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THE ROLE OF SNAP AND HABIT FORMATION ON HOUSEHOLD CONSUMPTION BEHAVIOR

Shaheer Burney
University of Kentucky, burney.shaheer@gmail.com
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Dr. Alison F. Davis, Major Professor

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THE ROLE OF SNAP AND HABIT FORMATION ON HOUSEHOLD CONSUMPTION BEHAVIOR

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Agriculture, Food and Environment at the University of Kentucky

By
Shaheer Burney

Lexington, Kentucky

Director: Dr. Alison F. Davis, Professor of Agricultural Economics

Lexington, Kentucky

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ABSTRACT OF DISSERTATION

THE ROLE OF SNAP AND HABIT FORMATION
ON HOUSEHOLD CONSUMPTION BEHAVIOR

This collection of essays examines the impact of two antecedents of household food consumption: SNAP and habit formation to nutrients. Household food choice invariably plays a substantial role in health outcomes such as obesity. Low-income households may be especially vulnerable to obesity as they face a more restricted set of food choices due to income constraints and may have less information on healthy eating relative to high-income households. This dissertation unravels this dynamic by providing causal estimates of the effect of two major determinants of food choice.

Chapter 2 and chapter 3 test the impact of SNAP participation on consumption of foods that are likely to cause obesity. With some exceptions, SNAP restricts benefits to be spent only on unprepared grocery food items from participating retailers. Chapter 2 considers the broad category of Food Away From Home (FAFH) which is shown to be less healthy than meals prepared at home and shows that SNAP significantly reduces FAFH expenditure of participants. However, the magnitude of this decrease is not large enough to have a tangible impact on obesity. Chapter 3 considers household expenditure on carbonated soda, which is the key source of sugar intake among low-income households. Not only is carbonated soda SNAP-eligible, it is cheaper when purchased with SNAP benefits relative to cash because benefits are exempt from all sales taxes. Results show that SNAP participation leads to a significant rise in carbonated soda sales in low-income counties. I also find that the SNAP tax exemption does not lead to higher consumption among participants relative to non-participants.

Chapter 4 tests habit formation to dietary fat using purchases of ground meat and milk products. Products in both categories have salient fat content information on the packaging. Products within each category differ only by fat content and are usually identical otherwise. Differences in habit formation are, therefore, caused by different levels of fat content. Results show a positive association between habit formation and fat content for all products in the ground meat category and all products, except fat-free milk, in the milk category. However, this relationship is modest leading to the conclusion that policy interventions, such as a saturated fat tax, might be effective in discouraging consumption of high fat products.

KEYWORDS: SNAP, Consumer Behavior, Habit Formation,
FAFH, Demand System, Carbonated Soda

Shaheer Burney

June 4, 2017

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By

Shaheer Burney

Dr. Alison F. Davis

Director of Dissertation

Dr. Carl R. Dillon

Director of Graduate Studies

June 4, 2017

To my parents, Tanveer and Samina Burney, for their love, encouragement, and sacrifice. Without their exemplary support, none of my successes in life would have been possible.

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CHAPTER 1: INTRODUCTION

The Supplemental Nutrition Assistance Program (SNAP) (formerly known as the Food Stamp Program) is the largest nutrition assistance program in the US. It provides in-kind benefits to food insecure households based on a broadly defined eligibility criteria. Relative to other nutrition assistance programs that target narrow demographics such as The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), which provides benefits for pregnant and nursing mothers and nutritionally at-risk infants and children, SNAP caters to generally all low-income households. As a result, it is an important safety net for impoverished families.

Over the last few decades, SNAP has gone through a series of drastic changes. While initially meant to alleviate food insecurity, the program's goals have expanded towards encouraging beneficiaries to consume healthy diets. This two-pronged approach has developed at the heels of a rapid surge in obesity rates among low-income households in the US. Moreover, SNAP has seen a consistent increase in program caseloads across the country since the early 2000s. In large part, this can be explained by state-level adoption of policies that substantially eased the eligibility criteria and reduced administrative burden. Some examples of these policies include the reduction of the asset limit or complete elimination of the asset test, introduction of the Electronic Benefit Transfer (EBT) system, extension of eligibility to non-citizen immigrants, and use of online application systems. The concomitant spread of obesity and expansion of SNAP have led some researchers to question the link between the two events.

Initiatives to promote healthy diets include an outright restriction on what beneficiaries can spend SNAP dollars on. The program restricts purchases to include only grocery food that requires at-home preparation for consumption. However, there are two major caveats that compromise the efficacy of this initiative. First, most SNAP participants have household food expenditure greater than the amount of benefits they receive. These households, called "inframarginal" households, are easily able to substitute current cash expenditure on food with SNAP benefits and utilize the now-available cash to purchase products ineligible with SNAP benefits. The fungibility of benefits with cash essentially renders the SNAP food restriction non-binding. Second, a controversial exception to the SNAP food restriction is Sugar-Sweetened Beverages (SSBs). It is well-established that SSBs, such as carbonated soda and sugar-sweetened fruit juices, are one of the primary contributors to America's obesity epidemic. Not only are SSB products SNAP-eligible they are also exempt from all state and local sales taxes when purchased with benefits. As a result, the extent to which SNAP achieves the objective of encouraging low-income households to make healthy eating choices is a question which has largely been unanswered.

An important factor that confounds our understanding of SNAP and its impacts on consumption behavior is selection bias that arises from participation. That is, households that choose to participate in the program may have unobservable differences from those that are eligible but do not participate. Selection bias, if unaddressed, poses a serious challenge to obtaining unbiased estimates and has led to lack of consensus on the effects of SNAP on nutritional outcomes. Researchers have employed a series of methods to overcome this issue, ranging from the use of instrumental variables to employing a natural experiment for identification.

This collection of essays explores the multifaceted nature of the obesity epidemic in the US. It spans the dynamic between household consumption behavior and government welfare policies that are in place to combat obesity. While much research has been devoted to analyzing the impact of these two antecedents, given the complex nature of their mutual interdependence there is a growing need to study them concurrently. This dissertation addresses this issue and provides insight into how public policy can be used to drive behavior modification. One of the main contributions of this dissertation is the use of innovative research design to provide causal estimates of the effect of SNAP on consumption behavior. I utilize state-level variation in SNAP participation arising from two major economic downturns in the US in the past two decades to circumvent the issue of selection bias. The first two essays (Chapter 2 and 3) provide estimates obtained from the application from this methodology. To the best of my knowledge, the use of recessions as natural experiments in this context is unprecedented.

The main focus of the first essay (Chapter 2) is to determine the impact of SNAP on obesity through the medium of Food Away From Home (FAFH) consumption. The paradoxical positive association between food insecurity and obesity has led researchers to identify FAFH expenditure as one of the possible causes of overweight among low-income individuals. While FAFH does not qualify for purchase with SNAP dollars, inframarginal households are able to circumvent this restriction. This study exploits variation arising from the early 2000s recession to identify the impact of SNAP on FAFH. Results show that SNAP has been largely successful in achieving its goal of encouraging households to decrease FAFH expenditure. However, an informal calculation shows that the FAFH decrease has a trivial effect on obesity.

The second essay (Chapter 3) explores the impact of SNAP participation on consumption of carbonated soda. It is not surprising that the inclusion of carbonated soda in the basket of SNAP-eligible products is widely debated given that carbonated soda is one of the largest sources of sugar consumption in the country. This essay utilizes state-level variation in SNAP participation arising from the Great Recession of 2008 to identify the effect of SNAP on carbonated soda sales. Results show that SNAP does lead to a non-trivial increase in weekly county-level soda sales but the tax exemption has little to no influence on this relationship. As a result, policymakers need to carefully consider whether imposing sales taxes on soda will produce a tangible decrease in soda consumption. In addition, these taxes might be regressive as there is some evidence that low-income households have a higher per-capita SSB consumption relative to high-income households.

The third essay considers the possibility that habit formation might be an impediment to behavior modification, thus subduing public efforts to encourage low-income households to make healthy nutrition choices. This study delves into the attributes of food to examine whether habit formation occurs at the nutrient level. I estimate habit formation to dietary fat using purchases of two categories of products that display salient fat content information on the packaging. I find that while these products exhibit strong habit formation, there is only weak evidence for a positive relationship between habit formation and fat content. These results have broad implications for whether a tax on saturated fat is a viable policy option. A saturated fat tax may not lead to substitution to lower-fat products, however, given the limited responsiveness of demand to price changes it might be an effective tool for raising revenue.

The three essays in this dissertation provide insight into one of the most penetrating issues of today. By many measures, obesity has reached epidemic proportions. SNAP has been a major driving force behind preventing households from falling into poverty and consequent food insecurity. Even though most beneficiaries are considered inframarginal, participation does lead to greater expenditure on FAH relative to FAFH. However, SNAP-eligible goods include SSBs which, consequently, leads households to increase consumption of carbonated soda. Welfare programs need to be designed such that they target the correct demographic and in an effective way. Poorly designed programs, though well-intentioned, may exacerbate the prevalence of obesity. Policy interventions such as Pigouvian taxes need to be considered concurrently with welfare programs. As a result, public policy must be comprised of a menu of options that target different aspects of household consumption behavior.

