Following the Money: The effects of SNAP Benefits Changes on the Consumption Habits of Snap Beneficiaries

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August 17, 2021
(Preliminary Version, Updated Version Coming Soon)

Abstract

This paper explores a proprietary point-of-sale dataset of encompassing the individual grocery spending habits of some 43 million Americans — including some 13 million Supplementary Nutritional Assistance Program (SNAP, formerly known as the Food Stamp Program) beneficiaries — during the period of of 2009 to 2014. We attempt to answer the following question: How do changes in SNAP benefits effect the consumption patterns of SNAP beneficiaries? Specifically, we focus on the consumption of sugar sweetened beverages but also consider a spectrum of food categories. In 2009 the American Recovery and Reinvestment Act increased the maximum level of SNAP benefits by 13.6%, set to expire in 2013. Using a differences-in-differences estimation, we find that the 2009 increase in benefits increased consumption of sugar sweetened beverages among SNAP beneficiaries by 5.4% above the baseline (.65% absolute). We also find that the subsequent expiration of SNAP benefits in 2013 saw a respective decrease of -1.6% below the baseline (.18% absolute). Ours is one the first papers to ever to use point-of-sale grocery scanner data to examine spending habits among impoverished Americans and our sample size is an order of magnitude larger than any other paper to date.

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Introduction

The Supplementary Nutritional Assistance Program (SNAP), formerly known as the Food Stamp Program (FSP), is the largest food assistance program in the United States. About 46.5 million Americans received SNAP benefits in 2014, which incurred a total budgetary cost of 74.1 billion dollars (USDA). Though much research has been done studying the effects of SNAP on food insecurity and on the total amount of money spent on food by the poor, little research has been done looking at how, and on what, this money is actually spent. It is fairly well established that giving people more food assistance raises the amount of their budget they spend on food more than rational economic theory would predict. But does increasing SNAP benefits actually increase the nutritional value of their total food portfolio? As policymakers often have to consider raising or lowering such benefits, the answer to this question could also inform debate and policy decisions. As a very recent front page headline from the *New York Times*, *"In the Shopping Cart of a Food Stamp Household: Lots of Soda"* shows, there is ample public interest in what private citizens do with their partially subsidized food budgets.

Using a novel proprietary dataset encompassing the individual spending habits of some 43 million Americans — including some 13 million SNAP beneficiaries during the period of of 2009 to 2014 — we attempt to answer these questions. We analyze the spending habits of individual SNAP beneficiaries after the increase of SNAP benefits in 2009 and their subsequent expiration in 2013. Specifically, we look at their consumption of sugar sweetened beverages (in addition to other types of purchases other types of purchases) and find that the 2009 increase in benefits induced a 5.6% increase over the baseline level (.62% absolute, baseline 10.9%) in the consumption of sugar sweetened beverages. On the other hand, the 2013 expiration of said benefits induced a -1.6% decrease below the baseline (-.18% absolute, baseline 11.2%).

The fact that our dataset covers the entire time range of the great recession (2007 to 2014) gives us a very clean natural experiment that we can use to test the effects of changing levels of SNAP benefits on the consumption patterns of SNAP beneficiaries. Starting in April 2009 and set to expire in November 2013, the US Congress appropriated an additional 46.2 billion dollars to increase SNAP benefits across the board (USDA). This translated into an 13.6% increase in 2009 of average benefits for SNAP recipients. The subsequent expiration of these benefits in November 2013 brought about a 5% decrease in average benefits (Beatty and Tuttle, 2012).[1]

This data is extraordinary because we can directly measure the impact (in food purchases at least) of giving someone a large amount of money and then, after a substantial period of time, taking it away. The levels involved are large enough to create wealth effects in the subjects studied. Since inciting wealth effects in people, especially negative ones, is a very controversial experimental design choice, this extremely detailed dataset provides us a prime quasi-experimental setting wherein to examine such effects. Thus the results of this paper could also speak more broadly to the general theory of consumer choice.

As a preview of the results, we use a basic differences in differences analysis to analyze the effect that the 2009 SNAP benefits increase had on the purchases of sugar sweetened beverages among SNAP recipients. After controlling for both seasonal and individual level fixed effects, the difference-in-difference coefficient on percent consumption of sugar-sweetened beverages for SNAP participants is .62% (0.0062, t-stat: 70.02) over a baseline consumption level of 10.9% (.109) for SNAP participants (see Table 3). This is a 5.6% increase over the baseline and can roughly be interpreted as

[1]The difference between these numbers can presumably be attributed to the increase in the total number of SNAP beneficiaries during this period as well as the total increase in the budget for SNAP during this time.

the effect that the extra ARRA benefits had on sugar-sweetened beverage consumption for the very poor. The subsequent expiration of SNAP benefits in 2013 saw a respective decrease of -.18% (-.0018, t-stat: -42.44), a -1.6% decrease over the baseline. The high t-statistics are a natural result of working with observations numbering in the dozens of millions but we believe these results are also very economically significant as well. We repeat this analysis for a selection of popular food groups.

The paper will proceed as follows: first we will discuss the background and previous literature associated with SNAP benefits, followed by data and methodology used, and finally we will present the results and general discussion.

Background and Previous Literature

During and just after the Great Recession of 2007-2008, federal assistance programs such as SNAP saw huge increases in enrollment and funding. From 2008 to 2011 the percentage of the US population on food stamps grew from 11% to 15% (USDA). The American Recovery and Reinvestment Act (ARRA) massively increased the funding of federal entitlement programs and increased the maximum benefit amount by 13.6% and in total, household benefit levels increased by an average of $80 a month for a family of four (Beatty and Tuttle, 2012). From Beatty and Tuttle, we also include the following graph of maximum benefits available to a family of 4 to illustrate the magnitude of this increase.

