The effect of SNAP benefits on expenditures: New evidence from scanner data and the November 2013 benefit cuts*

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Abstract

In November 2013, all SNAP benefits were reduced for the first time in the program's history when temporary increases in the American Recovery and Reinvestment Act expired. I quantify the impact of these cuts using scanner data from 400 grocery stores and the purchases of over 2.5 million households enrolled in SNAP. I estimate that each \$1 of cuts reduced grocery store spending by \$0.37. Importantly, the implied marginal propensity to consume food out of food stamps is more precisely estimated than in previous studies, at 0.3 with a 95% confidence interval of [0.154, 0.456]. The revenue impact for the U.S. grocery retailing industry is estimated to be a decline of 0.3% overall. In contrast, I project that the aggregate impact of the 2014 Farm Bill will be an order of magnitude lower.

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1 Introduction

The Supplemental Nutrition Assistance Program (SNAP) spent $80 billion in 2013 to provide monthly income to 47.6 million people in 23 million low-income households. In November 2013, benefits were reduced for all households when temporary benefit increases from the American Recovery and Reinvestment Act (ARRA) expired.[1] These cuts have been widely cited as adversely affecting retail sales and households' ability to feed their families.[2] However, no study has been able to quantify the impact of the expiration of these ARRA policies, because most datasets commonly used to study household expenditures are not yet available. This paper provides such estimates.

I use scanner data from 400 grocery stores, aggregated at the store-level, to quantify the impact of the benefit cuts on household expenditures. The stores are located in three large metropolitan areas: Los Angeles, Atlanta, and Columbus, Ohio. The stores have significant market share and make up 8% to 17% of the total number of supermarkets in each area. Household loyalty card identifiers and method of payment are used to measure household spending and establish SNAP participation. The data include the purchases of over 2.5 million households enrolled in SNAP and over 11 million non-participating households.[3]

The "treatment effect" of the expiration of the ARRA varies across stores in my sample depending on the fraction of customers at each store who participate in SNAP.[4] I use a difference in differences research design, where I define the degree of treatment at each store as the pre-period fraction of households shopping at that store who used SNAP to pay for at least one purchase.

[1] An exception to this is that benefits did not change in Hawaii.

[2] Examples include articles in the *New York Times* (e.g., "As Cuts to Food Stamps Take Effect, More Trims to Benefits Are Expected" by Catherine Rampell on October 28, 2013), *Wall Street Journal* (e.g., "Retailers Brace for Reduction in Food Stamps" by Shelly Banjo and Annie Gasparro on November 1, 2013), and *Slate* (e.g., "Did cuts to Food Stamps Undo Family Dollar?" by Alison Griswold July 28, 2014).

[3] The data only include grocery store spending, but over 80% of all SNAP benefits are redeemed at supermarkets, 96.3% of households redeem at least some of their benefits at these kinds of stores (Castner and Henke 2011, tables A-4 and II.11), and over 70% of low-income household expenditures on food consumed at home occur at grocery stores (Damon, King, and Leibtag 2013, table 3).

[4] The research design is similar to Card (1992).

Using this approach, I find that each $1 of benefit cuts reduced SNAP household spending by $0.37, with larger impacts in Atlanta than in Los Angeles or Columbus. About 3/4 of the decline was to spending on grocery items and meat, while 16% was from spending on non-food general merchandise and over the counter drugs. I estimate a marginal propensity to consume food out of food stamp benefits of 0.30, with a 95% confidence interval of [0.154, 0.456].

This paper is one of only a handful of studies to present estimates of the effect of SNAP benefits on expenditure using a quasi-experimental research design. The first paper to use a quasi experimental research design in this literature was Hoynes and Schanzenbach (2009), who study consumption in the Panel Study of Income Dynamics (PSID) during the initial staggered rollout of the Food Stamp Program across counties. Recently, Nord and Prell (2011) and Beatty and Tuttle (2012) measure the effect of the 2009 ARRA benefit increases by comparing changes in consumption and expenditures by SNAP eligible households with those by ineligible households.

Although all the results presented here should be interpreted as applying only to household expenditures at grocery stores, the estimates are in line with those of Hoynes and Schanzenbach (2009, table 6), which is noteworthy given the very different data used and four decades that have passed since the time period studied in that paper. Importantly, my data and research design yield more precise estimates than Hoynes and Schanzenbach, with confidence intervals that are 80% to half as wide. The magnitude of these estimates is about half to 1/3 the size of the largest estimates from the cross-sectional empirical literature from the 1970s and 1980s (surveyed in Fraker 1990 and Burstein et al. 2004).

This paper's broader context is as part of the literature on the impact of the ARRA on the economy (e.g., Chodorow-Reich et al. 2012) and on the optimal design of fiscal policy to stimulate domestic spending during recessions (e.g., Feldstein 2009). This paper also builds on previous studies in public economics that use scanner data to test hypotheses that have important implications for public policy (e.g., Chetty, Looney, and Kroft 2009, Hastings and Washington 2010).

The rest of this paper is organized as follows. The next section summarizes the basic economics of food stamps and provides abbreviated background information on the SNAP program, the November 2013 benefit changes, and how the program distorts labor supply. Section 3 describes the quasi-experimental research design. Section 4 describes the scanner data and presents summary statistics for the stores and households in my sample. I also compare my sample with those from other papers in the literature. Section 5 presents the estimates of the effect of the SNAP benefit cut on household spending, along with other supporting evidence and policy calculations. Section 6 discusses these results in the context of the 2014 Farm Bill, which further reduced SNAP benefits in 2014. Section 7 is a brief concluding section that ends with directions for additional research.

2 Background and the November 2013 benefit cuts

2.1 Background and economics of food stamps[5]

SNAP provides income to low-income households each month with the stated goal of helping them buy food.[6] In April 2014, the average SNAP household consisted of just over two people and received $256 in benefits per month. SNAP benefits are restricted in that they can only be used to pay for certain food items purchased at retailers that have applied for and received authorization to participate in the program from the U.S. Department of Agriculture. Excluded items include alcohol, hot foods, and toiletries. Households receive benefits via an Electronic Benefits Transfer (EBT) card. Similar to a debit card, households access their benefits by swiping the card and entering a pin number at the time of purchase.

The "textbook" economic analysis of SNAP benefits contrasts cash benefits, which are unrestricted, with in-kind benefits, like SNAP, which can only be used to purchase certain goods (Schanzenbach 2002 and Hoynes and Schanzenbach 2009). This analysis

[5] See Nord and Prell (2011), Farson Gray and Eslami (2014), and the USDA's *Facts About SNAP* (USDA 2013) for further details on the SNAP program.

[6] Benefits are federally funded, but states share in the administrative costs.

predicts that there should be no difference between giving households cash or food stamp benefits, as long as they would have spent at least as much on food as the dollar value of their SNAP benefits. These households are infra-marginal and this fungibility result implies that these households should treat a \$1 decrease in food stamp benefits in the same way that they would treat losing \$1 of other income.[7]

SNAP beneficiaries are exempt from paying local and state sales taxes on any of the products that they purchase with SNAP tender. However, many of the products that are eligible to be paid for with SNAP tender are often already not subject to sales taxes.[8] Whether this sales tax exemption is quantitatively important depends the local sales tax rates and bases in place, as well as the degree to which households pay attention to sales taxes (Chetty, Looney, and Kroft 2009).

SNAP benefits are paid out once per month. Some states pay benefits to all recipients at once, but it is becoming more common for benefits to be staggered so that different households receive benefits on different days. In Los Angeles, benefits are paid out over the first 10 days of each month. In Atlanta, benefits are paid out between 5th and the 23rd of each month. In Columbus, benefits had been paid out across the 1st to 10th of each month, but were recently spread out over the first 20 days (even days only) for SNAP recipients awarded benefits after February 28, 2014.[9,10]

In the next two sections, I discuss how benefit amounts and eligibility are determined and how this changed when the ARRA was enacted and when it expired. Finally, I discuss the labor supply incentives that SNAP households face due to the interaction of SNAP with the personal income tax system.

[7] Put differently, if a paternalistic government were to use in-kind benefits as an instrument to change households' consumption bundles (e.g., less alcohol and more vegetables), then this analysis implies that it would only be successful in influencing what marginal households consume (i.e., households who would not have eaten any vegetables or only very few vegetables if given cash income).

[8] SNAP households with complete information should spend their benefits on taxable items (e.g., carbonated beverages in California, but not in Massachusetts) and buy untaxed items with other resources (e.g., cookies in California and Massachusetts).

[9] The USDA maintains a webpage with information on the benefit issuance schedule for each state at <http://www.fns.usda.gov/snap/snap-monthly-benefit-issuance-schedule>.

[10] Although Hastings and Washington (2010) find that stores are able to raise prices when benefits are dispersed all at once, in Ohio it was grocery retailers who requested that benefits be staggered more evenly because uneven demand creates inventory and staffing challenges.

2.2 Benefit amounts

Benefit amounts increase as the number of people in the household increases, and decline at a 30% rate as total household income after deductions increases. Benefits decline at a 24% rate as earned income increases because of a 20% earned income deduction. In particular, benefit amounts are determined by the following formula:

$$B(N, Z, Y, D) = \begin{cases} B_0(N) - 0.3(Y + 0.8Z - D) & \text{if } 0.8Z + Y > D \\ B_0(N) & \text{otherwise} \end{cases}$$

where $\$B_0(N)$ is the maximum that a household of size N can receive, $\$Z$ is earned income, $\$Y$ is unearned income, and $\$D$ are deductions.[11] There are some differences in the allowable deductions across states. The maximum benefit amounts are the same in all states except for Hawaii and Alaska, where they are set higher to reflect higher food costs.

In an effort by policymakers to increase domestic spending during the Great Recession, part of the $800 billion ARRA fiscal package was devoted to raising SNAP benefit amounts. The ARRA modified the SNAP benefit formula by increasing $\$B_0(N)$, the maximum amount each household could receive. The higher benefits started in April 2009 and remained fixed at these levels until November 2013.

Figure 1 plots the benefit amount before and after ARRA as a function of earned income for one to four person households. Panel A shows the benefit amounts before (solid line) and after (dashed line) the expiration of the benefit increases in November 2013. Panel B plots the corresponding schedule before (solid line) and after (dashed line) the initial implementation of ARRA in April 2009. Average earned income for SNAP households in 2012 was $326 a month including zeros (Farson Gray and Eslami 2014). At this income level, average benefits per month would have been $168, $335, $493, and $639 in October 2013 for one to four person households, respectively. The decreases in November 2013 for each of these households were $11, $20, $29, and $36. The corresponding increases in April 2009 were larger both in nominal and in real 2013

[11] Households receive either $\$B(N, Z, Y, D)$ given by the formula or a minimum amount, currently $15, if the amount given by the formula is smaller than the minimum amount.

dollars. As shown in the figure, all households of a given size experienced the same dollar change in benefits, except for some higher-income one and two person households, whose benefits were only increased by $2 in April 2009 and were only reduced $1 a month in November 2013.

Figure 2 plots the average benefit amount per household actually paid out for each month between October 2010 and April 2014. After remaining relatively stable since 2012, mean benefits dropped sharply by $17 in November 2013. It is the impact of this $17 decrease in SNAP benefits that this paper seeks to estimate.