CHAPTER 2: HOUSEHOLD CONSUMPTION RESPONSES TO SNAP PARTICIPATION

Obesity is inordinately prevalent among food insecure households in the US. Some researchers have identified the consumption of unhealthy food a major source of this seemingly paradoxical relationship. One of the goals of the Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program, is to encourage healthy eating behavior among low-income households. However, literature lacks conclusive evidence for the success of the program in achieving that goal. This paper exploits an underutilized source of variation, the early-2000s recession in the US, to determine the impact of SNAP participation on household Food Away From Home (FAFH) expenditures. A Difference in Difference model is constructed using high post-recession growth in SNAP caseloads as treatment. The results show that households in the treatment cohort significantly decrease consumption of FAFH relative to households in the control group. This provides evidence that SNAP participation leads households to make healthier eating choices. However, reductions in FAFH are too small to have a tangible impact on obesity.

I. Introduction

Supplemental Nutrition Assistance Program (SNAP) is a federal nutrition-assistance program that is regulated by the Food and Nutrition Service (FNS) of the USDA and provides welfare benefits to numerous households throughout the United States. While the program has been touted for successfully targeting food insecurity in the US, it has also been criticized for having the unintended consequence of promoting obesity in low income households. The food insecurity-obesity paradox (Dietz, 1995), which states that there is a positive association between the contradictory states of food insecurity and obesity, has long puzzled researchers. Intuitively, households that are unable to fulfill the nutrition needs of their members should exhibit starvation. However, in practice food insecurity has been shown to be positively correlated with overweight and obesity, especially among women (Basiotis and Lino, 2003; Townsend *et al.*, 2001; Olson, 1999; Adams *et al.*, 2003; Centers for Disease Control and Prevention, 2003; Dinour *et al.*, 2007). In particular, individuals in food insecure households who also participate in SNAP have a greater likelihood of obesity (Meyerhoefer and Pylypchuk, 2008; Townsend *et al.*, 2001; Robinson and Zheng, 2011; Baum, 2011; Gibson, 2003; Chen *et al.*, 2005).

Economists have offered two major explanations for the role of SNAP in promoting obesity among food insecure households. First, obesity among SNAP beneficiaries might be attributed to the Food Acquisition Cycle (Wilde and Ranney, 2000). The monthly income shock from benefit receipt might cause severely food insecure to engage in binge-eating behavior and exhaust funds earmarked for food consumption well before the receipt of next month's benefits. This spell is followed by a period of hunger during which households cut back on food consumption to make funds last until the end of the cycle. This feast and famine cycle is hypothesized by researchers to cause obesity.

The second factor offered as explanation of SNAP’s role in obesity is that participation may lead households to increase expenditure on Food Away From Home (FAFH) (Fox *et al.*, 2004). However, there is some debate among researchers whether FAFH leads to obesity. Literature has shown that FAFH tends to be more energy dense (Binkley, 2008) and less healthy than Food At Home (FAH) (Mancino *et al.*, 2009). In particular, Currie *et al.* (2010) show that proximity to a fast food restaurant increases the likelihood of obesity among children and pregnant women significantly. On the other hand, Anderson and Matsa (2011) determine that there is no causal link between food consumption at restaurants and obesity. Cai *et al.* (2008) conclude that neither FAH nor FAFH expenditures have a significant influence on overweight rates. Other researchers have focused on the direct relationship between FAFH consumption and diet quality. Bowman *et al.* (2004), Paeratakul *et al.* (2003), Binkley (2008), and Todd *et al.* (2010) all find that fast food consumption leads to poor diet quality while the last two studies also find greater caloric intake as a consequence of fast food consumption.

While SNAP benefits are restricted to be spent on FAH only, households that spend more on food than the amount of SNAP benefits they receive can substitute current cash expenditure on food for SNAP dollars. These households are termed ‘inframarginal’ and the fungibility of SNAP benefits with cash allows them to utilize benefits for purchases of SNAP-ineligible items such as FAFH. While this effect has been repeatedly theorized by researchers, there is sparse empirical evidence to determine the true effect of

SNAP on FAFH expenditure. Among a handful of studies, Hoynes and Schanzenbach (2009) employ program introduction as source of variation and find a negative but insignificant association between SNAP and FAFH expenditure. Beatty and Tuttle (2015) use increases in SNAP benefits due to the American Recovery and Reinvestment Act (ARRA) as a natural experiment and also find a negative but statistically insignificant relationship between SNAP benefits and FAFH expenditure.

The focus of this study is the second alleged source of obesity outlined above. In particular, I provide a test of whether SNAP participation leads to changes in FAFH expenditure and FAFH as a share of total food expenditure. The early-2000s recession was followed by sudden spikes in SNAP caseloads across the country. However, there is tremendous state-level variation in the impact of the recession and in the willingness of states to expand eligibility, leading to significant differences in the rate and magnitude of the increase in SNAP participation. I exploit this variation to compare changes in household FAFH expenditures in states that experienced large spikes in SNAP participation to states in which the participation increases were milder. The Difference in Difference (DID) model utilized in this study defines treatment as high growth in SNAP caseloads. Consequently, the treatment group is comprised of 15 states with highest rate of growth in post-recession SNAP participation and the control group as comprised of 15 states with the lowest rate of growth in post-recession SNAP participation. Results show participation leads to a modest but statistically significant decrease in FAFH expenditure in the high growth cohort relative to the low growth cohort. In addition, participation has a significant negative effect on FAFH as a share of total food expenditure which indicates that participants substitute FAFH for FAH. As expected, the effect is stronger for households that have greater exposure to treatment, that is, a higher likelihood of participating in SNAP as a result of the recession. However, the magnitude of the decrease in FAFH is not large enough to have a meaningful impact on calorie intake and BMI.

This paper is organized in the following way. Section II provides a background of SNAP and the early 2000s recession in the contextual framework of DID estimation. Section III gives an overview of data above along with a discussion of summary statistics. Section IV presents descriptive evidence for the effect of SNAP participation on FAFH. Section V explains the research design and methodology employed in the construction of the empirical model. Section VI presents results of the DID estimation. Section VII includes a discussion of policy implications and section VIII concludes.

II. Background

In the past decade or so, SNAP participation has gone through a series of drastic changes. For the better part of the 1990s SNAP caseloads steadily declined nationwide, especially following the welfare reform of 1996 called the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA). Changes made by PRWORA included the elimination of immigrant eligibility and replacement of the traditional Aid to Families with Dependent Children (AFDC) program with a state block grant called Temporary Assistance for Needy Families (TANF) which consequently redefined categorical eligibility (Laird and Trippe, 2014). Part of the decrease in SNAP caseloads can be explained by the consistent rise in income of households at the bottom 20% of the income distribution, rising from a mean of $8,595 in 1996 to $10,157 in the year 2000 (US

Census Bureau, 2015). Following this period of contraction, SNAP caseloads sharply rebounded as the economy entered the early 2000s recession. Figure 2-1 shows the trend in national average SNAP participation rates from 1989 to 2012. Of particular note is the trend reversal in the year 2000 at which point participation rates started to rise across the country.

This sudden spike in SNAP caseloads in response to the recession can be explained by two major factors: decline in income of poor households (from $10,157 mean income in the year 2000 to $9,996 in 2003 (US Census Bureau, 2015)) and relaxation of SNAP eligibility requirements at the state level (such as the elimination of the asset test, introduction of Broad Based Categorical Eligibility (BBCE), and simplified reporting). There is substantial state-level variation in the impact of these two effects on SNAP participation. Participation growth rates between the year 2000 and 2011 ranged from a maximum of about 17% in Nevada to a minimum of 4% in Hawaii. This variation is even greater between the years 2000 and 2003, the period immediately following the start of the recession, with growth rates ranging from 23.5% in Arizona to -4.4% in Hawaii (Economic Research Service, 2013). Shortly after the sudden increase, participation growth started to plateau as the economy entered a period of recovery. However, the program experienced another large swell at the advent of the Great Recession of 2008. This increase has subsided in recent years as the economy recuperates.

III. Data

A household-level sample is generated from the 1999 to 2011 cycles of the Current Population Survey Food Security Supplement (CPS-FSS). The CPS is a large and nationally representative survey of the civilian non-institutionalized population conducted monthly and containing extensive labor-market and demographic information. The CPS-FSS is an annual supplement completed by about two-thirds of all CPS respondents each year and is conducted to elicit household-level information on issues regarding food security, food expenditure, food consumption patterns, program participation, etc. The CPS-FSS provides data on all variables needed to construct the model developed in this study including self-reported weekly expenditure on FAFH and FAH and geographic identifiers at the state level. The CPS-FSS represents households in all 50 states and District of Colombia.

Table 2-1 shows a snapshot of the sample generated from CPS-FSS. About 16% of the households in the sample participate in SNAP during the 15 year period considered. Mean food away from home expenditure is just under \$45 per week. Observations in the period following the start of the recession comprise about 73% of the total sample and households in the high growth cohort make up 69% of all households. Note that the sample is comprised only of households in the high growth and low growth cohorts which jointly represent a total of 30 states. The rest of the variables in Table 2-1 show demographic characteristics of the representative household in the sample. 54% of households have a male household head and the mean head is just under 50 years of age. About 10% of the entire sample has household heads that identify their race as black, 26% are at least college educated, 52% of household heads are married, 63% are employed (either part time or full time), and 2% are enrolled in some education program. The average number of members per household is 2.48 while the average number of children per household is 0.63. Finally, approximately 30% of all households in the sample report family income to be less than $15,000 per year.