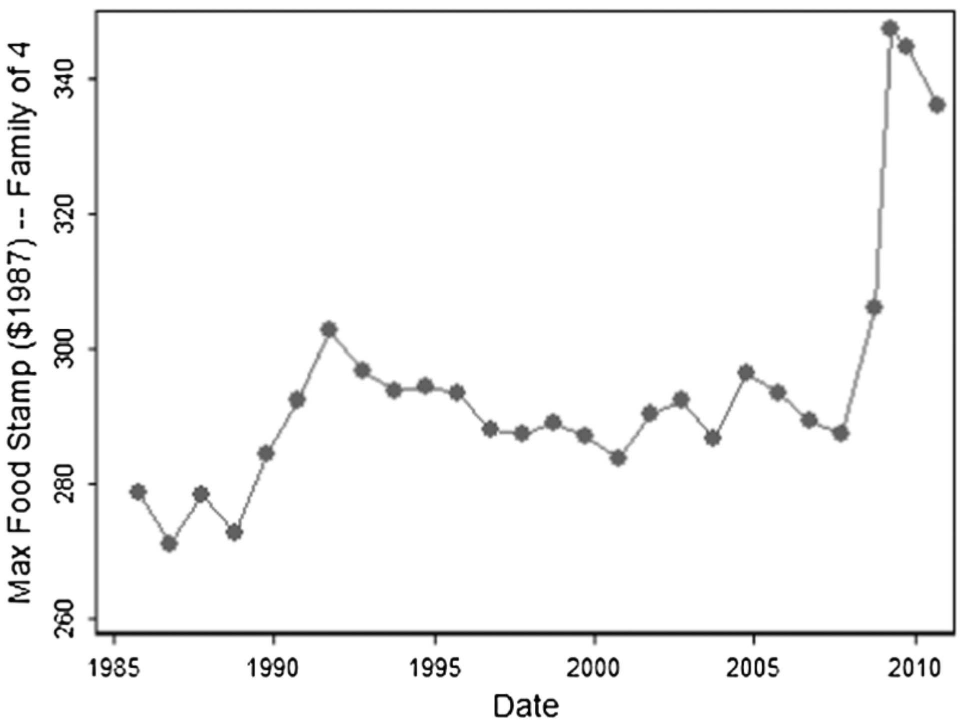

Figure 1: Maximum Amount of SNAP Benefits Available to a Family of 4 Over Time (Beatty and Tuttle, 2012)

In our paper we attempt to quantify the effect of the above-mentioned increase in benefits using a unique set of grocery store scanner-level data. To our knowledge, we are the only paper to attempt to quantify the effect of these changes on the distribution of food consumption and we are one of only two other papers (to our knowledge) to ever use this type of grocery store scanner-level data. The first is Bruich's (currently unpublished) 2014 paper, *"The effect of SNAP benefits on expenditures: New evidence from scanner data and the November 2013 benefit cuts"*. Since the data used in this paper is so similar to our own, we will take a brief detour to point out the major differences between our paper and theirs. The two papers differ in the observation level of data used, time period covered and questions answered, but the differences are nonetheless illustrative.

Bruich (2014) uses a smaller dataset, looking at a selection of grocery chains in 3 US cities (Los Angeles, Atlanta and Columbus, Ohio) whereas our paper is much more cross-sectional, covering stores in 38 of the 50 United States. Secondly, Bruich's base level of observation is month-store whereas our base level of observation is month-person. Thirdly, Bruich's time series only covers the 2013 expiration of the aforementioned benefits, whereas our time series covers both the 2009 appropriation and 2013 expiration of said benefits. This allows us to do a much more detailed analysis of the individual spending habits of consumers in response to both positive and negative shocks. Finally, Bruich's paper only looks at changes in total expenditure levels of Snap beneficiaries, while we are interested in the relative composition of their grocery baskets. One notable result Bruich finds in his paper is that, for each $1 in benefits cuts, grocery store spending was reduced by $0.37. He also estimates the implied marginal propensity to consume food out of food stamps as 0.3 (Bruich, 2014).

The second paper to use this type of grocery store scanner data is the extremely recent (as of the time of this writing) USDA report, *"Foods Typically Purchased by Supplemental Nutrition Assistance Program (SNAP) Households"* (Garasky, et al., November, 2016). In this report, subcontracted by Impaq International for the USDA, the authors examine in depth the consumption patterns of both SNAP and non-SNAP households. The paper uses one year of grocery scanner data from a major US retailer to do their analysis. The data used is most likely very similar to our own but on a much smaller time scale as they only examine the year 2011. In their sample they have 3.2 million unique SNAP households, while our own sample has about 13.6 million. In their paper they report the static distribution of consumption between categories with one of the main surprising findings being that the average SNAP household spends about 9.6% of their total food budget on sugar sweetened beverages. This is borne out as well in our own summary statistics. We find that (in our filtered, stabilized sample) the average SNAP household spent 10.9-11.2% of their total grocery budgets on sugar sweetened beverages. In general, this paper is an excellent source to reference for the static distribution of food consumption and the paper is mainly concerned with reporting means and top categories of consumption, with little to no econometrics. In our paper we are more interested in the time dynamics of the distribution of food consumption. Though we also report average consumption levels for a variety of categories, we are more interested in how these levels change over time, and in trying to establish a causal relationship for what drives this change.