2.3 Eligibility

There are two ways for a household to become eligible for SNAP. The first way is if all members of the household receive benefits through either the Supplemental Security Income[12] program, the Temporary Assistance for Needy Families program, or a county general assistance program. The second way is if household income and assets are below certain thresholds. Income and assets are measured the month prior to applying for benefits and are re-assessed at periodic intervals. In addition, there are minimum work requirements (20 hours per week) for non-disabled adults between 18 and 50 years old without children. SNAP benefits may only be received by adults who do not meet this work requirement for three months out of the previous three years. Beneficiaries can often substitute work training or volunteering for the work requirement.

In addition to changing the maximum benefit levels, the ARRA allowed states to waive this work requirement from April 2009 through September 2010. Nord and Prell (2011, page 13) argue that this eligibility part of the ARRA had a relatively minor effect on participation in SNAP because it impacted only a small fraction of potential recipients. Further, many states already had been granted state-wide or partial waivers based on economic conditions prior to the ARRA. When the ARRA waivers expired at the end of September 2010, most states still remained eligible to waive the work

[12] An exception is that in California, Supplemental Security Income payments have included an additional cash amount for food stamp benefits since 1974. Therefore, individuals in California who receive Supplemental Security Income cannot also receive SNAP benefits separately.

requirement based on these economic criteria, although even some waiver-eligible states have since re-instated the work requirement.

Enforcing the work requirement has two effects on SNAP benefit amounts. First, households who are unable to meet the requirement receive no benefits after three months. Second, households who are induced to work or work more receive lower benefits, because benefits amounts are phased out with income (as shown in Figure 1). However, the combined value of SNAP benefits and (now positive) earned income would likely increase.

As of 2014, California and Georgia still have state-wide waivers. Ohio has re-instated the work requirements in most counties, including those that make up the Columbus metro area where the stores in my sample are located. The earliest beneficiaries in Ohio could lose benefits because of the work requirement was January 2014.

2.4 Work disincentive effects

SNAP distorts labor supply by reducing the financial gains to entering the labor force and by increasing households' marginal tax rates by 24 percentage points over and above the payroll tax and personal income tax rates, resulting in very high rates for households whose income places them in the phase out range of other transfer programs and tax credits. Figure 3 illustrates how the personal income tax system interacts with the SNAP phase out rate for households consisting of one adult and either zero, one, two, or three children in 2014. See Appendix A for further discussion. SNAP also reduces labor supply through an income effect. Hoynes and Schanzenbach (2012) find evidence that SNAP does indeed reduce labor supply.[13]

While providing SNAP benefits to households that have suffered temporary or permanent income losses is potentially very valuable, the calculations described above show that beyond the direct costs of the program, SNAP also has efficiency costs due to the ways that it distorts labor supply. These distortionary effects of the program provide a

[13] The reduction to labor supply defined more broadly could be even greater (Feldstein 1999).

backdrop to results presented in the rest of the paper.[14]

3 Empirical strategy

As shown in Figure 2, the average monthly SNAP benefit amount fell by \$17 when the ARRA benefit levels expired in November 2013. In California, Georgia, and Ohio, the decrease was higher at \$20 per household. How did this decrease in benefits affect household spending? The main challenge in answering this question is separating the effect of the SNAP policies from all the other confounding factors that also could have affected household spending.

To address this identification problem, I use a difference in differences research design that compares changes in sales at stores with many customers whose income fell when the ARRA expired with sales at stores where very few customers were affected. Letting stores be indexed by $k = 1, \ldots, K$, I define the treatment at store k as the pre-period fraction of households shopping at store k who paid for at least one purchase using SNAP during a given month. This approach will recover the effect of the expiration of the ARRA benefit increases on SNAP households if household expenditures at stores with high and low SNAP shares would have changed by the same amount if ARRA did not expire, which is the parallel trends between treated and control units assumption, but here, I use a continuous treatment variable.

In particular, let $SNAP_{it}$ be an indicator variable for whether household i used SNAP to pay for at least one purchase during month t and let $\overline{SNAP}_k$ be the average of $SNAP_{it}$ across households who shopped at store k from January 2012 to April 2013. Conceptually, my estimates are based on equations of the form:

$$\overline{y}_{kt} = \alpha + \beta\overline{SNAP}_k + \delta post_t + \gamma\overline{SNAP}_k \times post_t + \overline{u}_{kt} \tag{1}$$

where $\overline{y}_{kt}$ is expenditure per household (or another outcome) at store k during month t,

[14] A program designed more like the EITC would lessen the distortion to labor force participation, but would not provide as much support to those with the least amount of resources. Saez (2002) formalizes the tradeoffs involved and Brewer, Saez, and Shephard (2010) discuss these results and apply them to the tax and transfer system in the United Kingdom.

$\overline{SNAP}_k$ is the SNAP intensity measure defined above, and $post_t$ is an indicator variable for whether the month is November 2013 or later.[15] Specifying this estimating equation as linear in $\overline{SNAP}_k$ is motivated by the non-parametric household-level regression that uses y_{itk} and $SNAP_{it}$ defined at the individual-level in place of $\overline{y}_{kt}$ and $\overline{SNAP}_k$ defined at the store-level.

The coefficient of interest is γ on the interaction term, which can be directly interpreted as measuring the effect of the benefit cuts on SNAP households' expenditures. To build intuition for Equation (1), note that a store with $\overline{SNAP}_k = 0$ would have no SNAP customers while a store with $\overline{SNAP}_k = 1$ would have all SNAP customers. The coefficient β in Equation (1) captures the impact of this one unit change on average household spending before November 2013. The coefficient γ measures the degree to which the effect of this one unit change differed for all the months after November 2013 compared with the earlier months.

Grocery expenditures per household are highly seasonal, with large increases during November and December. If this seasonal trend differs for stores with many SNAP customers and stores with fewer SNAP customers, then estimates based on Equation (1) will be biased. Therefore, I replace the dependent variable with the 12-month difference in spending per household at store k as a store-specific way of seasonally adjusting the series. Defining this variable as $\Delta\overline{y}_{kt}$, my preferred estimates are based on the following difference in difference in differences (triple difference) specification:

$$\Delta\overline{y}_{kt} = \alpha + \beta\overline{SNAP}_k + \delta post_t + \gamma\overline{SNAP}_k \times post_t + f_k(t) + \psi X_{kt} + \overline{u}_{kt} \qquad (2)$$

where the first three independent variables are defined as in Equation (1), $f_k(t)$ is a

[15] An alternative estimating equation would group the data into average expenditures for SNAP and non-SNAP households separately at each store, using $2 \times K \times T$ observations, where T is the number of months, to estimate a regression of the following form:

$$\overline{y}_{gkt} = \alpha + \beta SNAP_{gk} + \delta post_t + \gamma SNAP_{gk} \times post_t + \overline{u}_{gkt}$$

where g denotes group (i.e., SNAP or non-SNAP) and $SNAP_{gk}$ is a binary group indicator variable. Although the data are broken down into sales to SNAP and non-SNAP households, the groups are defined at the monthly level so that the composition of each group is changing over time. It would be useful to estimate this alternative estimating equation using data where the groups are defined instead using a stable, pre-treatment definition.

linear time trend interacted with store fixed effects, and X_{kt} is a vector of controls that vary by specification, including indicator variables for each store or region, interaction terms between region and $\overline{SNAP}_k$, and interactions between region and $post_t$ or between region and month fixed effects. The coefficient of interest is again the coefficient γ on the interaction term. I cluster standard errors at the store-level to allow for serial correlation in 12-month differences across months at a particular store. I weight observations by the number of households shopping at store k, averaged over the two months that are differenced.[16]

As a robustness check, I also use a less parametric form of Equation (2) where I include indicators for each month (instead of $post_t$) and the interaction of these month indicators with the $\overline{SNAP}_k$ treatment variable. To formally test whether the change in household spending is equal across regions, I also run specifications that include triple interaction terms of region, $post_t$, and $\overline{SNAP}_k$.

Note that in Equations (1) and (2), I define $\overline{SNAP}_k$ as measured during a base-period rather than concurrently. I follow this approach because the concurrent fraction of households who use SNAP to pay may not be exogenous. In all the regressions presented below, I define the main treatment variable using data ending six months before November 2013.

4 Data and Summary Statistics

4.1 Data

The panel data consist of daily sales at 431 grocery stores from January 1, 2012 to April 30, 2014. The grocery stores are located in Los Angeles, CA, Atlanta, GA, and Columbus, OH. In each market, the retail banner was chosen on the basis of having significant market share. I collapse the data at the month-store level. I restrict the

[16] Solon, Haider, and Wooldridge (2013) show that if there is within-group correlation in the error structure, weighting may make my estimates less precise than if I used ordinary least squares. I find slightly larger point estimates from unweighted regressions, but with larger standard errors. The difference is driven entirely by the presence of several smaller stores in Los Angeles. Unweighted and weighted results are virtually identical for Atlanta and Columbus.

sample to stores with observations in both January 2012 and April 2014, leaving 395 stores in my main analysis sample. On a pure number of establishments basis, the stores make up 8% to 17% of the total number of supermarkets in each area as reported in the U.S. Census Bureau's 2012 County Business Patterns data.

Household loyalty card identifiers and method of payment are used to measure household spending and establish SNAP participation. Each month, the data include the purchases of over half a million households enrolled in SNAP and millions of non-participating households. A household i is defined as a SNAP participating household in month t if it used SNAP benefits to pay for more than half of at least one purchase during month t. Sales for each store are tabulated separately for SNAP and non-SNAP households. The sales data are sales among households that have a loyalty card. Sales to households without loyalty cards are excluded.

Households transition in and out of SNAP as their income and family circumstances change (and enter and exit the sample depending on where they shop). Households may also transition out of SNAP because of the requirement that they pay for half of at least one purchase using SNAP tender in order to be counted as a SNAP household in these data. Therefore, it is useful to have a count of the number of unique households who ever used SNAP tender to pay for more than half of one purchase across the entire sample period. These counts are reported in rows 11 and 12 of Panel A in Table 1. There are 2.5 million unique households that ever used SNAP to pay for more than half of at least one purchase during the entire 26 month sample period. In the last 12 months in the data, there were 1.5 million such households. The corresponding counts for non-SNAP households are 14 million and 9.9 million, respectively. Therefore, households ever using SNAP make up 18% and 15% of all households in the sample across these two different time periods, respectively.

To assess the representativeness of the sample, Figure 4 plots the number of SNAP households nationally (left axis) and the number of SNAP household-store observations in my sample (right axis) over time. The two series track each other quite closely, first increasing from the beginning of 2012 to the middle of 2013, then declining sharply starting in the Fall of 2013 through 2014. This recent decline is notable because it reverses the trend of increasing SNAP rolls that had been on-going since the early 2000s (Wilde 2013, Ganong and Liebman 2013).

4.2 Summary statistics

Table 1 presents summary statistics for the households (panel A) and stores (panel B) in my sample. Average household expenditure, visits to the store, and units purchased are almost twice as large among SNAP households as for non-SNAP households. While the difference in my sample is larger, Hastings and Washington (2010) also find a similar pattern at three high poverty Nevada stores. They attribute this difference to larger household sizes, more food consumed at home, and fewer stores visited per month by welfare recipients.