IV. Descriptive Analysis

The central issue in any SNAP-related research is bias arising from selection into the program. To make causal inference, the researcher is tasked with isolating the effect of SNAP participation from other, often unobservable, factors that might influence the outcome variable. For example, if households that choose to participate in SNAP vary significantly in terms of their FAFH expenditure from households that do not participate, the estimates of an OLS regression will be biased and cannot be used to make causal inference. This may be due to household preferences which are commonly either unobserved or difficult to measure. I use a novel research design to overcome this issue by exploiting the recession of 2001 in the US as a natural experiment to identify a Difference in Difference (DID) model.

The economic slump at the turn of the century led to a rise in SNAP caseloads in all states in the country, essentially reversing the downward trend of the mid to late nineties. There is considerable variation, however, in how participation changed between states after the occurrence of the recession. Some states experienced a sharp rise in SNAP participation rates while others saw a gradual increase or even a decrease.

A. Treatment and Control Groups

Based on state-level participation growth rates, a treatment and a control group is constructed. The treatment group, also known as the high growth cohort, includes 15 states that experienced the highest growth rates in SNAP participation from the years 2000 to 2011. The control group, also referred to as the low growth cohort, includes 15 states that saw the lowest growth in SNAP participation during the same time period. Table 2-2 shows the list of states included in each of the cohorts. It follows that households residing in the high growth states have the highest probability of participating in SNAP after the start of the recession and households in the low growth states have the lowest probability of participation. Using the early 2000s recession as a natural experiment, the estimates of the DID model can be obtained by comparing the change in FAFH expenditure of households in treatment states with that of households in control states.

Unbiased estimation of the DID model is contingent on the validity of the parallel trends assumption. That is, the change in FAFH expenditure of households in the low growth cohort represents the counterfactual outcome of households in the high growth states. The validity of the parallel trends assumption is evident if the divergence in FAFH expenditures between the treatment and control groups coincides with the divergence in SNAP participation growth over the same period. Figure 2-2 shows the average percentage change in the level of total SNAP participation indexed to the year 2000 for the 15 states in the high growth cohort and for 15 states in the low growth cohort. As is clear from the graph, changes in total SNAP participation in each cohort prior to the year 2000 are largely similar. However, at the start of the recession, total SNAP caseloads increase much more in the high growth cohort relative to the low growth cohort. This divergence in SNAP participation lends credence to the notion that the recession was the primary catalyst for the resulting heterogeneity in state-level participation growth.

Similarly, Figure 2-3 shows annual aggregate FAFH expenditure in each cohort using data from the CPS-FSS. Until the early 2000s, FAFH expenditure is relatively similar in both cohorts. However, after the year 2002 there is an unambiguous divergence between the treatment and control group, with FAFH expenditure increasing sharply in both cohorts but to a smaller extent in the high growth cohort. Given that the FAFH expenditure of the low growth cohort represents the counterfactual outcome for the high growth cohort in the DID framework, Figure 2-2 and 2-3 provide evidence that SNAP is the main cause behind the muted increase in FAFH expenditure of the high growth cohort. I also conduct an empirical test for the validity of the parallel trends assumption following the approach of Autor (2003). The results are provided in Table 2-7 and elaborated in section VI. Results are well-aligned with graphical evidence and corroborate the strength of the DID research design.

It should be noted that while the divergence in SNAP participation occurred in the year 2000, the resulting divergence in FAFH expenditures between the two cohorts did not manifest until the year 2002. The delayed response in FAFH consumption to the recession might be explained by the theory that households generally exhibit habitual consumption of food, the empirical evidence of which is well-established in literature (Browning and Collado, 2007; Carrasco *et al.*, 2005; Dynan, 2000; Heien and Durham, 1991; Khare and Inman, 2006; Naik and Moore, 1996; Richards *et al.*, 2007). As a result, intertemporal dependence on food purchases might delay households in altering consumption behavior immediately after participating in SNAP. This effect is discussed in greater detail in the sections below.

B. The Effect of the Recession

The early-2000s recession led to changes in SNAP participation through two major channels: changes in household income and changes in state-level eligibility criteria. The heterogeneous effect of the recession on state-level SNAP participation can be explained by the differing magnitude of these two effects. First, household incomes declined and subsequently poverty rates spiked at a much faster rate in the high growth cohort relative to the low growth cohort. Figure 2-4 shows average state-level poverty rates for each cohort indexed to the year 2001. The graph shows that after the beginning of the early-2000s recession the poverty rate in the high growth cohort sharply increased while the low growth cohort experienced a milder increase relative to the base year and relative to the counterpart cohort. This is consistent with the idea that the post-recession increase in SNAP caseloads is partly explained by individuals falling below the poverty threshold and qualifying for SNAP under the stricter pre-recession eligibility requirements.

Second, in response to the recession states in the high growth cohort were quicker to implement policies that relaxed the eligibility criteria for participation relative to their low growth counterparts. This is apparent for a number of state-level options. Broad Based Categorical Eligibility (BBCE) is a policy which eases eligibility by allowing participants of other welfare programs such as Temporary Assistance for Needy Families (TANF) or Supplemental Security Income (SSI) to automatically qualify for SNAP benefits. Figure 2-5 shows the cumulative number of states in each cohort that had adopted BBCE in each year since 2000. It is obvious from the figure that states in the high growth cohort adopted BBCE sooner than states in the low growth cohort. In fact, most of the states in the low growth cohort adopted the policy as a result of the Great Recession of 2008. On the other hand, several high growth states adopted BBCE in the earlier part of the decade well before the 2008 recession. Similarly, Figure 2-6 shows changes in the percentage of households in each cohort that are required to seek recertification within a 1 to 3 month period as opposed to longer time intervals. Recertification imposes a transaction cost and makes it easier for a household to become ineligible. As shown in Figure 2-6, the proportion of households with short recertification periods declines sharply following the start of the early-2000s recession. However, the drop in high growth states is clearly more substantial than their low growth counterparts. Not long after the beginning of the descent does the proportion of short recertification households in the high growth cohort fall below those in the low growth cohort.

The two cohorts exhibited similar patterns as it relates to other SNAP policies as well. In general, states mostly relied on direct policy changes and administrative options to alter eligibility requirements. For example, high growth states more readily adopted simplified reporting, which eliminates the requirement that participants must report any changes in income and living conditions regularly. Other changes include using telephone interviews instead of in-person interviews at recertification without documenting household hardship and accepting online SNAP applications. These policies reduce the transaction cost of participation for the household. High growth states consistently show greater effort to ease eligibility using either streamlined administration or direct policy interventions relative to low growth states. Therefore, the variation in SNAP participation growth between the two cohorts can be largely explained by changes in the eligibility criteria in the wake of the early-2000s recession.

V. Research Design and Methodology

To determine the impact of SNAP participation on FAFH expenditure, I construct a DID model exploiting state-level variation arising from the early-2000s recession. The strength of the DID approach relies on the key assumption that trends in FAFH expenditure would have been similar for both high growth and low growth cohorts in the absence of treatment. Even though the two cohorts can differ, observable variation is captured by the inclusion of household-level covariates and unobservable differences are accounted for using state and time fixed effects.

This research design circumvents the most substantial issue that researchers encounter when studying the implications of SNAP. Participation in the program is generally believed to be endogenous to outcome variables, such as total food expenditure, obesity, type of food purchased, etc. Many approaches have been taken to tackle the selection issue including the use of various instrumental variables for participation such as county participation rate (Burgstahler et al., 2012), state-level SNAP eligibility rules (Boonsaeng et al., 2012; Ratcliffe et al., 2011; Gregory and Coleman-Jensen, 2013), and percentage of EBT benefits (Yen et al., 2008). However, there is some debate on whether instrumental variables completely satisfy the exclusion restriction assumption. Other researchers have relied on DID approaches, using natural experiments such as the county-level introduction of SNAP (Hoynes and Schanzenbach, 2009), the instatement of American Recovery and Reinvestment Act (ARRA) of 2009 (Beatty and Tuttle, 2015) which temporarily increased benefit disbursement, and the subsequent elimination of ARRA in 2013 (Bruich, 2014). In general, DID models provide cleaner identification relative to the use of instrumental variables as long as the exogeneity of the natural experiment is established.

I follow in the footsteps of the latter group of researchers by using an underutilized source of variation, the early-2000s recession, to identify the impact of SNAP participation on FAFH expenditure. The DID model is given by the following equation:

$$FAFH_{ist} = \tau D_t * Highgrowth_s + \rho X_i + \theta_s + \delta_t + \varepsilon_{ist}$$

where $FAFH_{ist}$ measures weekly FAFH expenditure in dollars and FAFH as a share of total expenditure on food for household i residing in state s in year t. The model is estimated separately for each outcome variable. The variable of interest is the interaction between the intervention dummy D_t, which marks the beginning of the early-2000s recession and equals 1 if the household is observed after the start of the year 2001, and the treatment group dummy $Highgrowth_s$, which equals 1 if the household resides in a state in the high growth cohort. The interaction term $D_t * Highgrowth_s$ captures the effect of the recession on high growth states relative to low growth states and determines the impact of SNAP participation on household FAFH expenditure. The coefficient τ can be interpreted as the average dollar change in FAFH expenditures of treatment households relative to control households. This coefficient is expected to have a negative sign, implying that SNAP participation decreases FAFH expenditure and consequently the FAFH restriction on SNAP benefits is effective. In other words, a dollar of cash is not equal to a dollar of SNAP benefits.