Though many published papers look at the effects of food stamps in general (on consumption, food security, etc), intensive research into the individual effects of SNAP benefits on recipient behavior have typically been hampered by a lack of good data on the subject. To be able to directly observe the behavior of SNAP participants is a very recent development. Previous important research on this subject includes Hoynes and Schanzenbach's 2009 AER paper which exploits the staggered roll-out of the original Food Stamp Program to isolate levels of food stamp recipients and estimate the effect of food stamps on food consumption. They find that the Food Stamp Program (the precursor to SNAP) significantly increased food expenditures among the poor, even among those which according to theory should be inframarginal (indifferent between a cash transfer and the in-kind benefit). Nord and Prell (2011) and Beatty and Tuttle (2012) also examine the changes in SNAP household expenditures arising from the 2009 increase in benefits. Though in both studies the authors can only see if a person is eligible or not for food stamps (as opposed to actually observing their use or enrollment), they find results that are broadly consistent with Hoynes and Schanzenbach. They both find that the 2009 ARRA increase in benefits caused inframarginal households to spend more on food than rational economic theory would predict. Finally, a very complete discussion of the literature associated with food stamps can be found in Fraker (1990) or Bartlett and Burstein (2004).

Data

The data we use in this paper includes transaction-level grocery store data from about 43 million consumers in the United States. The data comes from a number of large grocery store chains in the United States. Importantly, we can track individual consumers through time via loyalty card numbers which were anonymized for privacy reasons. Though we can follow anonymized card numbers through time, we (appropriately) have no other information on who these individuals are apart from their purchases. We cannot see (for example) names, gender, phone number nor any other identifying information.

For a given loyalty card number, what we can see is the complete panel of every purchase they made, what they bought, how much they paid for it (even if they used coupons) and the method of payment. The method of payment is particularly important because it allows us to distinguish between regular consumers and consumers using SNAP benefits. One unit of observation in the unprocessed dataset is one item bought by a specific card number on a given time and date. One unprocessed observation includes: prices with and without taxes and coupons, a description of the item, the number of the item bought, a department and general category for the good (bakery, deli, dairy, etc.), a UPC number, a basket identifier (roughly identifying one shopping trip), a time and date stamp, a store identifier and method of payment (cash, card, EBT card, etc.). We also include a hand-coded dummy variable for all sugar sweetened and carbonated beverages.

We then pre-process this data and collapse it to the monthly level. This allows us to see, by month and in percentages, how much a given person spends on popular categories such as dairy, deli, general grocery, etc. There are 11 such categories in total: Bakery, Beer/Wine/Liquor, Dairy, Deli, Floral, Frozen, General Merchandise, Grocery (dry goods, soups, general staples, etc.), Hygienics/Bathroom/Cosmetics (HBC), Meat and Non-food Grocery. We can also see the percent of their budget spent on sugar sweetened and carbonated beverages. This brings the total of categories we examine to 13. While these 13 categories are not comprehensive they can give us a fairly accurate picture of how the general SNAP and non-SNAP consumer allocates their budget. We can also see, at the card-monthly level, the most frequently visited store, the total number of unique stores visited, the total number of visits in a month, the maximum visits in a day, the total amount of dollars spent in that month and the total amount of dollars spend in each of the above categories.

The rest of this section will be comprised of 5 subsections. The first two subsections discuss two unique features of this data, the size in general and the fact that we can see method of payment. Subsection 3 discusses the filtering we do on the data to ensure our sample is comprised of people who do a non-trivial portion of their purchases at stores in our sample and that our sample is robust to what we will call, "cashier cards". Subsection 4 discusses the sample stabilization we have do on our data to ensure that our dataset is suitable for a standard econometric difference in difference analysis. Finally, subsection 5 discusses the summary statistics of the data we use.

Size

The size of this data is unique in and of itself. It constitutes a truly unprecedented individual consumption panel of the US population. If we assume one person per loyalty card, this gets us that we can sample the spending habits of about 13.5% or about $1/7^{th}$ of the US population. There is a very non-trivial chance that the reader of this paper shows up in our sample somewhere. [2]

The total dataset is about 3.5 Terabytes on disk with total observations numbering in the multiple billions. A significant amount of preprocessing had to be done to get this data into a workable format. Total preprocessing time was about one week on a multi-core system. Preprocessing transformed our data from multiple billions of individual purchases to about 320 million individual-month level observations. Further restricting our sample to stores that were in our sample for the entire time period, brings us to about 190 million individual-month observations.

After preprocessing, we have about 43 million total unique card numbers in our dataset, of which 13 million are SNAP recipients at some point. Since 30% of SNAP participants are beneficiaries for less than 12 months and an additional 17% are beneficiaries for less than 3 years [3] there is significant attrition in the sample. Thus, the number of unique card numbers fall significantly after the sample stabilization, but always stays in the millions. After stabilization we are left with about 71 million individual-month observations. This dataset we split into two datasets (outlined below) of 43 million observations for the 2009-2011 period and 26 million observations for the 2012-2014 period. It should be noted that our results are very robust to these filterings and are actually much stronger (and always in the same direction) without them.

Payment Method

Another factor that makes this data fairly unique is that for each individual consumer we can see the method of payment. This allows us to tag consumers by SNAP

[2]The critical observer might point out the anecdotal observation that many consumers have multiple loyalty cards for their one person, but since many households also have just one loyalty card for their whole family, we feel that the numbers above about balance out on average.

[3]http://www.huffingtonpost.com/2015/05/29/public-benefits-safety-net_n_7470060.html

beneficiary or not. This allows us to see not only purchases made with SNAP but the purchases made with personal money. This gives us a unique view into the complete grocery spending habits of SNAP beneficiaries. Previous studies of SNAP beneficiaries had to employ fairly advanced econometrics to isolate the effects of SNAP participation and SNAP participants in general, whereas we can simply see if consumers made purchases with SNAP.