Average spending by SNAP households in my sample at $161 accounts for 80% of monthly grocery store expenditures by low income households reported in Damon, King, and Leibtag (2013).[17] Estimates of total expenditures per month across all types of stores range from $269 for low income households (Damon, King, and Leibtag 2013) to $323.30 for food consumed at home by SNAP eligible households (Hoynes, McGranahan, Schanzenbach 2014).[18] Therefore, mean expenditures per store for SNAP households in my sample accounts for roughly 50% to 60% of monthly expenditure on food consumed at home by low income households.

Rows 4-9 in Table 1 disaggregate spending by store department. The largest department is the grocery department, which includes food such as cereal, snacks, dairy, frozen foods, and drinks as well as some non-food items such as pet food, cleaning products, and toilet paper. The meat department includes meat and fish. The deli and bakery department includes products such as deli meats and cheeses and baked goods.

[17] Damon, King, and Leibtag (2013) report 7 day average expenditure in 2003 at grocery stores in column 3 of Table 3, which I convert to monthly expenditures in inflation adjusted 2013 dollars.

[18] All types of stores refers to grocery stores, convenience stores, drug stores, and super-centers/warehouse club stores in Damon, King, and Leibtag (2013). I convert the 7 day average expenditure reported by those authors in column 1 of Table 2 to monthly expenditures measured in 2013 dollars.

The drug and general merchandise department includes automotive products, cosmetics, health and beauty care, housewares, toys, and candy. The other departments are natural foods and produce. The allocation of expenditures across store departments is nearly identical across household type.

It is sometimes helpful to focus on food spending for comparability with previous studies. To do so, I exclude sales within the drug and general merchandise department from total spending, even though non-food items are also included in some of the other categories. Using this working definition, total expenditures on food by SNAP households are roughly in line with what one would expect from food spending reported in Hastings and Washington (2010, table 1), but are quite a bit lower for non-SNAP households.

Panel B presents summary statistics for the stores in the sample by region. More than half the stores are located in Los Angeles, 32% are in Atlanta, and 15% are in Columbus. About 10% of the households who shop at these stores each month are SNAP households. However, there is substantial variation in the fraction of SNAP households across stores. The stores in Atlanta and Columbus are slightly larger and have higher SNAP shares than the stores in Los Angeles.

Figure 5 shows the distribution of $\overline{SNAP}_k$ calculated over the period January 2012 to April 2013. The range is 3% to about 40%, with most of the mass below 15%. My research design relies upon this variation to identify the impact of the expiration of the ARRA policies.

5 Results

In section 5.1, I first discuss my main estimates of the effect of the 2013 SNAP benefit cuts on household expenditures. In section 5.2, I use my point estimates to calculate estimates of the MPC, the incidence of SNAP benefits on grocery retailers, and the aggregate impact of the November 2013 SNAP benefit cuts. Section 5.3 presents supporting evidence. Finally, in section 5.4, I present estimates separately by region and show that the treatment effect was larger in Atlanta than in Los Angeles or Columbus. I discuss possible interpretations.

5.1 Effect of ARRA expiration on expenditures

The main results from estimating Equation (2) are shown in Table 2 and Figure 6. The dependent variable is the twelve month change in expenditures per household at each store. The results in Table 2 show that the point estimates are robust across specifications.

The model in column 1 of Table 2 is a version of Equation (2) that includes interaction terms between region and the post November 2013 indicator and between region and the SNAP share variable. This model therefore is flexible in that it does not restrict time trends to be the same in each region and allows the fraction of SNAP households to have different mean impacts in each region. Columns 2, 3, 4, and 5 add store fixed effects (and therefore drop variables included in column 1 that are constants for each store). Columns 1 through 4 are estimated over the twelve month period from May 2013 to April 2014.

The point estimate in Column 1 is that SNAP household monthly spending declined by \$5.92 in the months after the SNAP benefit cuts. Column 2 shows that adding store fixed effects only decreases the point estimate by \$0.01. Adding a linear time trend interacted with the store indicator variables in Column 3 increases the coefficient to \$6.30, while adding month fixed effects interacted with the region indicators in Column 4 increases the point estimate slightly to \$5.96. Column 5 restricts the regression in Column 2 to the two months before and two months after the benefit cuts (September through December). This column addresses the issue of the work requirements being reinstated in Ohio, which only resulted in beneficiaries losing eligibility as early as January 2014.[19] The point estimate is only slightly larger at \$6.14. Coefficients in all five of these columns are statistically significantly different than zero at the 1% level.

[19] This column also excludes the period after which extended unemployment insurance benefits expired, which happened in January 2014.

Column 6 of Table 2 presents a more non-parametric version of Equation (2) that includes separate indicator variables for each month and their interactions with $\overline{SNAP}_k$. The excluded month is May so the coefficients on the other indicator variables measure changes relative to May. The coefficients on the interaction terms with the month indicators for November through April are all negative and larger in magnitude than those for the six months before. The one exception is the coefficient on the interaction term with the June indicator variable, which is negative and large, but still smaller than most of the post November 2013 indicators.

Figure 6 plots the coefficients for July 2013 through March 2014. To scale the y-axis, I add back mean SNAP household expenditures from Table 1 to each coefficient. The series is stable for the four months preceding the benefit cut, drops in November 2013, and remains lower, suggesting that the timing of the decline in spending is consistent with being caused by the expiration of the ARRA and permanently lower SNAP benefit levels.

Table 3 explores this decrease in spending in more detail. Each column estimates the same specification as in Column 2 of Table 2 but changes the dependent variable to be the 12-month change in spending per household on items within each store department. These estimates can be expressed as a fraction of mean SNAP household spending in each department from Table 1 or as a fraction of the estimated drop in total store spending. Both are shown in the last two rows of the table. The estimates by store department show that about 3/4 of the decline was to spending on grocery items and meat. 16% was from spending on non-food general merchandise and over the counter drugs. One concern that is often voiced is that lower SNAP benefits may adversely impact consumption of healthy foods such as fresh fruit and vegetables, but both ways of expressing the point estimate indicate that spending on produce was not greatly affected by the November 2013 cuts.

5.2 Policy calculations

To put these estimates into context, it is helpful to scale the estimated change in household expenditure by the decrease in SNAP benefits. Scaling the estimates in this way produces an estimate of the marginal propensity to consume out of food stamps, where consumption refers to consumption of items purchased at the grocery store. I also inflate the \$5.91 point estimate by a factor of 5/4 to reflect that households shop at multiple stores.[20]

Between October and November 2013, average benefits decreased by \$20 per household in California, Georgia, and Ohio, implying a marginal propensity to consume out of SNAP benefits of 0.37 with a 95% confidence interval of [0.206, 0.532]. The literature usually focuses on food spending. Excluding over the counter drugs and general merchandise from the change in expenditures yields an estimate of the marginal propensity to consume food out of SNAP benefits of 0.30. The 95% confidence interval is [0.154, 0.456], which is 80% to half as wide as the confidence intervals reported in Hoynes and Schanzenbach (2009, table 6).

Under some stylized assumptions, the above calculations lead to an estimate of the incidence of the November 2013 benefit cuts (and of a marginal dollar of SNAP benefits more generally) on grocery retailers. The five year average cost of goods sold (excluding depreciation and amortization) for five of the largest publicly traded retailers in the U.S. grocery retailing industry was 75% of revenue. I assume that the marginal cost of these foregone sales is equal to this average COGS/revenue ratio. This implies that if each \$1 in SNAP cuts led to a \$0.37 decline in sales, $\$0.37 \times (1 - 0.75) = \$0.09$ would have been before tax profits. At a marginal corporate tax rate of 35%, after tax profits would have been about 65% of this, or \$0.06. These calculations imply that just 6% of the economic incidence of a marginal dollar of SNAP benefits accrues to grocery retailers. The other 94% accrues to other agents in the economy.

One can also use these estimates to calculate the aggregate effect of the November

[20] I inflate by 5/4 because mean expenditure in my sample is equal to 80% of total grocery store expenditures (Damon, King, and Leibtag 2013).

2013 SNAP benefit cuts on industry-wide grocery store spending. My estimates imply that total annual grocery store revenue will decline by $5.91 $\times$ 5/4 $\times$ 23 million households $\times$ 12 months = $2.039 billion. To put this number in perspective, the U.S. grocery retailing industry is a $600 billion a year market (Mintel 2012), so the November 2013 cuts caused a 0.3% reduction in aggregate revenue for this industry as a whole, with a range of 0.19% to 0.49% using the lower and upper endpoints of the 0.95 confidence interval for the point estimate. Using the same COGS/revenue ratio of 0.75 as before, this implies a decrease in profits of $510 million industry wide.

5.3 Method of payment and shopping frequency

This section presents two sets of supporting evidence.

Method of payment. The estimates of the marginal propensity to consume out of food stamps deserve some further comment. If a household lost $20 in SNAP benefits, then a MPC of 0.37 implies that it would reallocate resources in order to offset $12.70 of those lost benefits. One possibility would be to use cash to pay for products purchased at the grocery store. In this way, a piece of supporting evidence would be an increase in grocery store spending by SNAP households using methods of payment other than with their SNAP EBT card in the months after SNAP benefits were cut.

While I do not observe spending by SNAP households by method of payment directly, I am able to construct a measure as follows. For each store, I observe two sets of totals of expenditures by SNAP household. The first is SNAP household expenditures when more than half of the purchase was paid for with SNAP tender. The second are all other purchases by these households where this was not the case. I define the cash spending by SNAP households as this second measure plus the part of the first measure that was in the drug and general merchandise category, most of which by rule cannot be paid for with SNAP benefits.[21]

To test the prediction that SNAP households increased cash spending when their

[21] Note that the drug and general merchandise department includes candy, which can be paid for with SNAP tender. But most products in this department cannot be paid for with SNAP tender (e.g., automotive products, cosmetics, health and beauty care, housewares, and toys).

SNAP benefits declined, Table 4 presents estimates from equations of the following form:

$$\Delta y_{kt} = \alpha + \delta post_t + \psi X_{kt} + u_{kt} \tag{3}$$

where $post_t$ is an indicator variable for whether the month is November 2013 or later, X_{kt} is a vector of controls, and the dependent variable is cash expenditures by SNAP households either in dollars (columns 1 through 3) or as a percentage of total expenditures (columns 4 through 5). I take twelve month differences to address seasonality. The coefficient δ simply measures whether my measure of cash spending was higher in months following November 2013. There is no natural control group here since only SNAP households can pay with SNAP benefits.

The results in Table 4 suggest that SNAP households did increase their spending using other methods of payment when SNAP benefits were reduced in November 2013. In columns 1-2 and columns 4-5, the coefficients on the post-November 2013 indicator are all positive, with and without store fixed effects. Less parametric versions of Equation (3) that include indicator variables for each month are presented in Columns 3 and 6. The coefficients are negative and small before November, but turn positive and larger afterwards. Therefore, to the degree that I can measure it, SNAP households did increase their spending using cash to partially offset their lower SNAP benefits. These estimates support the interpretation of the main set of results.

Shopping frequency. Table 5 presents estimates of the impact of the reduced benefits on shopping frequency. I view this set of results as a placebo test, because the relatively small change in benefits should not have a large impact on visits to the store. However, I could possibly find large (positive or negative) effects on shopping frequency if the estimator is biased, which would indicate that my estimates for spending are also biased. Reassuringly, this is not what I find.