The vector X_i contains household-level covariates such as income, age of the household head, number of children in the household, etc., θ_s and δ_t capture state and year level fixed effects respectively, and ε_{ist} is the error term. The inclusion of state and year fixed effects is important as they remove any unobservable variation through which the early-2000s recession might influence FAFH expenditure independent of its effect through SNAP participation. In the absence of these controls, unaccounted for differences between the high growth and low growth cohort might bias estimates of the DID model.

In addition to estimation of the baseline model using the full sample of 15 states in each cohort, a series of sensitivity tests are conducted by restricting the sample to households that have a high likelihood of participating in the program in response to the recession. First, high growth and low growth cohorts are redefined to include only the 10 highest growth states and 10 lowest growth states respectively, essentially increasing the exposure to treatment for the high growth cohort and reducing exposure to treatment for the low growth cohort. Consequently, the average household in the high (low) growth cohort of 10 states has a higher (lower) likelihood of participation after the start of the early-2000s recession relative to the average household in the high (low) growth cohort of 15 states. Second, I estimate a specification of the model that excludes households with an annual income lower than \$25,000. The federal SNAP eligibility criteria specifies a gross income limit of 130% of Federal Poverty Guidelines with exceptions made for elderly and disabled households. For a family of four, this threshold translated to about \$23,000 annual income in the year 2001, about \$24,000 in the year 2003, and exactly

$26,000 by the year 2006. As a result, households with annual income under $25,000 are those which satisfied the eligibility criteria and were likely already participating before the occurrence of the recession. The intervention is unlikely to change the participation status of households in this group and their inclusion in the sample will attenuate the impact of participation on FAFH expenditure to zero. On the other hand, the group of households with an annual income above $25,000 includes those that are on the margin of being eligible for the program and therefore have a higher probability of participating in response to the recession. It will also include households who may have been eligible before the occurrence of the recession but did not participate. In addition to the sensitivity tests, I estimate a DID model to elicit the immediate effect of SNAP participation by limiting the sample to only the years 1999 to 2002. This specification captures the effect of participation on FAFH within a year of exposure to the treatment and will determine the short-term impact of participation on FAFH.

A. The Effect of Income

The identification strategy relies on the assumption that apart from the deviating impact on SNAP participation, there are no other factors through which the recession differentially impacted household FAFH consumption. In other words, there are no unaccounted-for variables that confound the impact of SNAP participation on FAFH expenditure and therefore FAFH expenditure is unrelated to the recession except through changes in SNAP participation. One such confounding variable that may undermine this assumption is income. During a recession, declining income may cause households to divert their spending from FAFH which is generally considered more expensive than

FAH. Todd and Morrison (2014) show that during the Great Recession of 2008 working-age adults decreased FAFH consumption by 12% and calories obtained from fast food and pizza places decreased by about 53%.

If the effect of income on FAFH expenditure is not accounted for, the estimates of the DID model will be biased upwards. To parse out this confounding effect, I include household-level income measures as covariates and rely solely on the second source of variation (state policy changes) to identify the model. The CPS-FSS provides a categorical measure of income with relatively narrow income brackets, especially for low-income households. Binary variables for each income category are included in the empirical model to capture time variant income effects for households in the two cohorts. In addition, baseline income differences between the high growth and low growth cohorts are controlled for by the treatment dummy. As a result, the effect of income is essentially removed from the model and the main source of identification is variation arising from changes in state-level eligibility criteria.

VI. Results

Table 2-3 and Table 2-4 show results from different specifications of the DID model. All specifications include state and year fixed effects and standard errors are multi-way clustered by state and year. The full set of results for the specifications in Table 2-3 and Table 2-4 are provided in Table 2-5 and Table 2-6 respectively. The specifications in Table 2-3 posit FAFH as a share of total food expenditure as the dependent variable and are estimated for a sample of 240,478 households observed over the years 1999 to 2011. Column I presents the results of a parsimonious DID model with the variable of interest,

$D_t * Highgrowth_s$, as the only independent variable in addition to state and year fixed effects. The coefficient shows that SNAP participation induces households to decrease FAFH's share of total food expenditure by 0.825% and the estimate is significant at the 10% confidence level. In column II, household level covariates are added to the specification in column I. The magnitude of the effect is slightly smaller and has the same level of significance. This shows that household demographics introduce noise to the effect of SNAP on FAFH. Column III shows results from controlling for annual household income in addition to household covariates. As expected, the magnitude of the coefficient is smaller than previous specifications. Participation in SNAP leads households to reduce FAFH share of total expenditure by about 0.774%. This provides evidence that the effect of income imposes an upward bias on the estimates and controlling for this confounding effect attenuates the coefficient towards zero.

Table 2-4 presents results for additional specifications discussed in the previous section. Column I specifies total weekly FAFH expenditure as the outcome variable and is estimated for a sample of 271,363 households generated over the period 1996 to 2011. This specification allows for a larger sample due to additional data available for the years 1996 to 1998. The results show that SNAP participation results in an approximate $1.50 decrease in weekly FAFH expenditure. Columns II through V specify FAFH's share of total food expenditure as the outcome variable. Column I is identical to column III of Table 2-3 and is juxtaposed with other specifications in this table for comparison. Column III presents results from the sample that redefines high growth and low growth cohorts to include 10 states each. The effect is of a substantially higher magnitude and is significant at the 1% confidence level. Participation in SNAP causes a 1.2% reduction in

FAFH's share of total food expenditure. This provides evidence of a dose-response effect because when the exposure to treatment is amplified, households exhibit a stronger response. Column IV shows estimates from the restricted model of households with annual income greater than $25,000. The coefficient from this specification shows a 0.8% decrease in FAFH as share of total food expenditure and is significant at the 1% confidence level. Results from columns III and IV lend support to the validity of the model because households with a greater likelihood of treatment exhibit a stronger impact of SNAP participation on FAFH. To further explore the influence of income heterogeneity on this relationship, Table 2-8 juxtaposes estimates from the restricted sample of households with income below $25,000 with a sample of households with income above $25,000. As expected, the effect of SNAP participation on households with income below $25,000 is smaller in magnitude and statistically insignificant. Finally, column IV presents results from the model which restricts the sample to the years 1999 to 2002. The immediate effect of participation is approximately 0.83% decrease in the outcome variable and the coefficient is significant at the 5% confidence level.

I provide an empirical test for the strength of the parallel trends assumption by including leads and lags in the DID model as shown in Table 2-7. An in-depth explanation of this technique can be found in Autor (2003). The model includes interactions of year dummies with the treatment variable $Highgrowth_s$ and is specified for both FAFH expenditure and FAFH share as the outcome variable. This allows us to compare the effect of treatment on FAFH for each year relative to the baseline period. For the parallel trends assumption to be satisfied, the coefficients on pre-recession interactions must be insignificant, denoting similar trends in each cohort. Column I shows results of the specification that poses FAFH expenditure as the outcome variable. Since the year 1996 was unlike the following years in the decade due to the passage of PRWORA, I consider both 1996 and 1997 as baseline years. Note that the year 1998 is not included in the analysis due to the absence of FAFH expenditure variable in that year's CPS-FSS cycle. Column I provides strong evidence for the validity of the parallel trends assumption. Pre-recession interactions are highly insignificant and have positive coefficients indicating that FAFH trends were relatively similar in the two cohorts. Post-recession interactions are also informative. The coefficient on the 2001 lead variable exhibits a clear divergence from the pre-recession trend, with FAFH expenditure in treatment states experiencing a sharper plummet relative to control states. This divergence not only persists over time but invariably grows as indicated by interactions for later years. Column II shows estimates for the regression on FAFH share. Although the interpretation of these results is not as unambiguous as column I, they provide some insight into the validity of the parallel trends assumption. Recall that the CPS-FSS does not include measures for FAFH share prior to the year 1999, therefore, the baseline for this regression is 1999. The year 2000 exhibits a large jump in the effect of treatment on FAFH share relative to the previous year and is followed by a sharp drop following the start of the recession. This divergence also strengthens over time leading to significantly lower FAFH expenditures following the SNAP expansion. While pre-recession FAFH share trends are not parallel, there is a clear post-recession trend reversal due to which SNAP led to a larger decline in FAFH share in the treatment group relative to the control group. Therefore, columns I and II provide ample evidence that the DID research design is sound.

VII. Discussion

According to economic theory, for inframarginal households in-kind benefits are similar to an equivalent cash transfer. Consequently, inframarginal households cannot be restricted to spend SNAP benefits on FAH only because benefits are fungible with cash. In this case, participation would not lead to a decrease, and might even result in an increase, in FAFH expenditure as the income shock might cause households to spend more on meals out. This is evident in the results obtained by Hoynes and Schanzenbach (2009) who show that the marginal propensity to consume food out of SNAP benefits is close to the marginal propensity to consume food out of cash income.