We can further tag SNAP households in two ways, if they used SNAP benefits in that specific month and if they have used SNAP benefits ever in our sample. This is important because SNAP benefits are not 'use-it-or-lose-it' but can be accrued up to 12 months or more in some states[4]. The second specification, while surely capturing some false positives (those who are no longer receiving food stamps) hopes to capture the effect from these 'savers'. For the purposes of this paper we only report the results from the first specification (individual-month observations that used SNAP benefits in a given month) but our results are robust to the second specification. The results for sugar sweetened beverages and carbonated beverages are in same direction, slightly less in magnitude, but still very statistically significant (unpublished here but available at request).

Filtering

After splitting up sample participants by payment method as described above, we filter our data on a number of criteria to ensure our sample is robust to both small volume visitors and what we denote "cashier cards". Small volume visitors are fairly easy to filter out as we simply drop observations who have less than $20 of purchases in a given month. The idea is that someone who is passing through the county and happens to drop in and buy something small, say a box of mints (even with an EBT

[4] http://www.foodstamps.org/blog/2013/01/30/what-happens-to-unused-benefits

card), is not doing the majority of their shopping at our stores and would have very biased purchases. "Cashier cards" refers to the anecdotally popular practice of cashiers keeping a dedicated loyalty card at their till for customers who do not have their own loyalty card. Since the purchases made on these cards would not represent an accurate individual-level observation, we take steps to drop them from our sample. To do this, we drop any card-month observation that has more than $2,000 in monthly purchases, more than 5 purchases in a day and more than 10 total purchases in a month. A recent USDA study looking at similar data (Garasky, et al., 2016) does many of the same types of filtering.

Sample Stabilization

Because our data covers both the 2009 increase and 2013 decrease of SNAP benefits, we split our data in two. To avoid any appearance of excessive data manipulation, we split our data exactly in half (yearly). The first half (which we will call Dataset 1) being the years 2009, 2010 and 2011, the second half (which we will call Dataset 2) being the years 2012, 2013 and 2014.

Within both Dataset 1 and Dataset 2, we tag the data as either pre-change or post-change. The ARRA benefit changes happened on April 2009 and November 2013 and we tag them thusly in each dataset. Unfortunately, due to the nature of our data, these changes are not in the middle of the Datasets 1 and 2. However, as the summary statistics show, our filtering and stabilization makes it so that in our final data the smaller period always includes at least 32% of the observations.

To address the above issue and stabilize the sample, we first make sure that we have the same set of stores all the way through our sample. Since a very large number of stores were added to our sample on January 1, 2009 we only use observations on or after this date. This is why we do not use the years 2007 and 2008 in the split above. We further take the complete intersection of the set of stores in each month from 2009 to 2014 to make sure that the set of stores in our sample is completely stable. Further stabilization is done to ensure that every card observation in each dataset is seen in both the pre-change and post-change period.

Summary Statistics

In Tables 1 and 2, we report the summary statistics for our two sample time periods. About 20% to 25% of our sample uses food stamps in any given month. In the national population at this point in time, about 45 million Americans received SNAP benefits, or about 15% of the population [5]. Thus our sample is roughly representative of the US population as a whole, at least inasmuch as their SNAP participation rates go.

In these summary statistics we can also see some of the secular trend away from consuming both carbonated and sugar sweetened beverages. Between our two samples, carbonated beverage consumption declined from 4.6% of total consumption to 4.5% of total consumption. Consumption of sugar sweetened beverages in our sample declined from 7.3% to 7.1%.

Other categories that saw significant changes were the beer/wine/liquor category and hygienics. Between our two samples, beer/wine/liquor consumption increased from 2.8% of total consumption to 4.1% of total consumption. The consumption of hygienics declined from 6.7% to 6.2% of total consumption.

[Insert Tables 1 and 2 here]

Tables 3 and 4 report the same summary statistics as above but further broken down by SNAP and non-SNAP participants. Our results are broadly consistent with

[5] https://www.theatlantic.com/national/archive/2011/07/chart-rise-food-stamps/352412/

the results reported by Garasky, et al., (2016) a recent USDA study looking at the spending habits of SNAP and non-SNAP households. For example, we find that the average SNAP household spent 10.9% of their budget in 2009-2011 and 11.2% of their budget in 2012-2014 on sugar sweetened beverages. This compares closely to the 9.8% number reported by Garasky, et al. (2016). We also find that the average non-SNAP household spent 6.3% of their budget in 2009-2011 and 5.7% of their budget in 2012-2014 on carbonated beverages, which is also consistent with Garasky, et al. (2016).

There exist large differences between SNAP and non-SNAP households for most general categories of consumption. The consumption of beer/wine/liquor, dairy, deli, general merchandise, grocery, hygienics, meat and non-food grocery all differ between SNAP and non-SNAP households by at least 1%. For the period of 2009 to 2011, consumption in a given category (as a percentage of total budget) for non-SNAP and SNAP households follows. Consumption of beer/wine/liquor was 1.4% for non-SNAP and 3.2% for SNAP. Consumption of dairy was 14.7% for non-SNAP households and 13.2% for SNAP households. Consumption of deli was 7.1% for non-SNAP households and 4.6% for SNAP households. Consumption of general merchandise was 3.6% for non-SNAP households and 1.9% for SNAP households. Consumption of grocery was 39.6% for non-SNAP households and 46.8% for SNAP households. Consumption of hygienics was 7% for non-SNAP households and 15.5% for SNAP households. Consumption of meat was 12% for non-SNAP households and 17% for SNAP households. Finally, consumption of non-food grocery was 3.3% for non-SNAP households and 2% for SNAP households. In general, these results are again broadly consistent with those found in Garasky, et al..