The dependent variable in Table 5 is the twelve month change in number of visits to the store per household. Columns 1 and 2 are estimated over the twelve month period from May 2013 to April 2014 and Columns 3 and 4 are restricted to the four month period from September 2013 to December 2013. The point estimates in all columns are negative, but very small. The key conclusion from these results, and those above, is that any remaining sources of bias would have to be caused by something occurring contemporaneously with the November 2013 benefit cuts, but not something that would cause households to change their shopping frequency.

5.4 Effect of ARRA expiration on expenditures by region

Table 6 presents estimates by region. Columns 1 and 2 are versions of Equation (2) that are fully interacted with the region indicator variables. Column 2 includes store fixed effects. The rest of the columns show results from models that are estimated separately for each of the three regions. The point estimate for Atlanta is about \$9.00, while the point estimates are smaller and imprecisely estimated in Los Angeles at \$2.97 and in Columbus at \$2.34. In columns 1 and 2, coefficients on the triple interaction terms correspond exactly to the difference in these treatment effects across regions. An F-test on these triple interaction terms indicates that the difference in treatment effects across regions is only marginally statistically significant, with a p-value of 4.4% in Column 1 and 5.6% when adding the store fixed effects in Column 2.

One explanation for these differences across regions is statistical. The cross-store estimator in Equation (2) is particularly well suited for estimating the treatment effect in Atlanta, and has less power in Los Angeles and Columbus. To see why, note that the standard deviation of $\overline{SNAP}_k$ in Panel B of Table 1 is larger in Atlanta than in Los Angeles. The standard deviation is greatest in Columbus, but the sample size in Atlanta is twice as large. Because the precision of this estimator is increasing with more variation in $\overline{SNAP}_k$ and with the number of stores in the sample, other research designs may be better suited for estimating the treatment effect in Los Angeles and Columbus.

More interesting but speculative explanations have to do with differences across regions. Panel C of Table 1 presents descriptive statistics for the United States and each of the three regions. Atlanta differs from Los Angeles and Columbus along many dimensions, including demographics and cost of living. One could test which factor is most strongly associated with larger observed effects using more detailed information on the locations of the stores within each region or potentially using household level data. In the conclusion, I discuss the importance of extending the results in this direction.

Perhaps the most salient difference across regions in Panel C is that the share of the population receiving SNAP had been much higher in Atlanta and was dropping precipitously at the end of 2013 and beginning of 2014. Between October 2013 and November 2013, the unemployment rate declined in Atlanta by 9% while the number of households receiving SNAP fell by 5%. In Los Angeles and Columbus, both figures were essentially stable. Including the zero SNAP benefits received by these 20,000 households in Atlanta would imply that benefits per household declined by $30.42 between October and November, but similar calculations imply benefits only fell by around $22 to $23 in Columbus and Los Angeles. In this way, one potential explanation for the larger observed effects in Atlanta is that the treatment was larger in Atlanta. However, it is not clear that these changes in participation in Atlanta are what is driving the larger estimated decreases in household expenditures, especially if these households were no longer eligible to receive SNAP benefits because their household income increased, as is suggested by the improved labor market conditions and the absence of changes to eligibility criteria across those months. On the other hand, if food consumed at home is complementary with leisure, while food consumed away from home is complementary with work (e.g., Aguiar and Hurst 2005), then shifting from SNAP rolls to employment could be an explanation for the large observed decreases in spending in the Atlanta sample.

Another possibility is that the decline in participation is due to several recent administrative issues in the processing of SNAP cases in Georgia. For example, in November some households were not notified or received delayed notifications that they were required to submit documents to recertify their benefits.[22] However, households who were affected were allowed extra time (until November 25) to submit the documents and receive full November SNAP benefits. Further, participation continued to decline in

[22] These issues have been reported on by the Georgia media. An example is the article "Many see delays in benefit renewals from DFACS" published on Nov 18, 2013 by Alyssa Hyman/WTOC-TV.

December, which is inconsistent with the decline in participation in November being entirely a temporary result of the delayed notifications. Finally, the coefficient on the November 2013 interaction term in Column 8 of Table 5 is of a similar size as the coefficient on the December 2013 interaction term, which is inconsistent with the treatment effect in November being caused by any temporary lapses in benefits.

6 The 2014 Farm Bill

In this section, I discuss the 2014 Farm Bill and show how one can use my estimates to project what its effect will be on household spending. In the months before and after the ARRA benefit increases expired, Congress debated further cuts to the program. The 2014 Agricultural Act that was passed and became law in February 2014 included some, but not all, of these proposed cuts. A major component of the law involved rules for SNAP beneficiaries who also receive Low-Income Home Energy Assistance Program (LIHEAP) payments. In January 2014, the CBO estimated this part of the law would reduce SNAP costs by \$3.73 billion between 2014 and 2018. Other parts of the law affected small subgroups such as lottery winners and convicted felons, which are not likely to have large aggregate impacts.

Recall the formula from section 2.2 that determines SNAP benefit amounts:

$$B(N,Z,Y,D) = \begin{cases} B_0(N) - 0.3(Y + 0.8Z - D) & \text{if } 0.8Z + Y > D \\ B_0(N) & \text{otherwise} \end{cases}$$

where $\$B_0(N)$ is the maximum that a household of size N can receive, $\$Z$ is earned income, $\$Y$ is unearned income, and $\$D$ are deductions. The 2014 Farm Bill reduced SNAP benefits by changing the rules for calculating the deductions that SNAP households can take, but only for a subset of SNAP households who also receive payments from their state's LIHEAP. I describe these changes in the following paragraph.

As a general rule, SNAP households whose shelter related costs are greater than half of income less deductions are allowed to take an additional deduction called the Excess Shelter Expense Deduction.[23] If a household has enough other income, a higher

[23] The amount that can be deducted is equal the amount that a household's shelter related costs exceed

value for this deduction increases the household's monthly SNAP benefits. Prior to the 2014 law, SNAP beneficiaries who received any support from LIHEAP could use a flat amount (a standard utility allowance) for their utility costs, rather than their actual utility costs, in the computation of their total shelter costs. There were 15 states, which are listed in Table 7, that awarded very low LIHEAP payments (e.g., \$1 per year in Massachusetts and \$0.10 per year in California) in order to increase their residents' SNAP benefit amounts by making them eligible for the Excess Shelter Expense Deduction (Aussenberg and Perl 2013). The 2014 law set a minimum LIHEAP payment of \$20 per year in order for households to be eligible to use the flat utility amount in this calculation.

The CBO estimated in September 2013 that creating a \$20 minimum LIHEAP payment for using the standard utility allowance would reduce 850,000 SNAP households' benefits by \$90 a month on average each year (CBO 2013). The estimates in this paper imply that this decline in benefits would result in a $\$90 \times 0.3 = \$27$ per household decrease in monthly spending on food and a $\$90 \times 0.37 = \$33.30$ per household decrease in monthly total store spending. These calculations imply annual aggregate reductions of \$230 million in spending on food and \$283 million in total grocery store spending. These numbers represent just a 0.05% reduction total industry revenue.

However, as shown in Column 2 of Table 7, all but four of the potentially affected states have since implemented policies to prevent SNAP beneficiaries from being impacted. Columns 3-5 of Table 7 present the number of households affected and dollar amounts from press releases for each of these states. Assuming no state response, the implied decreases in food and total store spending are \$644 million per year and \$780 million per year, respectively. The same estimates are \$214 million and \$260 million per year once I restrict the estimates to the four states that have not change their policies in response to the 2014 Farm Bill. These numbers are 1/3 of what they would have

half of its income less deductions (i.e., its total shelter related costs minus $0.5 \times \{Y + 0.8Z - D\}$), up to a maximum of \$478 in 2014. This deduction could therefore increase monthly SNAP benefits by up to $0.3 \times \$478 = \$143.40$. There is no maximum for elderly and disabled households (Farson Gray and Eslami 2014).

been if no state changed its LIHEAP payments.

The numbers from these press releases likely over estimate the scope of the bill. It is clear then that the 2014 Farm Bill is not likely to have a large impact on aggregate household food expenditure or retail sales once these state policy responses and modest consumer behavioral responses are taken into account. The reason that these aggregate impacts are so much smaller than the impact of the November 2013 benefit cuts calculated in section 5.2 is because the number of people affected by the 2014 Farm Bill is much smaller. Indeed, both the press releases and the CBO forecasts are in agreement that the households who will be affected by the 2014 Farm Bill stand to lose significantly more SNAP benefits than they did in November 2013.

7 Conclusion

I estimate that the November 2013 SNAP benefit cuts resulted in a $5.91 decline in monthly SNAP household spending, implying that each $1 of cuts led to $0.37 in less grocery store spending. The aggregate impact is estimated to be 0.3% of total industry revenue. In contrast, the aggregate impact of the SNAP benefit cuts associated with the 2014 Farm Bill is projected to be an order of magnitude lower.

My results imply that the marginal propensity to consume food out of food stamps at 0.3 is about half to 1/3 the size of the largest estimates from the cross-sectional empirical literature from the 1970s and 1980s. In contrast, my estimates are consistent with but more precise than those of Hoynes and Schanzenbach (2009, table 6) based on the initial roll out of the food stamp program in the 1960s and 1970s. The methodological contribution of this paper is to show how scanner data and partnering with industry can facilitate the timely evaluation of policy, while at the same time can provide sample sizes and allow for research designs that generate enough power to identify the impact of even relatively small treatments. Indeed, it is questionable whether a $5.91 treatment effect would be detectable in data that have a significantly higher degree of measurement error than those used here.

The finding that households increased their spending using non-SNAP dollars while cutting back on both food and non-food items is consistent with standard economic theory. The textbook analysis of SNAP benefits implies that (inframarginal) households should treat a \$1 decrease in SNAP benefits in the same way that they would treat losing \$1 of cash income. My point estimates support this prediction. For example, my estimate of the MPC out of food stamps is entirely consistent with estimates of the MPC out of (cash) unemployment insurance benefits (e.g., 0.21 to 0.27 on page 25 of Gruber 1996). This observation suggests that including both unemployment insurance benefit extensions and SNAP benefit increases as part of future fiscal stimulus packages may be a good strategy in order to increase domestic spending since each dollar of support from both programs lead to similar changes in expenditure.[24] Note though that since my estimates are limited to grocery store spending, SNAP benefits may actually be more effective than unemployment insurance benefits in stimulating total spending.

There are three promising directions for future research. First, it would be valuable to compare the estimates in this paper with those using survey data and to estimate the impact of the SNAP cuts on non-grocery store spending. Second, I have not considered the welfare implications of these findings. Third, it would be valuable to extend the analysis to study treatment effect heterogeneity and to identify to which households it is most critical to provide SNAP benefits. Evidence from Denmark and recent work on the effects of the 2001 and 2008 stimulus payments show that there are significant differences across households in the degree to which household consumption responds to transitory income (e.g., Bruich 2014, Kaplan and Violante 2014, Parker 2014). My results for each of the three regions in section 5.4 suggest that there is likely also heterogeneity across households in consumption responses to changes in SNAP benefit levels. A key distinction with the evidence from the stimulus payments is that benefit levels were set lower permanently and that all SNAP households have very low income and little liquid wealth, suggesting that the factors that determine consumption

[24] However, any definitive statement would additionally require a comparison of the efficiency costs of the two programs during recessions.

responses by SNAP households could be very different than those identified previously. With additional changes to SNAP very much on the table in Washington, such insights would provide very important guidance to policymakers as they debate the future of this program.