The results of the model developed in this study show that SNAP participation not only leads to a decrease in FAFH expenditure but also in FAFH as a share of total food expenditure. In other words, SNAP participation causes households to reallocate food expenditure away from FAFH and towards FAH. As a consequence, even though households are generally considered inframarginal (and therefore SNAP benefits are fungible with cash) the restriction on using SNAP benefits for FAFH expenditure out of SNAP benefits is effective in altering behavior for most participants. A possible explanation for the deviation from the predictions of canonical economic theory is that households might fail to assess the fungibility of SNAP benefits with cash. In this case, the “power of suggestion” of the program design might induce tangible changes in household consumption behavior. Another explanation might be that the fungibility of benefits has been overstated in literature. Households might not be as inframarginal as previously shown and therefore participation may significantly distort utility-maximizing consumption. A third possible explanation is that even though inframarginal households do not increase their total expenditure on food, SNAP might cause them to change the mix of FAH and FAFH in their total food consumption.

While SNAP participation causes a statistically significant decrease in household FAFH expenditures, the effect on obesity is trivial. A $1.50 decrease in weekly FAFH can be expressed as a calorie change using a simple back-of-the-envelope calculation. Mancino *et al.* (2009) report that each meal away from home adds about 130 calories to daily intake relative to FAH. Assuming a range of $5 to $15 for the cost of a FAFH meal purchased by a low income household (depending on the type and source of food obtained), we can infer that additional daily calories per dollar range from about 26 to 9. Reduction in FAFH expenditure resulting from SNAP participation is approximately $0.214 daily ($1.5 weekly) which translates to a decrease ranging from 6 to 2 calories per day. In addition, Mancino *et al.* (2009) determine that if all weekly FAFH meals are replaced by FAH meals, it would lead to an annual weight reduction of 8 lbs per individual or annual BMI reduction ranging from 1.16 to 1.36. Given the average weekly FAFH expenditure of $46 in my sample, it can be inferred that a $1.50 decrease in weekly FAFH expenditure would be associated with an annual weight reduction of 0.3 lbs for each participant. This equals a BMI reduction in the range of 0.04 and 0.05 per year. Overall, while SNAP has been largely successful in inducing households to cut FAFH expenditure, the effect is too small to have a tangible impact on obesity.

This result has immense policy implications. The SNAP restriction on FAFH was designed to couple efforts to alleviate food insecurity with the fight against obesity. However, as is clear from the results the program falls short of producing an economically significant change in obesity. As a result, the gain from obesity reduction is likely not enough to offset the welfare loss from the SNAP restriction on FAFH and this policy might not be as effective as previously thought. While there may be other reasons to advocate for cutting FAFH expenditure, the magnitude of the relationship between FAFH and obesity is insufficient to warrant the use of SNAP as a viable intervention to tackle obesity.

VIII. Conclusion

This study provides a direct test for the relationship between SNAP participation and household FAFH expenditure. I exploit an underutilized source of variation in state-level SNAP caseloads, the early-2000s recession, as a natural experiment to identify a simple Difference in Difference model. Treatment is defined as the probability of a household participating in SNAP and is based on the state's participation growth in the years following the early-2000s recession. The treatment group consists of households that reside in any of the 15 states with the highest participation growth rate and the control group consists of households that reside in 15 states with the lowest participation growth rate. Variation used to identify the Difference in Difference model arises from state-level policy changes directed at relaxing the eligibility criteria and easing the administrative burden of participation on households. The results show that following the early-2000s recession households in the high growth cohort reduced FAFH expenditure by approximately $1.50 relative to their low growth counterparts. In addition, households in the high growth cohort also exhibited a decline in FAFH as a share of total food expenditure, indicating a reallocation of food expense towards FAH. The effect is manifest immediately following the event of the recession but also persists over the long run. These results are robust to a series of sensitivity tests which lend validity to the Difference in Difference research design. It follows that SNAP has been successful at encouraging households to substitute FAFH for FAH although the magnitude of the change is insufficient to substantially reduce obesity.

IX. Tables

Table 2-1. CPS Food Security Supplement Descriptive Statistics by Cohort

Variable	**Treatment**	**Control**
SNAP (%)	14.3	17
FAFH ($)	45.7	46.7
FAFH Share (%)	35	35.6
Post-recession (2001) (%)	73.9	71.3
Male (%)	53.8	53.6
Age	49.5	49.6
Black (%)	10	11
College (%)	27.6	26
Married (%)	52.4	50
Employed (%)	64.3	62.7
Student (%)	1.5	1.6
Number of HH members	2.5	2.5
Number of children	0.6	0.7
Family Income < $15K (%)	33	37.3

Table 2-2. SNAP Participation Growth Rate by Cohort between 2000 and 2011

High Growth Cohort		Low Growth Cohort	
Nevada	16.9%	California	7.6%
Delaware	14.5%	New York	7.6%
Idaho	14.0%	Missouri	7.5%
Arizona	13.6%	Nebraska	7.5%
Wisconsin	13.4%	Illinois	7.4%
Utah	13.0%	Mississippi	7.3%
Massachusetts	12.8%	Montana	6.9%
Florida	12.7%	Kentucky	6.6%
Washington	12.4%	Arkansas	6.3%
North Carolina	11.6%	Washington DC	5.7%
New Hampshire	11.5%	Louisiana	5.6%
Maryland	11.4%	North Dakota	5.0%
Georgia	11.3%	Wyoming	4.8%
Michigan	10.9%	West Virginia	4.3%
Colorado	10.8%	Hawaii	4.0%

Table 2-3. OLS Regression on Weekly FAFH Share of Total Food

	(I)	(II)	(III)
D*HighGrowth	-0.825*	-0.811*	-0.744*
	(0.5)	(0.42)	(0.4)
HH Demographics	No	Yes	Yes
HH Income	No	No	Yes
Observations	240,478	240,478	240,478

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note 1. All specifications include state and year fixed effects

Note 2. Standard errors for all specifications are multi-way clustered by state and year

Note 3. Income measures include binary variables for each category. Demographics are given in Table 1.

Table 2-4. OLS Regression on Weekly FAFH Expenditure and FAFH Share

	I	II	III	IV	V
	FAFH Expense	**FAFH Share**			
	Full Sample	Full Sample	20 States	Income>$25K	Immediate effect
D*High Growth	-1.473*	-0.774*	-1.182***	-0.807***	-0.825**
	(0.87)	(0.4)	(0.45)	(0.2)	(0.36)
HH Demographics	Yes	Yes	Yes	Yes	Yes
HH Income	Yes	Yes	Yes	Yes	Yes
Observations	271,363	240,478	126,263	175,078	85,481

* p<0.10, ** p<0.05, *** p<0.01

Note 1. All specifications include state and year fixed effects

Note 2. Standard errors for all specifications are multi-way clustered by state and year

Note 3. Income measures include binary variables for each category. Demographics are given in Table 1.

Table 2-5. OLS Regression on Weekly FAFH Share of Total Food (Full)

	I	II	III
D *High Growth	-0.825*	-0.811*	-0.774*
Male	-	2.691***	2.569***
Age	-	-0.104***	-0.116***
Black	-	-0.705	-0.042
College	-	1.312***	0.512***
Married	-	-2.144***	-3.626***
Employed	-	1.540***	0.254
Student	-	2.216***	3.229***
No. of HH Members	-	-2.897***	-3.280***
No. of Children in HH	-	-1.385***	-0.982***
$0<Family Income <$5,000	-	-	-4.386***
$5,000<Family Income<$7,499	-	-	-6.416***
$7,500<Family Income<$9,900	-	-	-5.236***
$10,000<Family Income<$12,499	-	-	-5.668***
$12,500<Family Income<$14,999	-	-	-5.565***
$15,000<Family Income<$19,999	-	-	-4.583***
$20,000<Family Income<$24,999	-	-	-4.323***
$25,000<Family Income<$29,999	-	-	-3.659***
$30,000<Family Income<$34,999	-	-	-3.162***
$35,000<Family Income<$39,999	-	-	-2.833***
$40,000<Family Income<$49,999	-	-	-2.431***
$50,000<Family Income<$59,999	-	-	-1.501***
$60,000<Family Income<$74,999	-	-	-0.974**
$75,000<Family Income	-	-	2.260***
Constant	36.313***	47.921***	53.145***
Observations	240478	240478	240478

* p<0.10, ** p<0.05, *** p<0.01

Note 1. All specifications include state and year fixed effects

Note 2. Standard errors for all specifications are multi-way clustered by state and year

Table 2-6. OLS Regression on Weekly FAFH Expenditure and FAFH Share (Full)

