (< 0.001)	-0.001** (< 0.001)	-0.012*** (0.002)
Constant	0.938 (0.010)	2.661 (0.147)		0.934 (0.010)	0.932 (0.009)	
Clusters	1167	1167	1167	1167	1167	1167
N	8169	8169	6784	25,571	25,571	21,225

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. All variables are binary on the individual level. Averaged within a household, the variables are defined continuously between 0 and 1. Columns (3) and (6) have fewer observations than the other models at the same analysis unit because of the first differencing. Marginal effects are presented in column (5).

Table A6: Breakfast Consumption Trend by Age Group						
Sample:	All			Non-Imputed Data Only		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.004*** (0.001)	-0.001* (0.001)	-0.010*** (0.002)	-0.006*** (0.001)	-0.002** (0.001)	-0.011*** (0.002)
Age < 6	0.215*** (0.028)	0.223*** (0.027)		0.197*** (0.040)	0.211*** (0.037)	
Days since receipt X age < 6	0.005*** (0.001)	0.003* (0.001)	0.009** (0.004)	0.006*** (0.002)	0.003* (0.002)	0.011*** (0.004)
5 < age < 12	0.175*** (0.030)	0.211*** (0.027)		0.182*** (0.039)	0.237*** (0.036)	
Days since receipt X 5 < age < 12	0.005*** (0.002)	< 0.001 (0.001)	-0.001 (0.004)	0.005** (0.002)	-0.001 (0.002)	< 0.001 (0.004)
11 < age < 18	0.040 (0.036)	0.105*** (0.029)		-0.021 (0.058)	0.082* (0.044)	
Days since receipt X 11 < age < 18	0.004* (0.002)	< 0.001 (0.002)	-0.007 (0.005)	0.007** (0.003)	0.002 (0.003)	-0.006 (0.005)
Constant	0.625 (0.020)			0.681 (0.027)		
Clusters	1167	1167	1167	1088	1088	1044
N	25,571	25,571	21,225	21,119	21,119	17,738

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. Breakfast consumption is a binary variable. We use linear probability models for fixed-effect flexibility and because the mean of the dependent variable is not too close to zero or one. Columns (3) and (6) have fewer observations than the other specification on the same sample because of the first differencing.

Table A7: Lunch Consumption Trend by Age Group						
Sample:	All			Non-Imputed Data Only		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.002*** (0.001)	< 0.001 (0.001)	-0.003 (0.002)	-0.004*** (0.001)	> -0.001 (0.001)	-0.004 (0.003)
Age < 6	0.165*** (0.025)	0.114*** (0.020)		0.146*** (0.035)	0.090*** (0.026)	
Days since receipt X age < 6	0.001 (0.001)	0.001 (0.001)	-0.004 (0.004)	0.003 (0.002)	0.002* (0.001)	-0.001 (0.004)
5 < age < 12	0.134*** (0.030)	0.128*** (0.023)		0.154*** (0.036)	0.130*** (0.032)	
Days since receipt X 5 < age < 12	0.001 (0.002)	> -0.001 (0.001)	-0.002 (0.004)	< 0.001 (0.002)	> -0.001 (0.002)	-0.003 (0.004)
11 < age < 18	0.072** (0.033)	0.093*** (0.022)		0.040 (0.049)	0.090*** (0.033)	
Days since receipt X 11 < age < 18	0.001 (0.002)	-0.001 (0.001)	-0.010* (0.005)	0.003 (0.003)	> -0.001 (0.002)	-0.012** (0.006)
Constant	0.718 (0.018)			0.762 (0.025)		
Clusters	1167	1167	1167	1088	1088	1044
N	25,571	25,571	21,225	21,119	21,119	17,738

***: $p < 0.01$, **: $p < 0.05$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. Lunch consumption is a binary variable. We use linear probability models for fixed-effect flexibility and because the mean of the dependent variable is not too close to zero or one. Columns (3) and (6) have fewer observations than the other specification on the same sample because of the first differencing.

Table A8: Dinner Consumption Trend by Age Group						
Sample:	All			Non-Imputed Data Only		
Model:	OLS	HH FE	FD	OLS	HH FE	FD
	(1)	(2)	(3)	(4)	(5)	(6)
Days since receipt	-0.001* (0.001)	< 0.001 (< 0.001)	-0.009*** (0.002)	-0.002** (0.001)	> -0.001 (0.001)	-0.009*** (0.002)
Age < 6	0.061*** (0.022)	0.040** (0.018)		0.059** (0.030)	0.056** (0.022)	
Days since receipt X age < 6	0.001 (0.001)	0.001 (0.001)	0.007* (0.004)	0.001 (0.002)	< 0.001 (0.001)	0.008* (0.004)
5 < age < 12	0.027 (0.024)	0.027** (0.013)		0.042 (0.035)	0.036* (0.019)	
Days since receipt X 5 < age < 12	0.001 (0.001)	0.001 (0.001)	0.005 (0.003)	0.001 (0.002)	< 0.001 (0.001)	0.007* (0.004)
11 < age < 18	-0.048 (0.030)	0.004 (0.019)		-0.089* (0.046)	-0.004 (0.024)	
Days since receipt X 11 < age < 18	0.004** (0.002)	0.001 (0.001)	0.004 (0.005)	0.006** (0.002)	0.001 (0.001)	0.003 (0.006)
Constant	0.855 (0.014)			0.869 (0.021)		
Clusters	1167	1167	1167	1088	1088	1044
N	25,571	25,571	21,225	21,119	21,119	17,738

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$. Standard errors clustered by household are in parentheses beneath the estimates. Week of month and a weekend indicator are included as controls in all specifications. Dinner consumption is a binary variable. We use linear probability models for fixed-effect flexibility and because the mean of the dependent variable is not too close to zero or one. Columns (3) and (6) have fewer observations than the other specification on the same sample because of the first differencing.