[Insert Tables 3 and 4 here]

Finally, SNAP households make more monthly visits on average, have a higher average maximum visits in a day and higher monthly net sales. While this last statistic might seem counterintuitive on the face of it, it could be easily explained by wealthier consumers diversifying their grocery shopping (especially to big box and subscription retailers), poorer people generally belonging to larger households which make larger purchases or a host of other reasons. It also makes sense that SNAP households would make more frequent visits as the poor typically tend to avoid making large scale purchases (Orhun and Palazzolo, 2016).

Results

The model we use for our results is a standard differences in differences model with high levels of fixed effects. Since we can nearly perfectly identify our treatment group, the econometrics of this model are relatively simple. The first difference is the time period before and after the change and the second difference is being in the treatment group or not. These are coded as binary variables. For the time variable, 0 is the before change period and 1 is the after change period. Similarly, 0 is untreated and 1 is treated. The difference-in-difference coefficient (did) is the interaction between these two binary variables.

Using the percent consumption of sugar sweetened beverages as our example independent variable, the two regression models we run (on two different data sets) are,

$$ssb_{it} = \beta_1' \cdot time_t^{\{1\}} + \beta_2' \cdot treat_i + \beta_3' \cdot did_{it} + card\_FE_i + store\_FE_i + month\_FE_t + \mu_{it} \quad (1)$$

and,

$$ssb_{it} = \beta_1' \cdot time_t^{\{2\}} + \beta_2' \cdot treat_i + \beta_3' \cdot did_{it} + card\_FE_i + store\_FE_i + month\_FE_t + \mu_{it} \quad (2)$$

where $time^{\{1\}}$ and $time^{\{2\}}$ are dummy variables indicating if the time period is before or after the 2009 or 2013 changes, respectively.

We do not include any other controls for two reasons. The first is simply because, due to the nature of the data, we have very little identifying information on these card numbers to start with. And the second reason is that any control we could use would be completely subsumed by the individual level fixed effects we include. Using individual-level fixed effects and with the stabilization of our sample, we feel this is enough to sufficiently isolate the effect we wish to study.

We repeat this model for a number of left-hand side variables and report the results in Tables 9 and 10. Having so many observations, nearly all of the results of our regressions are significant. It is much more important to look for the economic significance of results, something we will attempt to highlight where we can by comparing results to baseline levels of consumption.

Sugar Sweetened and Carbonated Beverages

After controlling for both seasonal and individual level fixed effects (and stabilizing our sample to only include SNAP households that are in both the before and after periods), the difference-in-difference coefficient on percent consumption of sugar-sweetened beverages (SSB) for SNAP participants is estimated at .65% (0.0065, t-stat: 70.02). Considered against a baseline SSB consumption level of 10.9% (.109) for SNAP participants, this is a 5.4% increase over the baseline and can roughly be interpreted as the effect that the extra ARRA benefits had on sugar-sweetened beverage consumption for the very poor. The subsequent expiration of SNAP benefits in saw a respective decrease of -.18% (-.0018, t-stat: -42.44), a -1.6% decrease below the baseline. The high t-statistics are a natural result of working with observations numbering in the dozens of millions. It should be noted that the above reported numbers are results including fixed effects controlling for seasonal and individual effects. When we fail to include these, the effect only grows stronger. Using only month and store fixed effects, we get a difference in difference coefficient of 1.16% (0.0116, t-stat: 152.02) and using only month fixed effects gives us a difference in difference coefficient of 1.17% (0.0117, t-stat: 156.02). The results of this can be seen in Table 6.

Tables 5-8 present the regression results of models (1) and (2) for carbonated beverages as well as for all sugar sweetened beverages. Tables 5 and 6 cover the effects of the benefits increase and tables 7 and 8 cover the effects of the decrease. We include the results for carbonated beverages as a kind of sanity check, mainly to show that the effects all go in in the same direction as those of sugar sweetened beverages and are all significant. Though they are all extremely statistically significant, they are not economically very interesting after including fixed effect controls.

All Categories

We repeat this same analysis for a selection of popular food groups. Tables 9 and 10 examine the effects of the 2009 and 2013 changes on all categories of consumption. Though these effects are generally not as striking as those for sugar sweetened beverages, they are almost all extremely statistically significant and quite a few are very economically significant as well.

The difference in difference coefficient for the 2009 increase is positive for the bakery, dairy, deli, frozen, and grocery categories while it is negative for the beer/wine/liquor, floral, general merchandise, hygienic, meat and non-food grocery categories. Of these, the effects for grocery (.39%), bakery (.16%) and hygienics (-.2%) are the most significant. On the other hand, the difference in difference coefficient for the 2013 decrease is positive for the dairy, frozen and non-food grocery categories while it is negative for the bakery, beer/wine/liquor, deli, floral, general merchandise, hygienics and meat categories. Of these, the effects for dairy (.3%), hygienics (-.2%) and frozen (.09%) are the most significant. It is also important to note that these popular categories are not comprehensive, so the numbers involved need not necessarily add to zero.

As opposed to the sugar sweetened beverage results, most of the above effects are not economically significant (in spite of their statistical significance). In terms of their baseline, most of these effects are something near a 1% increase/decrease on the baseline. This makes it difficult to develop a strong narrative as to why the results went one way or the other. One important takeaway however is that the effect of the change on sugar sweetened beverage consumption completely dwarfed any other change in consumption.