	I	II	III	IV	V
	FAFH Expense	**FAFH Share**			
	Full Sample	Full Sample	20 States	Income> $25K	Immediate effect
D*High Growth	-1.473*	-0.774*	-1.182***	-0.807***	-0.825**
Male	5.176***	2.568***	2.515***	2.093***	2.563***
Age	-0.164***	-0.115***	-0.113***	-0.117***	-0.118***
Black	0.459	-0.841***	-0.348	-0.072	-0.953**
College	2.842***	0.511***	0.439**	0.488**	1.086***
Married	-1.814***	-3.603***	-3.292***	-3.947***	-3.881***
Employed	1.003*	0.259	0.069	-0.137	0.291
Student	2.964**	3.237***	3.917***	0.401	3.720***
No. of HH Members	2.545***	-3.292***	-3.301***	-3.330***	-3.419***
No. of Children in HH	-4.582***	-0.975***	-0.910***	-0.760***	-0.976***
$0<Family Income <$5,000	-16.029***	-4.418***	-4.645***	0	-3.871***
$5,000<Family Inc<$7,499	-20.094***	-6.433***	-6.763***	0	-7.829***
$7,500<Family Inc<$9,900	-19.673***	-5.258***	-4.576***	0	-6.476***
$10,000<Family Inc<$12,499	-17.624***	-5.683***	-5.378***	0	-5.437***
$12,500<Family Inc<$14,999	-17.273***	-5.568***	-6.080***	0	-4.886***
$15,000<Family Inc<$19,999	-15.893***	-4.588***	-4.562***	0	-4.284***
$20,000<Family Inc<$24,999	-13.703***	-4.324***	-4.081***	0	-4.330***
$25,000<Family Inc<$29,999	-11.870***	-3.654***	-3.748***	0	-2.613***
$30,000<Family Inc<$34,999	-9.192***	-3.160***	-2.794***	0.546*	-2.657***
$35,000<Family Inc<$39,999	-7.389***	-2.826***	-2.419***	0.899***	-1.819***
$40,000<Family Inc<$49,999	-4.470***	-2.423***	-2.426***	1.329***	-1.722***
$50,000<Family Inc<$59,999	-0.298	-1.489***	-1.257***	2.314***	-1.230***
$60,000<Family Inc<$74,999	3.782***	-0.962**	-0.755	2.885***	-0.068
$75,000<Family Inc	25.165***	2.280***	2.234***	6.187***	3.092***
Constant	36.560***	50.440***	52.630***	49.888***	53.300***
Observations	271,363	240,478	126,263	175,078	85,481

* p<0.10, ** p<0.05, *** p<0.01

Note 1. All specifications include state and year fixed effects

Note 2. Standard errors for all specifications are multi-way clustered by state and year

Table 2-7. OLS Regression on Weekly FAFH Expenditure and FAFH Share with Leads and Lags

	FAFH Expenditure	FAFH Share
1999*HighGrowth	0.0757	-
	(0.485)	-
2000*HighGrowth	0.559	.848***
	(0.636)	(.311)
2001*HighGrowth	-0.98	-.452
	(0.918)	(.286)
2002*HighGrowth	-0.62	-.138
	(0.901)	(.255)
2003*HighGrowth	-1.006	-.046
	(1.238)	(.393)
2004*HighGrowth	-1.327	-.603
	(1.253)	(.432)
2005*HighGrowth	-1.223	.221
	(1.567)	(.328)
2006*HighGrowth	-1.512	-.236
	(0.946)	(.316)
2007*HighGrowth	-0.882	.294
	(1.471)	(.295)
2008*HighGrowth	-2.333**	-.637**
	(1.068)	(.315)
2009*HighGrowth	-2.54**	-.902***
	(1.007)	(.348)
2010*HighGrowth	-0.979	-.928***
	(1.152)	(.329)
2011*HighGrowth	-1.573*	-.629**
	(0.817)	(.301)
HH Demographics	Yes	Yes
HH Income	Yes	Yes
Observations	271,363	240,478

* p<0.10, ** p<0.05, *** p<0.01

Note 1. All specifications include state and year fixed effects

Note 2. Standard errors for all specifications are multi-way clustered by state and year

Note 3. Income measures include binary variables for each category. Demographics are given in Table 1.

Table 2-8. OLS Regression on Weekly FAFH Expenditure and FAFH Share by Household Income

	Income > $25K		Income ≤ $25K	
	FAFH Expenditure	FAFH Share	FAFH Expenditure	FAFH Share
Post-recession*High Growth	-1.540	-0.807***	-1.058	-0.577
Male	4.766***	2.093***	5.238***	3.749***
Age	-0.162***	-0.117***	-0.148***	-0.108***
Black	-11.185***	-0.072	-7.195***	0.313
College	2.176***	0.488**	4.245***	0.378
Married	-3.473***	-3.947***	-0.099	-3.111***
Employed	-0.638	-0.137	3.997***	0.971***
Student	2.210*	0.401	2.863*	4.702***
No. of HH Members	1.895***	-3.330***	4.466***	-3.153***
No. of Children in HH	-3.792***	-0.760***	-5.890***	-1.496***
$0<Family Income <$5,000	-	-	0	0
$5,000<Family Income<$7,499	-	-	-12.628***	-3.978***
$7,500<Family Income<$9,900	-	-	-16.459***	-5.770***
$10,000<Family Income<$12,499	-	-	-16.550***	-4.730***
$12,500<Family Income<$14,999	-	-	-15.195***	-5.225***
$15,000<Family Income<$19,999	-	-	-15.229***	-5.195***
$20,000<Family Income<$24,999	-	-	-14.245***	-4.270***
$25,000<Family Income<$29,999	-	-	-12.514***	-4.086***
$30,000<Family Income<$34,999	2.771***	0.546*	-	-
$35,000<Family Income<$39,999	4.729***	0.899***	-	-
$40,000<Family Income<$49,999	7.714***	1.329***	-	-
$50,000<Family Income<$59,999	12.052***	2.314***	-	-
$60,000<Family Income<$74,999	16.341***	2.885***	-	-
$75,000<Family Income	37.794***	6.187***	-	-
Constant	35.945***	49.888***	35.639***	52.354***
Observations	195098	175078	76265	65400

* p<0.10, ** p<0.05, *** p<0.01

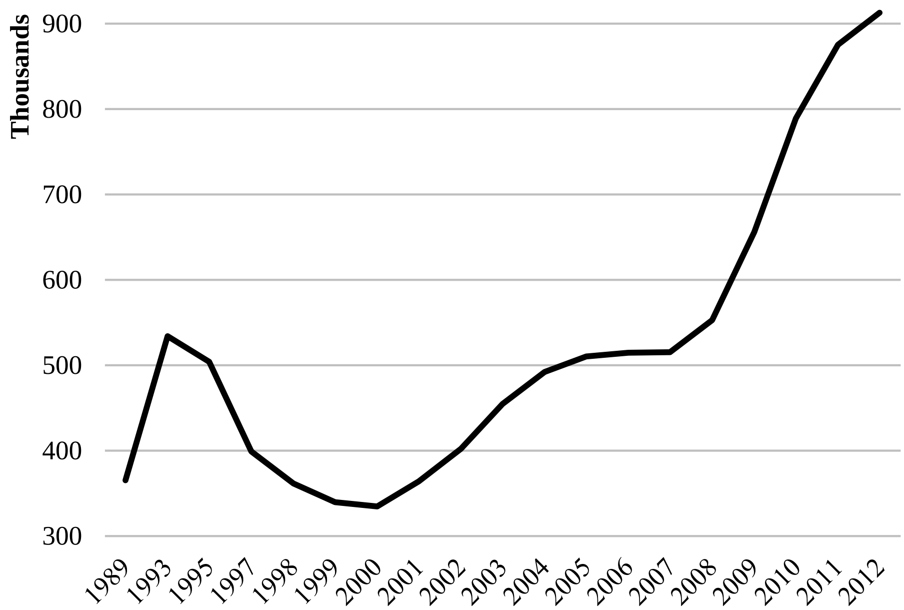
Note 1. All specifications include state and year fixed effects

Note 2. Standard errors for all specifications are multi-way clustered by state and year

Note 3. Income measures include binary variables for each category. Demographics are given in Table 1.

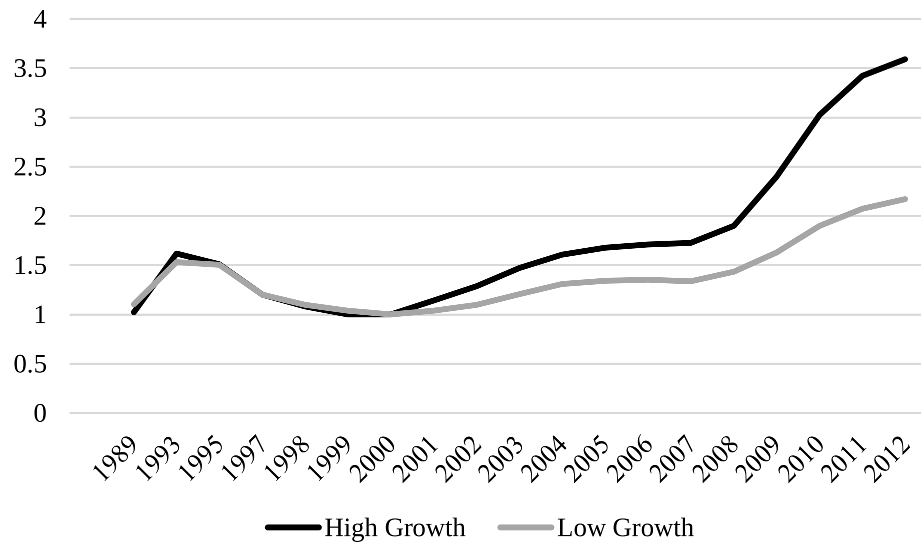
X. Figures

Figure 2-1: National Average SNAP Caseloads



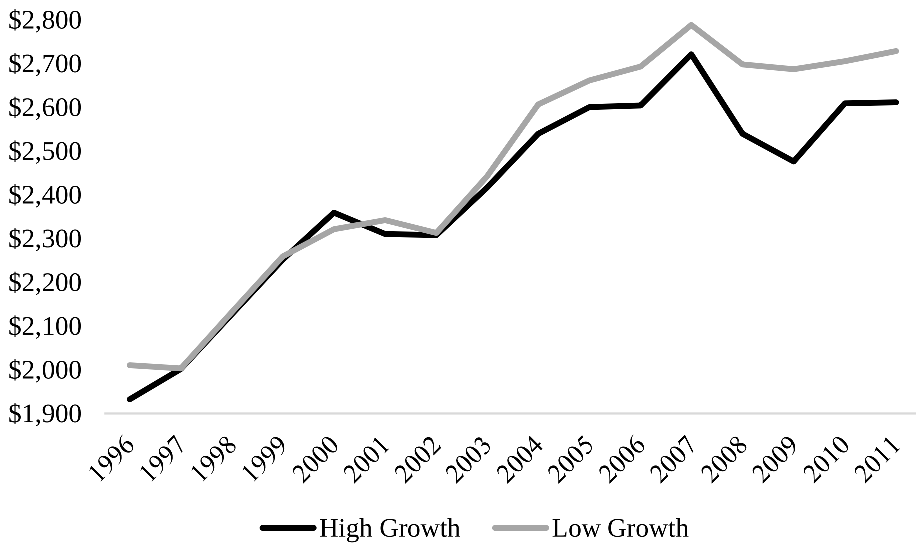
Source: Economic Research Service (ERS), U.S. Department of Agriculture (USDA).
Supplemental Nutrition Assistance Program (SNAP) Data System