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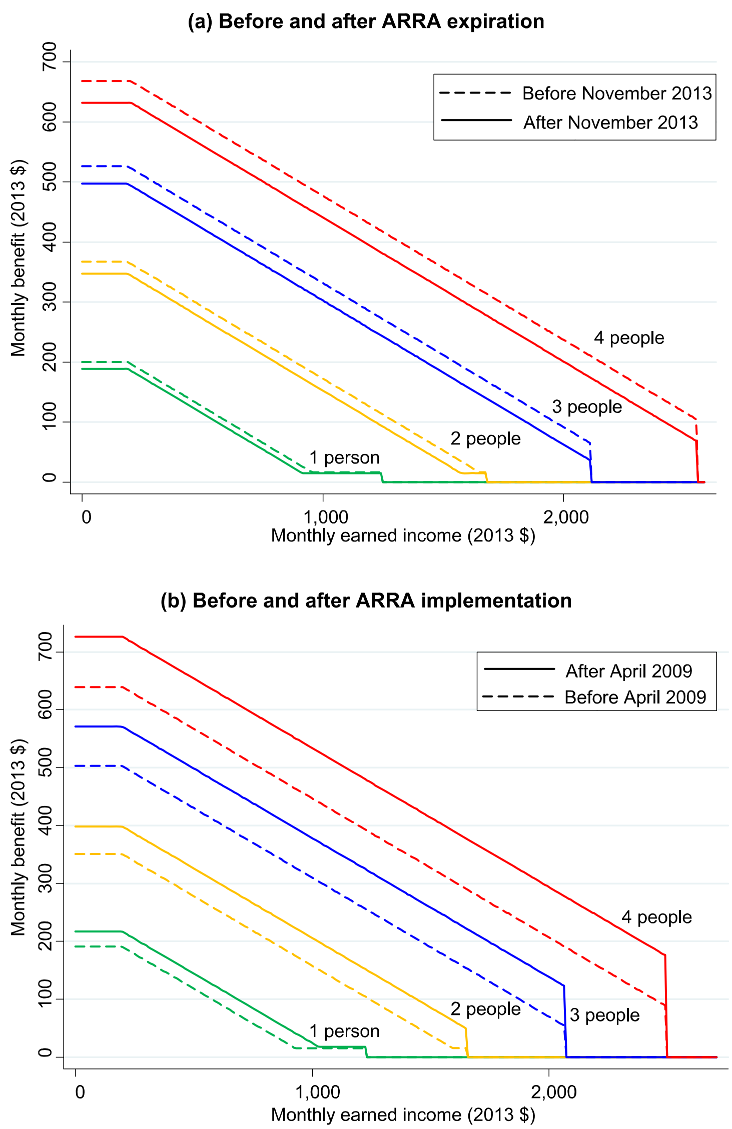
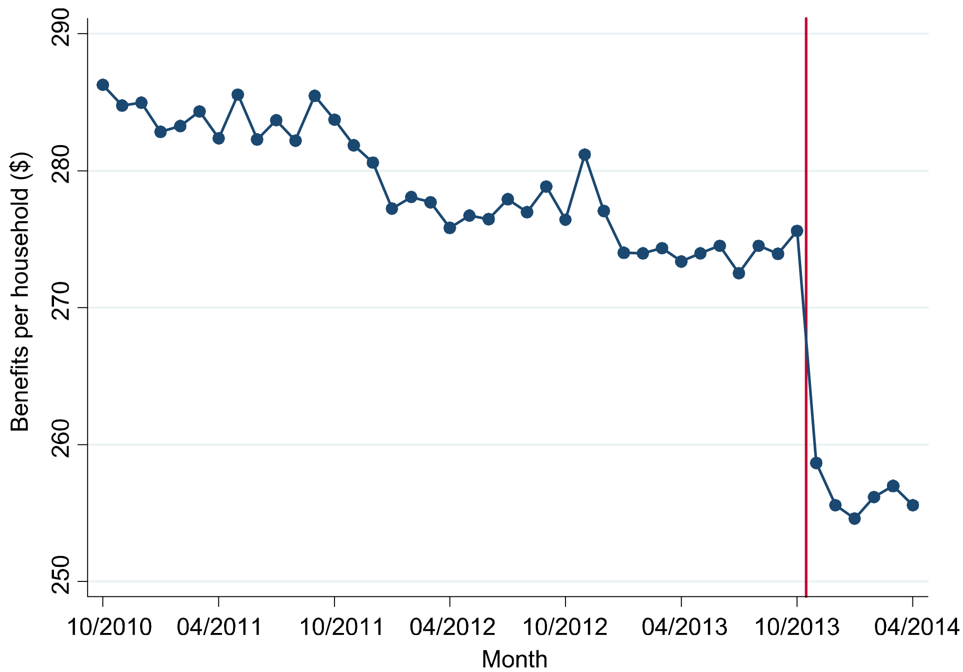
FIGURE 1

SNAP benefits before and after the ARRA by household size and earnings



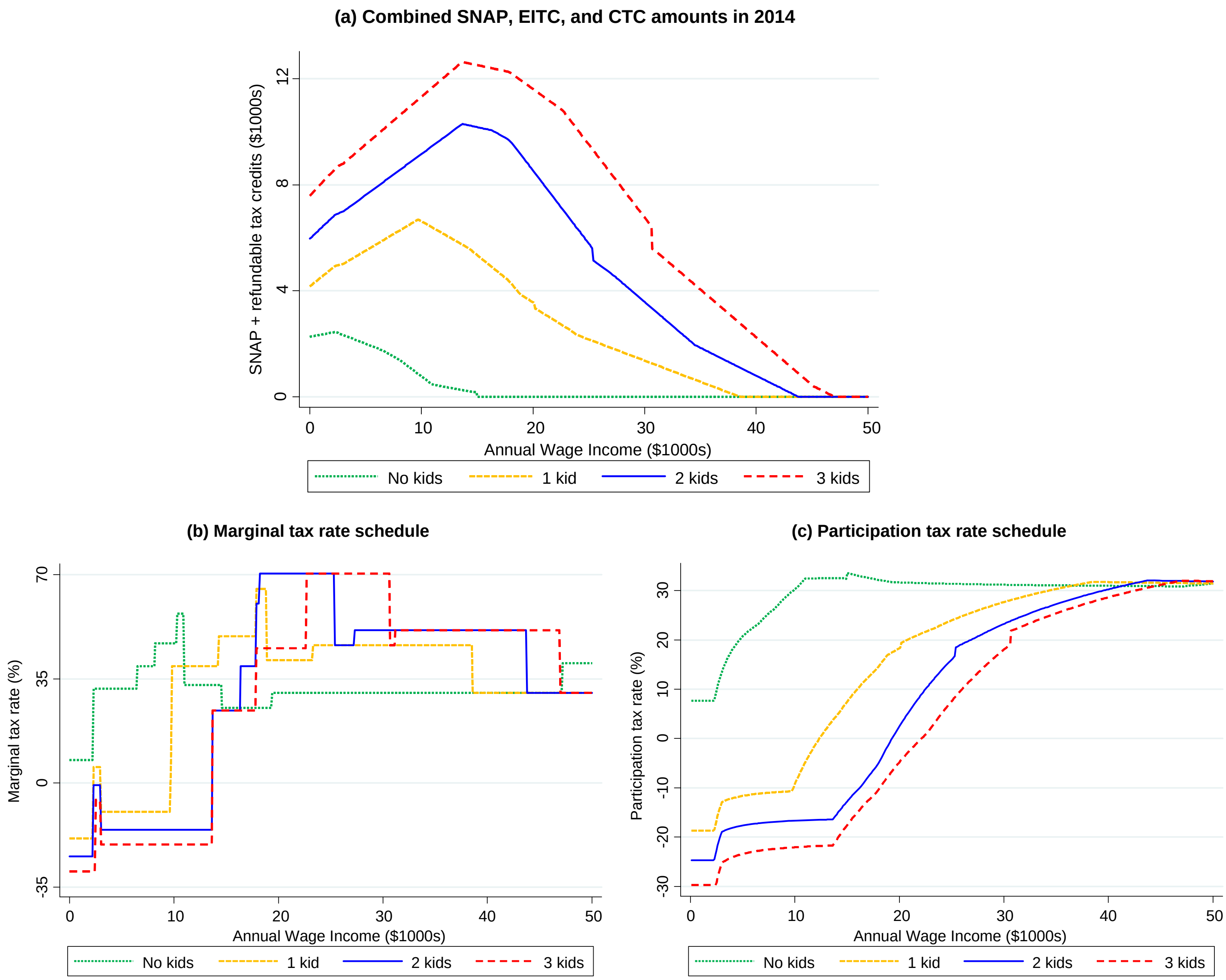
NOTE–This figure plots the SNAP benefit amount as a function of earnings before and after the ARRA expired (panel A) and before and after it was implemented (panel B). Each panel plots the monthly benefit amount along the y-axis with earned income along the x-axis, for one (green), two (yellow), three (blue), and four (red) person households. Panel A shows the decrease in benefits when the ARRA expired in November 2013; the dotted line plots benefit amounts in October 2013 and the solid line shows the benefit amount in November 2013. Panel B shows the increase in benefits when ARRA was implemented in April 2009; the dotted line plots benefit amounts in place in October 2008 to March 2009 and the solid line plots benefit amounts after April 2009. To calculate the benefit amount, I assume that the household has no income other than that shown along the x-axis and that the only deductions taken are the standard deduction and the 20 percent earned income deduction. Benefit amounts and earnings are adjusted for inflation using the CPI-U.

FIGURE 2
Average Monthly SNAP Benefits per Household, 2010–2014



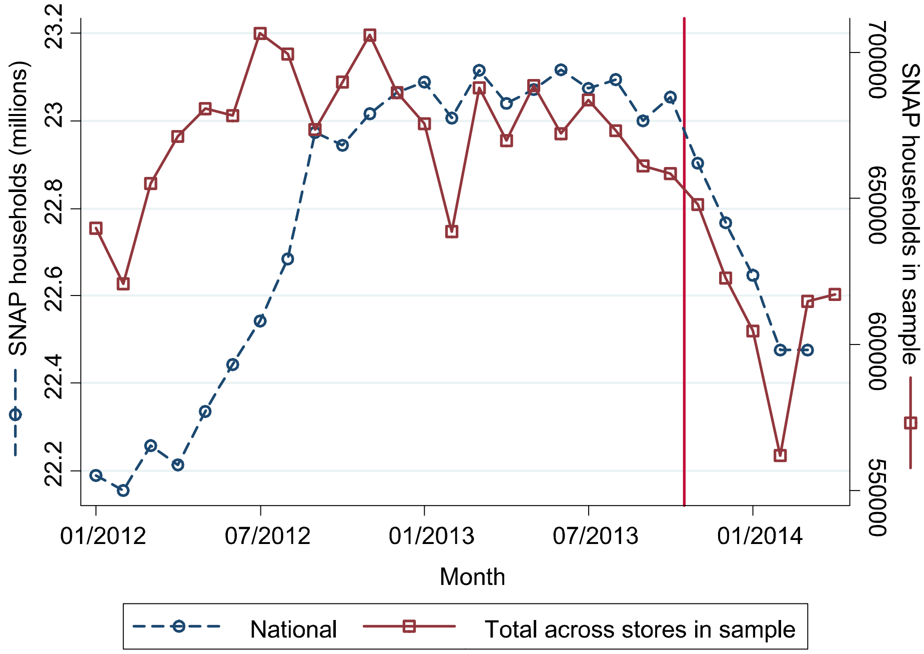
NOTE–This figure plots the average monthly SNAP benefit amount per household from October 2010 to April 2014. The red line at November 2013 is when the ARRA benefit increases expired. The change in average benefits from October 2013 to November 2013 is $17. Benefit amounts are nominal (not inflation adjusted). The series plotted is from the United States Department of Agriculture Food and Nutrition Service (2014), Supplemental Nutrition Assistance Program (SNAP) Monthly Data, National level, available at <http://www.fns.usda.gov/sites/default/files/pd/34SNAPmonthly.pdf>.