Conclusion

In conclusion, we find that the 2009 ARRA increase in SNAP benefits (and subsequent expiration in 2013) significantly shifted the consumption patterns of SNAP households. A perhaps unintended consequence of the 2009 benefits increase was to increase consumption of sugar sweetened beverages among the poor by 5.4% above the baseline (.65% absolute). This was the result of the ARRA increasing the maximum redeemable SNAP benefits (for a family of four) by just 13.6% in 2009. When considered against the context of the fact that this was a relatively minor increase, the subsequent change in behavior and increase in sugar sweetened beverage consumption is staggering.

This paper is notable for being the first to use point-of-sale, scanner-level data to examine how increases in SNAP benefits effect the consumption patterns of the poor. We are also among the very first papers to use such scanner-level data in any fashion in a paper and are using what is most likely the most comprehensive form of this data currently available. Our dataset includes vastly more consumers and for a much longer time period than any previous paper on the subject and so provides what is arguably one of the most comprehensive panels of US consumption ever assembled. Having 43 million unique household loyalty card numbers gives us a sample of roughly one seventh of the US population (assuming one household card roughly corresponds to one person). The sheer size of this data on disk (about 3.4 TB) also presented unique technical challenges that necessitated processing on multiple supercomputers.

Though it is far from our purpose to establish any sort of normative judgment on what consumers do with their own private money, the results of this paper could be used to inform policy on the relation between SNAP benefits and public nutrition. If indeed the purpose of increasing SNAP benefits is to increase the nutritional value of a consumers' basket of goods, it appears, in one section at least, that this policy is failing. As a holistic view though, we cannot currently say if the well established health risks posed by increase consumption sugar sweetened beverages are outweighed by the health benefits resulting from increased consumption of healthier foods too. There remains though the very robust result, that the increase in sugar sweetened beverage consumption dwarfed all other consumption changes coming from the 2009 ARRA SNAP benefits increase.

Future iterations of this paper will look at consumption changes on a hand-coded produce category as well as match up the UPC of each good to a holistic measure of nutrition to give us a better idea of how the nutritional value of the food portfolios of

SNAP households changes with SNAP benefits changes. If sugar sweetened beverages can be assumed to have a lower nutritional value than most other goods, then the above results would seem to suggest that the introduction of extra benefits in 2009 might have actually *decreased* average nutritional value of a SNAP household's food portfolio (and the reverse that it possibly increased with the expiration of benefits in 2013). If true, this would be an even further staggering result and hopefully one that future iterations of this paper can speak to.

References

[1] Bartlett, Susan and Nancy Burstein. 2004. Food Stamp Program Access Study: Eligible Nonparticipants. Washington, DC: U.S. Department of Agriculture, Economic Research Service. EFAN-03-013-2.

[2] Bruich, Gregory A. "The Effect of SNAP Benefits on Expenditures: New Evidence from Scanner Data and the November 2013 Benefit Cuts." N.p., Dec. 2014. Web. <http://scholar.harvard.edu/files/bruich/files/bruich_2014b.pdf?m=1418428726>

[3] Delaney, Arthur. "How Long Do People Stay On Public Benefits?" The Huffington Post. TheHuffingtonPost.com, n.d. Web. 18 Jan. 2017. <http://www.huffingtonpost.com/2015/05/29/public-benefits-safety-net_n_7470060.html>.

[4] Fraker. T 1990. The Effects of Food Stamps on Food Consumption: A Review of the Literature. Current Perspectives on the Food Stamp Program Participation. USDA, Food and Nutrition Service.

[5] Garasky, Steven, Kassim Mbwana, Andres Romualdo, Alex Tenaglio, and Manan Roy. FOODS TYPICALLY PURCHASED BY SUPPLEMENTAL NUTRITION ASSISTANCE PROGRAM (SNAP) HOUSEHOLDS (n.d.): n. pag. USDA/Impaq International. Web.

[6] Hoynes, Hilary W., and Diane Whitmore Schanzenbach. "Consumption Responses to In-Kind Transfers: Evidence from the Introduction of the Food Stamp Program." American Economic Journal: Applied Economics 1.4 (2009): 109-39. Web.

[7] Nord, Mark. Effects of the Decline in the Real Value of SNAP Benefits From 2009 to 2011 (n.d.): n. pag. Web. <https://www.ers.usda.gov/webdocs/publications/err151/39326_err151.pdf>.

[8] O'Conner, Anahad. "In the Shopping Cart of a Food Stamp Household: Lots of Soda." New York Times. New York Times, 13 Jan. 2017. Web. <https://www.nytimes.com/2017/01/13/well/eat/food-stamp-snap-soda.html>

[9] Orhun, A. Yesim, and Mike Palazzolo. "Frugality Is Hard to Afford." SSRN Electronic Journal (n.d.): n. pag. Web.

[10] Rosenberg, Eli. "Chart: The Rise of Food Stamps." The Atlantic. Atlantic Media Company, n.d. Web. 18 Jan. 2017. <https://www.theatlantic.com/national/archive/2011/07/chart-rise-food-stamps/352412/>.

[11] "SNAP Costs and Caseloads Declining." SNAP Costs and Caseloads Declining — Center on Budget and Policy Priorities. N.p., n.d. Web. 18 Jan. 2017. <http://www.cbpp.org/research/food-assistance/snap-costs-and-caseloads-declining>.

[12] "Supplemental Nutrition Assistance Program (SNAP)." Supplemental Nutrition Assistance Program (SNAP) — Food and Nutrition Service. N.p., n.d. Web. 18 Jan. 2017. <https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap>.