Figure 2-2: Changes in SNAP Participation in High Growth and Low Growth Cohorts: Index=2000



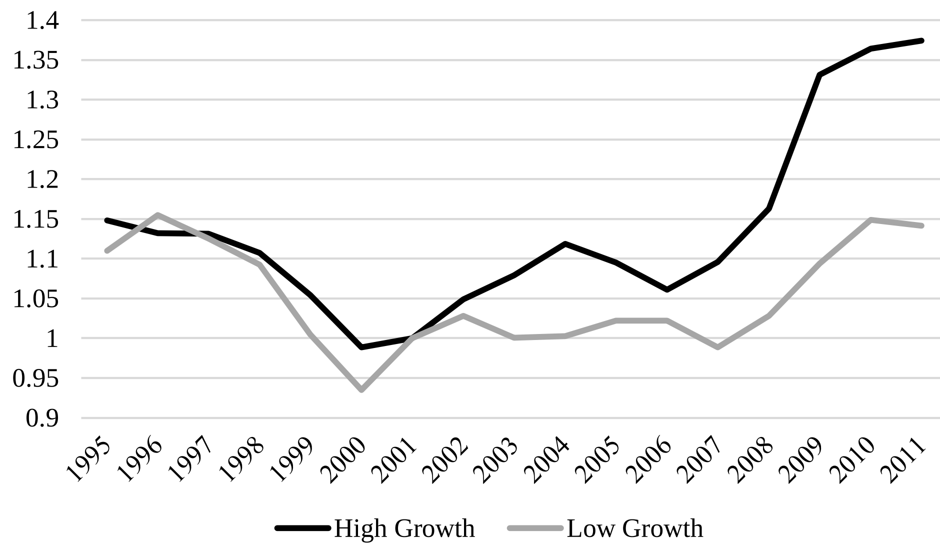
Source: Economic Research Service (ERS), U.S. Department of Agriculture (USDA). Supplemental Nutrition Assistance Program (SNAP) Data System

Figure 2-3: Annual Aggregate FAFH Expenditure



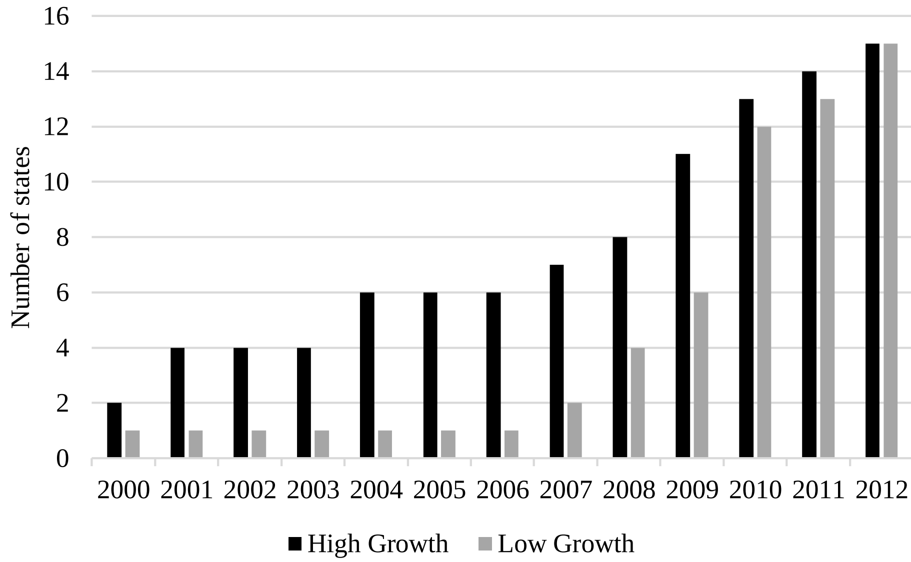
Source: Current Population Survey Food Security Supplement, 1996 – 2011.

Figure 2-4: Average State Poverty Rate by Cohort, Index=2001



Source: U.S. Bureau of the Census, Current Population Survey, Annual Social and Economic Supplements.

Figure 2-5: BBCE Adoption of High Growth and Low Growth States by Year



Source: Economic Research Service (ERS), U.S. Department of Agriculture (USDA). Supplemental Nutrition Assistance Program (SNAP) Policy Database

CHAPTER 3: THE IMPACT OF SNAP PARTICIPATION ON SALES OF CARBONATED SODA

This study estimates the effect of SNAP participation on carbonated soda sales. Sugar-Sweetened Beverages (SSBs) are the largest source of added-sugar in the US and are one of the main reasons for rampant obesity in the county. To make matters worse, most SSBs are eligible for purchase with SNAP benefits which makes low-income household particularly vulnerable to obesity. I exploit variation arising from the Great Recession of 2008 to test whether participation induces households to increase carbonated soda consumption. In addition, I explore the role of state and county sales taxes on the relationship between SNAP and soda sales. Results show SNAP participation has a non-trivial positive effect on carbonated soda sales. However, sales taxes on soda do not exert any influence on this relationship.

I. Introduction

Sugar-Sweetened Beverages (SSBs) have been attributed as one of the main culprits that lead to obesity, especially among low-income households because SSBs are the largest source of calories and added-sugar in the US. Center for Disease Control and Prevention (CDC) reports that among adult men and women, and girls aged 2 to 19 years, the largest proportion of total daily calories consumed from SSBs is among households with income less than or equal to 130% of Federal Poverty Guidelines (FPG). The proportion consistently tapers off with higher income groups such that households with income over 350% of FPG consume the lowest proportion. In addition, non-Hispanic blacks and Hispanics consume the highest daily calories of SSBs on average relative to other races and Hispanic origin status (Rosinger *et al*., 2017). Trends in obesity rates are in consonance with trends in SSB consumption. Obesity is especially prevalent among low-income households as more than 33 percent of adults who earn less than $15,000 per year are classified as obese relative to about 25% of those who earn at least $50,000 per year (Levi *et al*., 2011). Similarly, non-Hispanic blacks have the highest rates of obesity compared to individuals of other races and Hispanic origin (Ogden *et al*., 2010).

Exacerbating the effect of obesity is the addictive nature of sugar as shown in recent studies. That is, individuals who regularly consume excessive sugar can develop a habit such that utility in future periods is a function of sugar consumption in previous periods. Zhen et al. (2011) show that households exhibit habit formation to SSBs such as carbonated soda, sports and energy drinks, fruit juices, etc. As a result, SSBs may have a long term effect on obesity and reducing consumption might be hindered by the habit forming properties of sugar.

Given the disproportionate prevalence of obesity and SSB consumption among disadvantaged socioeconomic groups, it is plausible that SNAP participation might be the facilitator of SSB consumption among low income households. Most SSBs (including carbonated soda beverages and sugar-sweetened fruit juices) are eligible for purchase with SNAP benefits. Moreover, SSBs are less costly when purchased with SNAP benefits relative to cash because, in general, SNAP exempts all purchases from state and county sales taxes. SNAP benefits may be even less fungible with cash in states that impose a grocery tax on food and/or a sugar tax on SSBs. As a result, SNAP participants face a lower price of SSBs relative to non-participants to the extent that benefits are utilized. It is important to note that the tax exemption does not apply to cash purchases made by SNAP participants. Therefore, SNAP only partially offsets the cost of purchasing SSB products.

The results of this study show that SNAP participation leads to an increase in SSB consumption. While the benefit transfer is meant to target food insecurity and encourage healthy eating, including carbonated soda in the list of eligible products negates that goal. If SNAP beneficiaries use their extra benefits for consumption of unhealthy calories, it not only defeats the purpose of making low-income households food insecure but it also exacerbates the obesity epidemic that is already quite severe. The results of this study also show that sales taxes on soda do not influence the relationship between SNAP participation and soda sales. In other words, eliminating the tax exemption on soda might not have a tangible impact on soda consumption.

The rest of the paper is organized in the following way: Section II provides a short review of literature, section III discusses research design, section IV gives an overview of data, section V presents the empirical model, and section VI explains results and policy implications. Finally, section VII concludes and is followed by tables and figures in section VIII and section IX respectively.