FIGURE 3
Combined SNAP, income tax, and payroll tax schedules in 2014



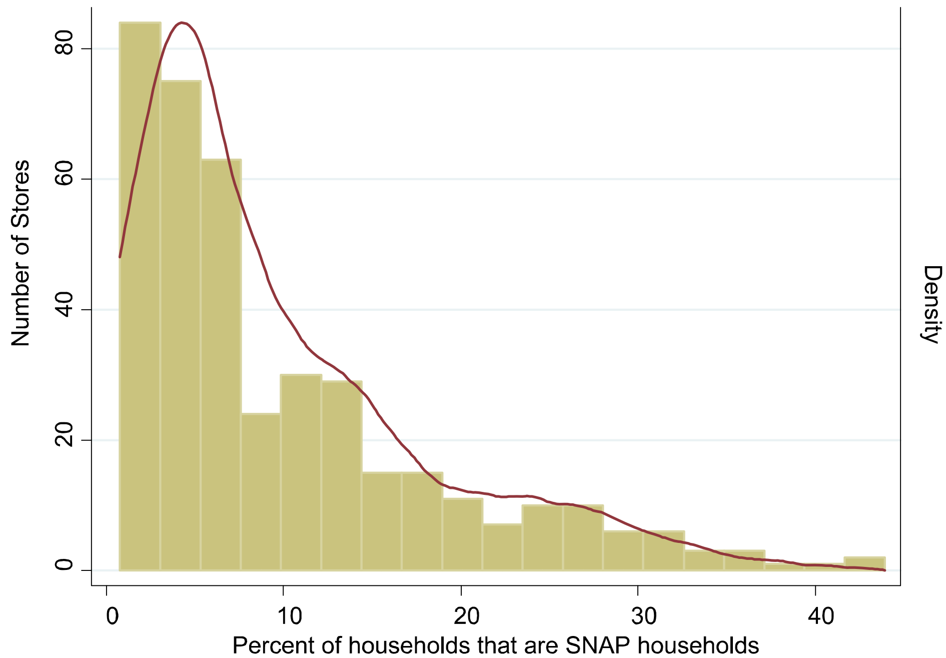
NOTE–This figure plots the combined SNAP, income tax, and payroll tax schedules in 2014 for a one person household (green dotted line) and households consisting of one adult and one child (yellow dotted line), one adult and two children (blue solid line), and one adult and three children (red dotted line). Panel A plots the combined value of the SNAP benefits, earned income tax credits (EITC), and refundable child tax credits (CTC) for which each household would be eligible. Panel B plots the marginal tax rates faced by each household, including the SNAP benefit reductions, payroll taxes (both employee and employer portions), and federal personal income taxes. Panel C plots the participation tax rate for each of these households. The participation tax rate is calculated as: 1 – (after tax income + SNAP benefits at this income – SNAP benefits at zero income)/pre-tax income. In all three panels, I calculate SNAP benefits assuming that the household has no income other than that shown along the x-axis and that the only SNAP deductions taken are the standard deduction and the 20 percent earned income deduction. I use the NBER TAXSIM calculator to compute taxes owed and tax credit amounts for these households, assuming that they have no other exemptions or deductions.

FIGURE 4
Number of SNAP Households Nationally and in Sample, 2012–2014



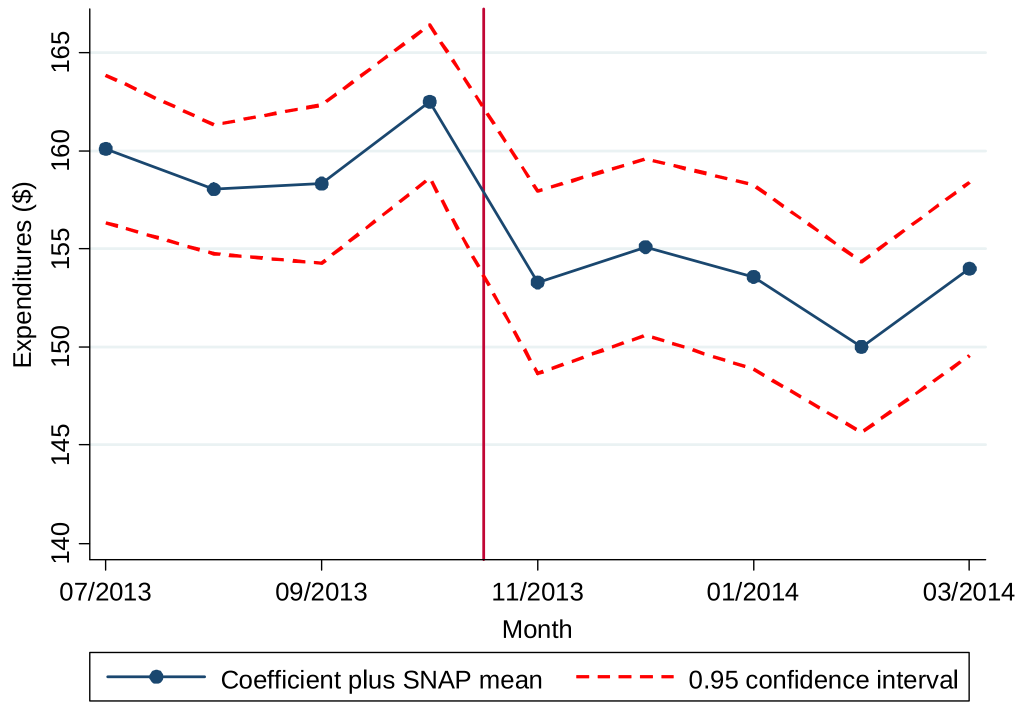
NOTE–This figure plots the total number of people receiving SNAP from 2012 to 2014 nationally (dotted line, left axis) and the number of SNAP households in my sample (solid line, right axis). A household shopping at multiple stores is counted more than once. The national series is from the United States Department of Agriculture Food and Nutrition Service (2014), Supplemental Nutrition Assistance Program (SNAP) Monthly Data, National level, available at <http://www.fns.usda.gov/sites/default/files/pd/34SNAPmonthly.pdf>.

FIGURE 5
Distribution of SNAP share of households across stores in sample



NOTE–This figure shows the distribution of the fraction of households that use SNAP. The variable is constructed as follows. For each month, I compute the fraction of households shopping at each store that used SNAP to pay for more than half of at least one purchase using SNAP benefits. The variable is the average of these monthly observations from January 2012 to April 2013 for each store.

FIGURE 6
Estimated Effect of Expiration of ARRA on SNAP Household Expenditures



NOTE–This figure plots the coefficients and 95% confidence intervals on the interaction terms between the fraction SNAP and the July 2013 through March 2014 month indicators from column 4 of Table 2. I scale the y-axis by adding the mean SNAP household monthly expenditures from Table 1 to each coefficient. The red line signifies when the ARRA expired in November 2013.

TABLE 1
Summary Statistics

Panel A. Household characteristics

Household type:	All (1)	SNAP (2)	Non-SNAP (3)
1. Total expenditures per month per store	**$96.13**	**$160.71**	**$89.26**
	(25.79)	(40.79)	(27.18)
2. Number of visits to store per month per store	**3.42**	**6.73**	**3.12**
	(0.56)	(1.40)	(0.50)
3. Number of units purchased per month per store	**36.49**	**66.07**	**33.42**
	(8.97)	(14.89)	(9.13)
4. Expenditures in produce department	**$11.24**	**$15.70**	**$10.81**
	(3.32)	(4.19)	(3.56)
5. Expenditures in grocery department	**$52.27**	**$89.54**	**$48.24**
	(13.72)	(22.83)	(14.25)
6. Expenditures in meat department	**$11.59**	**$23.32**	**$10.18**
	(3.82)	(7.38)	(3.37)
7. Expenditures in drug and general merchandise dept.	**$11.01**	**$17.11**	**$10.41**
	(4.83)	(8.12)	(4.74)
8. Expenditures in deli/bakery department	**$6.32**	**$10.48**	**$5.97**
	(2.40)	(3.89)	(2.51)
9. Expenditures in natural foods department	**$3.39**	**$4.04**	**$3.36**
	(3.10)	(3.70)	(1.74)
10. Number of household x store observations per month	**7,075,351**	**633,310**	**6,442,042**
	(170,723)	(29,059)	(158,675)
11. Number of unique households in sample from January 2012 to April 2014	**14,011,395**	**2,501,204**	**11,510,191**
12. Number of unique households in sample from May 2013 to April 2014	**9,885,582**	**1,524,998**	**8,360,584**

Panel B. Store characteristics

Region:	All (1)	Los Angeles (2)	Atlanta (3)	Columbus (4)
1. Households shopping at store per month	**17,919**	**16,579**	**19,691**	**18,912**
	(8,359)	(10,458)	(4,461)	(4,706)
2. Fraction of households that are SNAP	**9.93%**	**8.46%**	**11.60%**	**11.59%**
	(8.60)	(7.89)	(8.75)	(9.88)
3. Number of stores in sample	**395**	**210**	**125**	**60**
4. Census Bureau count of supermarkets in each region in 2012	**3,899**	**2,598**	**950**	**351**
5. SNAP participating retailers in each region in 2014	**14,330**	**8,453**	**4,411**	**1,466**

NOTE -- Table reports means with standard deviations in parentheses. The sample is restricted to 395 stores with observations in both January 2012 and April 2014, except in rows 11 and 12 which use the full 431 store sample. Sample statistics in panel A rows 1-9 are estimated by weighting monthly store-level observations by the number of households shopping at each store each month. SNAP households are households that used SNAP to pay for more than half of at least one purchase that month. The total number of stores in each region is reported in the U.S. Census Bureau's County Business Patterns (CBP) data for 2012. Number of SNAP participating retailers is from the USDA. Columbus is Columbus, Ohio.