[13] Wilde, Parke E. "The New Normal: The Supplemental Nutrition Assistance Program (SNAP)." EconPapers: The New Normal: The Supplemental Nutrition Assistance Program (SNAP). N.p., 15 Apr. 2013. Web. 18 Jan. 2017. <http://econpapers.repec.org/RePEc:oup:ajagec:v:95:y:2013:i:2:p:325-331>.

Appendix A: Summary Statistics

Table 1: Summary Statistics SNAP and Non-SNAP 2009-2011

Variable	Mean	Std. Dev.	Min.	Max.	N
card	38350733.254	20612128.948	11493433	72404471	56154505
max_daily_visits	1.183	0.437	1	5	56154505
monthly_visits	3.386	2.248	1	10	56154505
monthly_netsales	126.019	132.956	20	2000	56154505
pct_bakery	0.037	0.082	0	1	56154505
pct_beer/wine/liquor	0.028	0.109	0	1	56154505
pct_dairy	0.147	0.126	0	1	56154505
pct_deli	0.069	0.118	0	1	56154505
pct_floral	0.008	0.052	0	1	56154505
pct_frozen	0.041	0.076	0	1	56154505
pct_general_merch	0.033	0.085	0	1	56154505
pct_grocery	0.41	0.205	0	1	56154505
pct_hygienics	0.067	0.129	0	1	56154505
pct_meat	0.13	0.156	0	1	56154505
pct_non-food_grocery	0.03	0.072	0	1	56154505
pct_carbonated_bev	0.046	0.094	0	1	56154505
pct_sugar_sweet_bev	0.073	0.106	0	1	56154505
storeid	1061.035	561.263	143	2270	56154505
treatment	0.192	0.394	0	1	56154505
month_fe	5.482	3.451	0	11	56154505
month_store_fe	3823.991	2182.297	0	7600	56154505
month_card_fe	40186695.494	24575181.985	232658	82069718	56154505
time	0.63	0.483	0	1	56154505
did	0.13	0.337	0	1	56154505

Table 2: Summary Statistics SNAP and Non-SNAP 2012-2014

Variable	Mean	Std. Dev.	Min.	Max.	N
card	61935674.464	27552034.52	11492515	107707720	41096379
max_daily_visits	1.201	0.461	1	5	41096379
monthly_visits	3.452	2.281	1	10	41096379
monthly_netsales	127.594	130.158	20	2000	41096379
pct_bakery	0.039	0.087	0	1	41096379
pct_beer/wine/liquor	0.041	0.139	0	1	41096379
pct_dairy	0.147	0.131	0	1	41096379
pct_deli	0.071	0.126	0	1	41096379
pct_floral	0.009	0.06	0	1	41096379
pct_frozen	0.04	0.078	0	1	41096379
pct_general_merch	0.032	0.092	0	1	41096379
pct_grocery	0.404	0.214	0	1	41096379
pct_hygienics	0.062	0.128	0	1	41096379
pct_meat	0.13	0.162	0	1	41096379
pct_non-food_grocery	0.026	0.071	0	1	41096379
pct_carbonated_bev	0.045	0.097	0	1	41096379
pct_sugar_sweet_bev	0.071	0.109	0	1	41096379
storeid	1309.559	597.439	143	2270	41096379
treatment	0.259	0.438	0	1	41096379
month_fe	5.549	3.372	0	11	41096379
month_store_fe	3848.678	2103.019	0	7600	41096379
month_card_fe	42587337.477	23512839.125	1	83953735	41096379
time	0.325	0.468	0	1	41096379
did	0.085	0.279	0	1	41096379

Table 3: Summary Statistics for SNAP Beneficiaries

Variable	Mean	Std. Dev.	Mean	Std. Dev.
Years	**2009-2011**		**2012-2014**	
card	42558767.599	20965996.78	67143628.144	26200385.489
max_daily_visits	1.353	0.591	1.348	0.6
monthly_visits	3.72	2.431	3.742	2.422
monthly_netsales	173.394	170.11	165.429	160.469
pct_bakery	0.032	0.078	0.036	0.085
pct_beer/wine/liquor	0.014	0.066	0.021	0.085
pct_dairy	0.132	0.113	0.138	0.12
pct_deli	0.046	0.092	0.049	0.102
pct_floral	0.002	0.024	0.003	0.027
pct_frozen	0.042	0.073	0.043	0.077
pct_general_merch	0.019	0.055	0.017	0.058
pct_grocery	0.468	0.199	0.457	0.207
pct_hygienics	0.055	0.119	0.052	0.122
pct_meat	0.17	0.167	0.166	0.173
pct_non-food_grocery	0.02	0.056	0.017	0.054
pct_carbonated_bev	0.06	0.099	0.059	0.104
pct_suager_sweet_bev	0.112	0.122	0.109	0.126
snap_dummy	1	0	1	0
storeid	1214.757	554.599	1460.132	569.64
treatment	1	0	1	0
month_fe	5.471	3.436	5.52	3.406
month_store_fe	3818.315	2174.869	3838.764	2131.979
month_card_fe	40536050.386	24355893.669	42706591.447	23811472.208
time	0.678	0.467	0.327	0.469
did	0.678	0.467	0.327	0.469
	N = 10786705		N = 10786705	