TABLE 1 (continued)
Summary Statistics

Panel C. Region characteristics

	National (1)	Los Angeles (2)	Atlanta (3)	Columbus (4)
I. Demographics				
1. Population in 2013	**316,128,839**	**13,131,431**	**5,522,942**	**1,967,066**
2. Percent white in 2010 Census	**72.4%**	**52.8%**	**55.4%**	**77.5%**
3. Percent black or African American in 2010 Census	**12.6%**	**7.1%**	**32.4%**	**14.9%**
4. Percent hispanic or latino (of any race) in 2010 Census	**16.3%**	**44.4%**	**10.4%**	**3.6%**
5. Percent urban in 2010 Census	**80.7%**	**99.5%**	**89.1%**	**85.6%**
II. Labor and housing markets				
6. Median household income (2012 $)	**$53,046**	**$60,583**	**$57,470**	**$54,628**
7. Median home price in 2013	**$197.4K**	**$405.6K**	**$139.5K**	**$142.8K**
8. Percent with income below poverty level	**14.88%**	**15.84%**	**14.49%**	**14.88%**
9. Unemployment rate in October 2013	**7.00%**	**8.50%**	**7.70%**	**6.10%**
10. Unemployment rate in November 2013	**6.60%**	**8.40%**	**7.00%**	**6.10%**
11. ∆ Unemployment (Nov. '12 to Nov. '13)	**-0.80%**	**-0.80%**	**-1.10%**	**+0.8%**
III. SNAP enrollment and benefits				
12. Number of SNAP households in 2013, per month on average	**23,027,261**	**658,419**	**444,748**	**131,628**
13. Number of people in 2013, per month on average	**47,486,717**	**1,365,475**	**951,420**	**286,339**
14. Percent of population in 2013	**15.02%**	**10.40%**	**17.23%**	**14.56%**
15. Mean monthly SNAP benefit per household in October 2013	**$276.41**	**$328.44**	**$300.28**	**$295.43**
IV. Changes from October 2013 to November 2013				
16. ∆ Mean SNAP benefit per household	**-$16.97**	**-$22.17**	**-$16.76**	**-$20.23**
17. ∆ Total benefits/number of HHs in Oct.	**-$18.66**	**-$22.72**	**-$30.42**	**-$21.82**
18. ∆ Unemployment rate (% of Oct. rate)	**-5.71%**	**-1.18%**	**-9.09%**	**0.00%**
19. ∆ SNAP Households (% of total in Oct.)	**-0.65%**	**-0.18%**	**-4.82%**	**-0.58%**
20. ∆ SNAP Households (number)	**-150,851**	**-1,230**	**-20,449**	**-758**

NOTE -- Population estimates are from the Census Bureau. The unemployment rates are unadjusted estimates from the Bureau of Labor Statistics. Median home price is the median sales price for existing single family homes from the National Association of Realtors. Income and poverty are from the 2008-2012 American Community Survey 5-Year Estimates. National SNAP enrollment is from the SNAP Research and Analysis Division of the USDA. Regional SNAP enrollment is from monthly county totals provided by the California Department of Social Services, Georgia Division of Family and Children Services, and the Ohio Department of Job and Family Services. SNAP enrollment is for the 2013 calendar year, except for Atlanta, where enrollment is during the 2013 fiscal year which runs from July 1, 2012 to June 30, 2013. Columbus is Columbus, Ohio.

TABLE 2

Effect of ARRA Expiration on SNAP Household Expenditures

Dependent variable:	12 month change in sales per HH, All regions					
	($)	($)	($)	($)	($)	($)
	(1)	(2)	(3)	(4)	(5)	(6)
Fraction SNAP HHs	**-7.873*** **					
	(2.725)					
Post November 2013	**3.370*** **	**3.369*** **	**5.003*** **		**2.819*** **	
	(0.369)	(0.388)	(0.432)		(0.379)	
Fraction SNAP HHs x Post November '13	**-5.915*** **	**-5.905*** **	**-6.299*** **	**-5.960*** **	**-6.138*** **	
	(1.268)	(1.331)	(1.532)	(1.334)	(1.352)	
Fraction SNAP HHs x June '13						**-6.985*** **
						(2.144)
Fraction SNAP HHs x July '13						**-0.615**
						(1.924)
Fraction SNAP HHs x August '13						**-2.678**
						(1.685)
Fraction SNAP HHs x September '13						**-2.396**
						(2.066)
Fraction SNAP HHs x October '13						**1.807**
						(1.997)
Fraction SNAP HHs x November '13						**-7.403*** **
						(2.381)
Fraction SNAP HHs x December '13						**-5.612** **
						(2.302)
Fraction SNAP HHs x January '14						**-7.136*** **
						(2.408)
Fraction SNAP HHs x February '14						**-10.71*** **
						(2.232)
Fraction SNAP HHs x March '14						**-6.731*** **
						(2.265)
Fraction SNAP HHs x April '14						**-9.164*** **
						(2.335)
Store fixed effects		x	x	x	x	x
Month fixed effects				x		x
Controls for region	x	x	x	x	x	x
Linear time trend x store fixed effects			x			
Number of months	12	12	12	12	4	12
Number of stores	395	395	395	395	395	395
Store x month observations	4739	4739	4739	4739	1580	4739

NOTE -- Each column reports results from weighted least squares regressions where the dependent variable is the twelve month change in total monthly sales per household. Standard errors are clustered by store and are reported in parentheses below each coefficient estimate. May 2013 is the excluded month in column 4. Regressions are estimated over the twelve month period from May 2013 to April 2014, except in column 3 which restricts the sample to September 2013 through December 2013. The fraction SNAP is the average from January 2012 to April 2013 of the monthly fraction of all households shopping at each store that used SNAP to pay for more than half of at least one purchase that month. The regressions are weighted by the number of households shopping at each store each month (averaged across the two months that are differenced). Region controls in column 1 consist of indicator variables for region and interactions of region with the fraction SNAP and with the post November 2013 indicator. In other columns, region controls consist of the region indicator variables interacted with post or month indicator variables because these columns include store fixed effects. *** p<0.01, ** p<0.05, * p<0.1

TABLE 3

Effect of ARRA Expiration on SNAP Household Expenditures by Store Department

Dependent variable:	12 month change in sales per household, All regions					
Department:	Produce	Grocery	Meat	Drug/GM	Deli/Bakery	Natural Foods
	($)	($)	($)	($)	($)	($)
	(1)	(2)	(3)	(4)	(5)	(6)
Post November 2013	**0.0460**	**1.927*** **	**0.847*** **	**0.362*** **	**0.0623**	**0.169*** **
	(0.0727)	(0.186)	(0.0675)	(0.0840)	(0.0526)	(0.0543)
Fraction SNAP HHs x Post Nov. '13	**-0.0652**	**-3.138*** **	**-1.385*** **	**-1.022*** **	**-0.389** **	**-0.283* **
	(0.246)	(0.778)	(0.312)	(0.237)	(0.186)	(0.152)
Store fixed effects	x	x	x	x	x	x
Controls for region	x	x	x	x	x	x
Number of months	12	12	12	12	12	12
Number of stores	395	395	395	395	395	395
Store x month observations	4739	4739	4739	4738	4737	4687
Mean sales per month in department for SNAP households (Table 1)	**$15.70**	**$89.54**	**$23.32**	**$17.11**	**$10.48**	**$4.04**
Point estimate/SNAP mean (Table 1)	**-0.42%**	**-3.50%**	**-5.94%**	**-5.97%**	**-3.71%**	**-7.00%**
Point estimate/Sum of coefficients	**1.04%**	**49.95%**	**22.05%**	**16.27%**	**6.19%**	**4.50%**

NOTE -- Each column reports results from weighted least squares regressions where the dependent variable is the twelve month change in total monthly sales per household. Standard errors are clustered by store and are reported in parentheses below each coefficient estimate. Regressions are estimated over the twelve month period from May 2013 to April 2014. The fraction SNAP is the average from January 2012 to April 2013 of the monthly fraction of all households shopping at each store that used SNAP to pay for more than half of at least one purchase that month. The regressions are weighted by the number of households shopping at each store each month (averaged across the two months that are differenced). Region controls consist of indicator variables for region interacted with the post November 2013 indicator. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 4

SNAP Household Expenditures using Cash as Method of Payment

Dependent variable:	Δ spending w/ cash per SNAP HH			Δ cash share of SNAP HH spending		
	($)	($)	($)	(%)	(%)	(%)
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of cash spending:	*$74.38*			*47.38%*		
[Standard deviation]	*[25.36]*			*[7.54]*		
Post November 2013	**4.156*** **	**4.162*** **		**2.033*** **	**2.038*** **	
	(0.241)	(0.251)		(0.0915)	(0.0957)	
June 2013			**-1.090*** **			**-0.337*** **
			(0.338)			(0.122)
July 2013			**-2.921*** **			**-1.166*** **
			(0.339)			(0.115)
August 2013			**1.886*** **			**0.286*** **
			(0.312)			(0.106)
September 2013			**-0.549**			**-0.0745**
			(0.334)			(0.153)
October 2013			**-3.326*** **			**-1.344*** **
			(0.341)			(0.116)
November 2013			**2.891*** **			**1.729*** **
			(0.376)			(0.136)
December 2013			**0.844** **			**0.904*** **
			(0.389)			(0.142)
January 2014			**5.689*** **			**2.233*** **
			(0.483)			(0.160)
February 2014			**6.409*** **			**2.335*** **
			(0.475)			(0.157)
March 2014			**-0.634**			**0.195**
			(0.396)			(0.133)
April 2014			**4.206*** **			**2.309*** **
			(0.435)			(0.128)
Store fixed effects		x	x		x	x
Controls for region	x			x		
Number of months	12	12	12	12	12	12
Number of stores	395	395	395	395	395	395
Store x month observations	4739	4739	4739	4739	4739	4739

NOTE -- Cash refers to all methods of payment other than with SNAP benefits. Each column reports results from weighted least squares regressions where the dependent variable is the twelve month change in total monthly cash sales per SNAP household or the fraction of sales to SNAP households that are paid for with cash. See section 5.3 for details on construction of the dependent variables. Standard errors are clustered by store and are reported in parentheses below each coefficient estimate. May 2013 is the excluded month in column 3 and 6. Regressions are estimated over the twelve month period from May 2013 to April 2014. The regressions are weighted by the number of SNAP households shopping at each store each month (averaged across the two months that are differenced). Region controls consist of indicator variables for region. *** p<0.01, ** p<0.05, * p<0.1

TABLE 5

Effect of ARRA Expiration on SNAP Household Shopping Frequency

Dependent variable:	12 month change in visits per HH, All regions			
	(1)	(2)	(3)	(4)
Fraction SNAP HHs	**0.201*** **		**0.172** **	
	(0.0622)		(0.0747)	
Post November 2013	**-0.00578**	**-0.00583**	**0.00952**	**0.00888**
	(0.00905)	(0.00956)	(0.00724)	(0.00834)
Fraction SNAP HHs x Post November '13	**-0.173*** **	**-0.173*** **	**-0.0586* **	**-0.0578**
	(0.0458)	(0.0478)	(0.0317)	(0.0364)
Store fixed effects		x		x
Controls for region	x	x	x	x
Number of months	12	12	4	4
Number of stores	395	395	395	395
Store x month observations	4739	4739	1580	1580

NOTE -- Each column reports results from weighted least squares regressions where the dependent variable is the twelve month change in total visits to the store per household. Standard errors are clustered by store and are reported in parentheses below each coefficient estimate. Regressions in columns 1 and 2 are estimated over the twelve month period from May 2013 to April 2014. Columns 3 and 4 restrict the sample to September 2013 through December 2013. The fraction SNAP is the average from January 2012 to April 2013 of the monthly fraction of all households shopping at each store that used SNAP to pay for more than half of at least one purchase that month. The regressions are weighted by the number of households shopping at each store each month (averaged across the two months that are differenced). Region controls in columns 1 and 3 consist of indicator variables for region and interactions of region with the fraction SNAP and with the post November 2013 indicator. In other columns, region controls consist of the region indicator variables interacted with post indicator variable because these columns include store fixed effects. *** p<0.01, ** p<0.05, * p<0.1

TABLE 6

Effect of ARRA Expiration on SNAP Household Expenditures by Region

Dependent variable: 12 month change in sales per household											
Region:	All regions		Los Angeles, CA			Atlanta, GA			Columbus, OH		
	($)	($)	($)	($)	($)	($)	($)	($)	($)	($)	($)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Fraction SNAP HHs	**-9.672*** **		**7.906**			**-10.36*** **			**-9.672*** **		
	(3.231)		(6.188)			(1.778)			(3.257)		
Post November 2013	**2.934*** **	**2.943*** **	**-0.919*** **	**-0.939*** **		**2.037*** **	**2.032*** **		**2.934*** **	**2.943*** **	
	(0.515)	(0.545)	(0.199)	(0.210)		(0.289)	(0.299)		(0.519)	(0.549)	
Fraction SNAP HHs x Post Nov. '13	**-2.288**	**-2.362**	**-3.194**	**-2.970**		**-8.982*** **	**-9.013*** **		**-2.288**	**-2.362**	
	(2.578)	(2.719)	(2.516)	(2.667)		(1.745)	(1.826)		(2.598)	(2.739)	
Fraction SNAP HHs x Post Nov. '13 x Atlanta, GA	**-6.694** **	**-6.651** **									
	(3.110)	(3.273)									
Fraction SNAP HHs x Post Nov. '13 x Los Angeles, CA	**-0.906**	**-0.607**									
	(3.601)	(3.807)									
Fraction SNAP HHs x June '13					**11.78*** **			**-12.35*** **			**-10.93*** **
					(3.246)			(2.810)			(2.516)
Fraction SNAP HHs x July '13					**13.99*** **			**-4.100* **			**-4.826* **
					(3.866)			(2.357)			(2.576)
Fraction SNAP HHs x August '13					**6.489** **			**-6.569** **			**-2.173**
					(3.033)			(2.530)			(2.131)
Fraction SNAP HHs x September '13					**12.75*** **			**-7.933*** **			**-3.333**
					(3.214)			(2.482)			(3.748)
Fraction SNAP HHs x October '13					**12.19*** **			**-3.922* **			**4.785**
					(3.031)			(2.355)			(4.264)
Fraction SNAP HHs x November '13					**9.387** **			**-15.64*** **			**-4.568**
					(3.849)			(2.965)			(4.531)
Fraction SNAP HHs x December '13					**10.89** **			**-14.54*** **			**-1.294**
					(4.415)			(2.716)			(3.774)
Fraction SNAP HHs x January '14					**10.07** **			**-12.80*** **			**-9.342** **
					(4.987)			(3.216)			(3.584)
Fraction SNAP HHs x February '14					**4.885**			**-18.68*** **			**-7.436* **
					(4.862)			(2.675)			(3.976)
Fraction SNAP HHs x March '14					**2.960**			**-11.13*** **			**-5.711**
					(4.284)			(2.709)			(5.272)
Fraction SNAP HHs x April '14					**0.708**			**-16.38*** **			**-3.176**
					(4.172)			(3.070)			(5.142)
Controls for region	x	x									
Store fixed effects		x		x	x		x	x		x	x
Month fixed effects					x			x			x
Number of months	12	12	12	12	12	12	12	12	12	12	12
Number of stores	395	395	210	210	210	125	125	125	60	60	60
Store x month observations	4739	4739	2519	2519	2519	1500	1500	1500	720	720	720
p-value for test of joint significance of triple interaction terms	0.045	0.0557									

NOTE -- Each column reports results from weighted least squares regressions where the dependent variable is the twelve month change in total monthly sales per household. Standard errors are clustered by store and are reported in parentheses below each coefficient estimate. May 2013 is the excluded month in columns 5, 8, and 11. Regressions are estimated over the twelve month period from May 2013 to April 2014. The fraction SNAP is the average from January 2012 to April 2013 of the monthly fraction of all households shopping at each store that used SNAP to pay for more than half of at least one purchase that month. The regressions are weighted by the number of households shopping at each store each month (averaged across the two months that are differenced). *** p<0.01, ** p<0.05, * p<0.1

TABLE 7

Implied Effect of 2014 Agricultural Act on Household Expenditures

Panel A. By state (total and per household)

State	Decision to Increase LIHEAP in Response to 2014 Agricultural Act?	Total Annual SNAP cuts (millions)	Households affected	Changes per household per month: SNAP benefits	Changes per household per month: Food spending	Changes per household per month: Total store spending
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1. California	Yes.	$223	300,000	$62	$19	$23
2. Connecticut	Yes.	$66	50,000	$112	$34	$41
3. Maine		$7	5,500	$106	$32	$39
4. Massachusetts	Yes.	$142	163,000	$73	$22	$27
5. Michigan		$250	235,000	$88	$27	$32
6. Montana	Yes.	$2	2,000	$83	$25	$31
7. New Jersey		$172	157,000	$91	$28	$34
8. New York	Yes.	$457	300,000	$127	$39	$47
9. Oregon	Yes.	$56	78,000	$58	$18	$21
10. Pennsylvania	Yes.	$300	400,000	$65	$20	$24
11. Rhode Island	Yes.	$69	69,000	$83	$25	$31
12. Vermont	Yes.	$14	19,400	$60	$18	$22
13. Washington	Yes.	$70	200,000	$29	$9	$11
14. Washington, DC	Yes.					
15. Wisconsin		$276.20	255,000	$90	$27	$33

Panel B. Totals across states

	SNAP Cuts	Households affected	Δ Food Spending	Δ Store Spending
	(1)	(2)	(3)	(4)
1. Total with no state response (millions per year)	$2,104	2.234	$644	$780
2. Total for ME, MI, NJ, and WI (millions per year)	$705	0.653	$214	$260

NOTE -- States listed in column 1 of Panel A reported in a Congressional Research Services Report (Aussenberg and Perl 2013) as using "heat and eat" policies to increase SNAP benefits; Delaware is excluded because it no longer does this as of 2012. Information in column 2 is from the Food Research and Action Center and the National Conference of State Legislatures. Information in columns 3-5 are from press releases. Relevant numbers for Washington, DC have not been reported. Columns 6-7 use estimates from Section 5.2 to forecast changes in spending. Column 6 uses the MPC for food of 0.3 and Column 7 uses the MPC for total grocery store spending of 0.37.

Appendix A

This appendix describes the calculations in Figure 3. In order to be eligible for SNAP, households who also have earned income would typically be eligible to receive the earned income tax credit (EITC) and, if they have dependent children, the refundable Additional Child Tax Credit (CTC). Panel A of the figure plots the annual combined SNAP, EITC, and CTC payments, Panel B plots the combined marginal tax rate schedule, and Panel C plots the participation tax rate for each of these households. Single adults with children and non-disabled, non-elderly single adults without children accounted for 49% of SNAP households in 2012, so the schedules shown in the figure are the relevant ones for a large fraction of SNAP households. In 2012, only 33% of these households had earned income (Farson Gray and Eslami 2014, table 3.2). The Hicksian labor supply elasticity on the intensive margin is of a similar magnitude as on the extensive margin after accounting for optimization frictions (Chetty 2012), indicating that the (long run) effects of SNAP on labor supply through marginal tax rates and participation tax rates are of similar importance.

I use the 2014 SNAP benefit schedule to calculate SNAP benefits and the NBER TAXSIM calculator to calculate personal income tax rates and tax credit amounts. Previous studies have made similar calculations that additionally incorporate state taxes and transfer programs other than SNAP but do so for earlier years (e.g., Dickert, Houser, and Scholz 1995). My calculations assume that each household has no other sources of income other than that shown along the x-axis and that the only SNAP deductions taken are the standard SNAP deduction and the earned income deduction. The figures plot income up to $50,000, but households lose eligibility for SNAP at much lower levels. These annual limits are $14,940 for the household without children and $20,172, $25,392, and $30,624 for the households with one, two, and three children.[25,26]

Panel A shows the sum of the annual SNAP, EITC, and CTC amounts for these

[25] These limits on gross earned income are binding before the limits on income after deductions.

[26] As can be seen in Figure 1, there are notches in the household budget constraint at these incomes levels, similar to the Medicaid notch studied by Yelowitz (1995). The effect of these notches on marginal tax rates cannot be seen in Figure 3(b) because I plot income in $100 increments.

households. The combined value of these benefits increases until reaching about \$12,630 for the three child household at around \$13,700 in earned income. The annual value of these benefits is much more modest for the household without children, reaching a maximum of \$2,440 at earnings of \$2,300. All but \$496 of these benefit amounts come from SNAP for the childless household.

Panel B plots the marginal tax rates for each household, taking into account the SNAP benefit schedule, personal federal income schedule, and the payroll tax (both employer and employee portions).[27] Once earned income exceeds the sum of a household's SNAP deductions, the phase out of SNAP benefits adds 24 percentage points to the marginal tax rates that the household would have otherwise faced. Adding this additional 24 percentage points from SNAP to a household's marginal tax rate reduces its net–of–marginal tax rate by as much as 30% to 50%, depending on income levels and family composition. Chetty, Friedman, and Saez (2013) present strong evidence in the context of the EITC that the labor supply of low-income households with children can be quite responsive to changes to these marginal incentives to earn additional income. Figure 3(b) shows that for low incomes, households with children face negative marginal tax rates because of the subsidies provided by the EITC (34%, 40%, and 45% rates for one, two, and three children) and CTC (15% rate), which sum to more than the SNAP phase out rate. However, as incomes increase above \$15,000, marginal tax rates increase up to 70% as households enter the bottom personal income tax bracket, the EITC begins to be phased out, and the CTC amount reaches its maximum of \$1000 per child. Households without children also face high rates, but only up to 57% because the EITC amount is much smaller and is phased out at a lower rate for them. Overall, this figure shows that once household income exceeds \$10,000 to \$15,000, the returns to earning additional income are very low for SNAP households.

Panel C plots the participation tax rate, which is defined as one minus the financial gains to entering the labor force as a fraction of pre-tax income: $1-$(after tax income $+$ SNAP benefits at that income level $-$ SNAP benefits with zero income)/pre-tax income.

[27] If labor demand is perfectly elastic, then the full incidence of the payroll tax will fall on workers.

While the marginal tax rate is relevant for a household's decision to earn an extra dollar, the participation tax rate is the relevant measure for the decision of whether or not to enter the labor force at all. The figure shows that the participation tax rates for all four households are always less than 100%, so that despite the reduced SNAP benefits each household would still have higher net income by entering the labor force. However, households may lose other benefits such as Medicaid and housing vouchers that would increase the participation tax rates beyond those shown in the figure. Further, in addition to the disutility of working, there are fixed costs to entering the labor force (e.g., child care costs, haircuts) so that any reduction to the financial gains to working will lead some households to optimally choose not to work.

Panel C of the figure shows that these participation effects of SNAP are likely most severe for childless SNAP beneficiaries. The participation tax rates start at negative rates for low levels of earnings for the households with children because the EITC and CTC more than make up for the lower SNAP benefits and taxes that these households would owe. However, the rates are always positive for childless households, increasing from 7.65% to 33% when the household loses eligibility for SNAP at around $15,000, before leveling off at 30%. Therefore, a job paying $15,000 would only increase the net income of a SNAP beneficiary without children by $6,000 because of taxes and the lost SNAP benefits. The same job would increase the net income of the household with three children by $17,630, which is well over the $15,000 in pretax wages, because of the tax credits the household can receive.