Table 4: Summary Statistics for Non-SNAP Beneficiaries

Variable	Mean	Std. Dev.	Mean	Std. Dev.
Years	**2009-2011**		**2012-2014**	
card	37350225.733	20399766.281	60111747.433	27780100.487
max_daily_visits	1.143	0.381	1.15	0.389
monthly_visits	3.307	2.194	3.35	2.221
monthly_netsales	114.755	119.748	114.344	114.801
pct_bakery	0.038	0.082	0.04	0.088
pct_beer/wine/liquor	0.032	0.117	0.048	0.153
pct_dairy	0.15	0.129	0.149	0.134
pct_deli	0.074	0.123	0.078	0.132
pct_floral	0.009	0.056	0.011	0.068
pct_frozen	0.041	0.076	0.04	0.079
pct_general_merch	0.036	0.091	0.037	0.101
pct_grocery	0.396	0.204	0.385	0.214
pct_hygienics	0.07	0.131	0.066	0.13
pct_meat	0.121	0.152	0.118	0.156
pct_non-food_grocery	0.033	0.076	0.029	0.075
pct_carbonated_bev	0.043	0.092	0.041	0.094
pct_suager_sweet_bev	0.063	0.1	0.057	0.099
snap_dummy	1	0	0	0
storeid	1214.757	554.599	1256.826	597.976
treatment	1	0	0	0
month_fe	5.485	3.454	5.559	3.36
month_store_fe	3825.341	2184.057	3852.15	2092.77
month_card_fe	40103632.436	24626303.948	42545572.41	23407207.93
time	0.619	0.486	0.324	0.468
did	0	0	0	0
	N = 45367800		N = 30436813	

Appendix B: Regression Results

Table 5: Percent Change in Consumption (SNAP Participants) of Carbonated Beverages due to ARRA 2009 Increase in SNAP Benefits

	(1)	(2)	(3)
	pctmonthly_cb	pctmonthly_cb	pctmonthly_cb
Diff-in-Diff	0.00468***	0.00386***	0.000525***
	(69.64)	(56.78)	(6.82)
Fixed Effects (Month)	Yes	Yes	Yes
Fixed Effects (Store)	No	Yes	Yes(+)
Fixed Effects (Card)	No	No	Yes
N	56154505	56154505	43636833

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

+: Effect subsumed by individual-level fixed effects

Table 6: Percent Change in Consumption (SNAP Participants) of Sugar Sweetened Beverages due to ARRA 2009 Increase in SNAP Benefits

	(1)	(2)	(3)
	pctmonthly_ssb	pctmonthly_ssb	pctmonthly_ssb
Diff-in-Diff	0.0117***	0.0116***	0.00625***
	(156.03)	(152.51)	(70.02)
Fixed Effects (Month)	Yes	Yes	Yes
Fixed Effects (Store)	No	Yes	Yes(+)
Fixed Effects (Card)	No	No	Yes
N	56154505	56154505	43636833

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

+: Effect subsumed by individual-level fixed effects

Table 7: Percent Change in Consumption (SNAP Participants) of Carbonated Beverages due to ARRA 2013 Expiration of SNAP Benefits

	(1)	(2)	(3)
	pctmonthly_cb	pctmonthly_cb	pctmonthly_cb
Diff-in-Diff	-0.000826***	-0.000390***	0.000723***
	(-31.79)	(-39.32)	(-48.36)
Fixed Effects (Month)	Yes	Yes	Yes
Fixed Effects (Store)	No	Yes	Yes(+)
Fixed Effects (Card)	No	No	Yes
N	41096379	41096377	26777889

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

+: Effect subsumed by individual-level fixed effects

Table 8: Percent Change in Consumption (SNAP Participants) of Sugar Sweetened Beverages due to ARRA 2013 Expiration of SNAP Benefits

	(1)	(2)	(3)
	pctmonthly_ssb	pctmonthly_ssb	pctmonthly_ssb
Diff-in-Diff	-0.00101***	-0.00101***	-0.00177***
	(-23.41)	(-23.64)	(-42.44)
Fixed Effects (Month)	Yes	Yes	Yes
Fixed Effects (Store)	No	Yes	Yes(+)
Fixed Effects (Card)	No	No	Yes
N	41096379	41096377	26777889

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

+: Effect subsumed by individual-level fixed effects

Table 9: Percent Change in Consumption (SNAP Participants) due to ARRA 2009 Increase in SNAP Benefits

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	bakery	beerwineliquor	dairy	deli	floral	frozen	generalmerchandise	grocery	hygienics	meat	nonfoodgrocery
Diff-in-Diff	0.00163***	-0.000907***	0.000510***	0.000180	-0.000818***	0.000688***	-0.00168***	0.00394***	-0.00233***	-0.000730***	-0.000495***
	(22.66)	(-11.78)	(4.50)	(1.74)	(-17.47)	(9.81)	(-20.02)	(21.92)	(-20.19)	(-5.41)	(-7.47)
Fixed Effects (Card)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects (Month)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	43636833	43636833	43636833	43636833	43636833	43636833	43636833	43636833	43636833	43636833	43636833

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Percent Change in Consumption (SNAP Participants) due to 2013 Expiration of ARRA SNAP Benefits

	(1) bakery	(2) beerwineliquor	(3) dairy	(4) deli	(5) floral	(6) frozen	(7) generalmerchandise	(8) grocery	(9) hygienics	(10) meat	(11) nonfoodgrocery
Diff-in-Diff	-0.000409***	-0.000265**	0.00299***	-0.000299**	-0.000290***	0.000962***	-0.000540***	-0.000101	-0.00203***	-0.000856***	0.000835***
	(-5.14)	(-2.75)	(24.66)	(-2.66)	(-5.29)	(12.65)	(-5.82)	(-0.52)	(-16.85)	(-5.91)	(12.48)
Fixed Effects (Card)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects (Month)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	26777889	26777889	26777889	26777889	26777889	26777889	26777889	26777889	26777889	26777889	26777889

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$