II. Literature Review

Recent literature in economics and public health has looked into household demand for macronutrients such as carbohydrates (including sugar) and protein (Bray and Popkin, 1998; Richards *et al*., 2007; Bruijn *et al.*, 2008). In addition, researchers have shown evidence of changes in Food At Home (FAH) and Food Away From Home (FAFH) resulting from participation in SNAP (Hoynes and Schanzenbach, 2009; Beatty and Tuttle, 2015).

However, only a handful of studies examine the link between SNAP and SSB consumption. Those that do show only mixed evidence of whether this relationship exists. Some studies depict a positive relationship (Andreyeva *et al.*, 2012; Bleich *et al.*, 2013; Leung *et al.*, 2012; Nguyen *et al.*, 2014; Watt *et al.*, 2013) while others show no effect (Todd and Ver Ploeg, 2014; Fernandes, 2012). Of the studies mentioned, only one study (Andreyeva *et al.*) considers grocery store sales of SSBs as a measure of consumption. However, Andreyeva *et al.* include only SNAP participants with a history of WIC participation and only one grocery store chain in the New England area in their sample. This study adds to literature by considering the impact of SNAP participation on retail sales of SSBs using a nationally representative sample generated from a large store-level scanner dataset, and by employing a novel source of variation to identify the causal impact of SNAP participation on retail SSB sales.

III. Research Design

I exploit state-level variation arising from the Great Recession of 2008 to identify the effect of SNAP participation on carbonated soda consumption. The occurrence of the recession caused changes in SNAP caseloads due to two major reasons. First, household income fell sharply due to which households that were previously ineligible for benefits qualified for SNAP. Second, there was considerable variation in how states reacted to the economic downturn. States that were traditionally more lenient towards participation in SNAP readily adopted a series of policies that eased the eligibility criteria. States that have historically been more conservative in regards to SNAP participation had a more restrained response in terms of SNAP participation. As a result, changes in SNAP caseloads happened at drastically different rates in each group. This study relies on the second source of state-level variation in SNAP caseloads and explicitly removes the confounding effect of the first source.

A. Factor Analysis

I hypothesize that an underlying common factor explains state adoption of policies to ease eligibility. These policies include a range of options that either directly eliminate hurdles to eligibility (for example, broad-based categorical eligibility, removal of vehicle restriction in the asset test, and extending participation to include noncitizen immigrants) or simplify the administrative process of participation (for example, use of biometric technology and accepting online applications). Descriptions of policies used in this analysis is given in Table 3-1. I identify a measure of “willingness” using factor analysis that determines each state’s readiness to ease eligibility and construct an index to rank states based on their willingness score. States high on the scale are were more open to implementing these policies while states low on the scale largely refused to adopt the same policies after the start of the Great Recession. Naturally, willing states represent the treatment group and unwilling states comprise the control group in this analysis.

The results of factor analysis are shown in Tables 3-2(a) and 3-2(b). Table 3-2(a) depicts the list of identified factors and their corresponding eigenvalues. While several factors are identified that explain policy adoption, the Kaiser rule (often cited as the rule of thumb) justifies retaining only components with eigenvalues greater than 1. However, the Factor 1 explains an overwhelming amount, about 53%, of variation in state-level policy adoption while the second factor explains only about 34%. These results indicate that while there may be multiple factors that influence state level policy adoption, the majority of the variation is explained by Factor 1. Table 3-2(b) depicts factor loadings of Factor 1 and Factor 2. The direction of factor loadings of Factor 1 are consistent with state's willingness to ease eligibility. Imposing short recertification periods and disqualifying beneficiaries for noncompliance are policies that tighten eligibility while all other policies ease the eligibility criteria. The factor loadings of Factor 2, however, show no discernible correlation with state's efforts to expand participation. Therefore, out of the two factors retained using the Kaiser rule, I rely only on Factor 1 to explain policy adoption. I term this factor "willingness" and disregard the rest of the factors. As a robustness check, I construct the willingness index using both factors, Factor 1 and Factor 2, and find that only a handful of states receive a treatment or control assignment different from the assignment using only one factor. The coefficients of this index are simply the averages of predicted coefficients for Factor 1 and Factor 2, indicating equal weights for each factor. This is a conservative measure because Factor 1 explains substantially greater variation (53%) than Factor 2 (34%). Accounting for this will generate an index that is even closer to the index based on Factor 1 only.

Note that by assumption the factors obtained from factor analysis are orthogonal to each other. That is, the second factor explains residual variation in policy adoption after accounting for the first factor and is therefore uncorrelated with willingness. It is also important to note that the willingness factor might represent other state characteristics that might influence its readiness to adopt these policies. However, this does not pose an issue for the research design as long as other characteristics are not correlated with carbonated soda consumption except through changes in SNAP participation. To the best of my knowledge, literature does not identify any such characteristic and therefore we can safely rely on the first factor for ranking. Factor analysis is conducted separately for years 2007 and 2008. It is important to compare pre-recession and post-recession results as willingness might change with the occurrence of the recession. In other words, states that experienced a more severe economic downturn may become more willing relative to the prerecession period. However, the results do not vary drastically between factor analyses conducted for the two years. Most states retain their relative ranking on the index.

Figure 3-1 shows a map of states categorized by their ranking on the willingness index. I choose an arbitrary threshold on the index that roughly equally divides the states into two cohorts. States above the threshold are classified as treatment states and those below are classified as control states. With some clear exceptions (such as Texas and Tennessee), Figure 3-1 aligns well with each state's political majority in the 2008 presidential election. Not surprisingly, most states in the Midwest and Southern US that were characterized as having a conservative majority in 2008 also rank low on the willingness index. Similarly, most states that had a liberal majority in 2008 ranked high on the willingness index. For comparison, Figure 3-2 maps states based on the willingness index using both Factor 1 and Factor 2. With a small number of exceptions (for example, California), the Figure 3-2 is identical to Figure 3-1. Table 3-3 shows growth rates of SNAP participation and soda sales for each cohort. The treatment group comprises 24 states and the control group comprises 24 states and District of Columbia.

B. Difference-In-Difference

I use a Difference In Difference (DID) model to determine the causal effect of SNAP participation on carbonated soda consumption. Based on ranking of the willingness index, each state is assigned to either the treatment or the control group. Intuitively, the treatment group is likely to exhibit a greater increase in SNAP participation following the economic downtown in 2008 because it had a more relaxed eligibility criteria relative to the control group. Therefore, the difference in the carbonated soda consumption of the treatment group and the control group can be attributed to SNAP participation.

The validity of the DID research design is contingent on whether the parallel trends assumption is satisfied. That is, to obtain an unbiased estimator we must ensure that pre-treatment trends in SNAP participation and carbonated soda consumption are similar across the two cohorts. Figure 3-4 shows trends in aggregate SNAP participation in each group, indexed to the year 2008. As is clear from the figure, the two cohorts experienced very similar changes in total SNAP caseloads before the occurrence on the

Great Recession of 2008. However, this trend is disturbed in 2008 as the recession causes SNAP participation to rise at a faster rate in the treatment group versus the control group. The divergence between the two groups widens steadily with time. In addition, I observe analogous trends in carbonated soda consumption in the two cohorts. Figure 3-5 shows changes in weekly-aggregated carbonated soda consumption for states in the treatment and control groups indexed to the year 2008. Carbonated soda consumption moved in relative lockstep in the two cohorts prior to 2008 and is followed by a stark deviation after the advent of the economic downturn. The divergence in carbonated soda consumption corresponds with the divergence in participation in the two groups. This indicates that the parallel trends assumption is satisfied and lends credence to the DID research design. An empirical test of the parallel trends assumption is conducted as well. The results are shown in Table 3-9 and are discussed in the results section.

The biggest strength of the DID methodology is that it allows us to control for selection on unobservables. There might exist unobservable differences between the treatment and control groups that confound the effect of SNAP participation on carbonated soda consumption. For example, households in the treatment group might have a higher preference for carbonated soda than households in the control group. Since preferences are unobservable it is nearly impossible to explicitly control for this effect by including them in the vector of explanatory variables. However, DID allows us to remove baseline differences such as household preference through the inclusion of state-specific fixed effects. Similarly, time-variant factors that may influence soda consumption but are similar across states can be removed with time-specific fixed effects.

A possible source of bias that is not directly accounted for in the DID model is the effect of income. It is likely that states experienced the consequences of the Great Recession of 2008 at different levels of severity. Some states might experience a sharp decline in median income at the immediate forefront of a recession while others may see a gradual and less severe economic downturn. As a result, to the extent that income influences store-level carbonated soda the estimates obtained from DID will be biased. I circumvent this issue by adding median county income as an explanatory variable in the empirical specification. This removes the confounding effect of income on carbonated soda consumption arising from the economic downturn. The inclusion of income is expected to have a positive effect on the estimate of SNAP participation on soda sales because it removes downward bias on the coefficient.

IV. Data

Store-level data is obtained from Nielsen RetailScan, a large and nationally representative scanner-generated dataset that includes weekly information on pricing, volume, and store attributes. The dataset is available for years 2006 to 2015 and provides detailed information on product and store characteristics (including geography) for a litany of SSBs. Moreover, it covers 61 geographic areas (52 major markets and 9 Census Divisions) and includes SSB sales from grocery, drug, mass merchandiser, and other stores. It represents more than half of the total sales volume of grocery and drug stores and 30 percent of mass merchandiser sales volume. The level of detail afforded by the data and the years available make it ideal for estimating the model specified below.

Among SSBs, this study focuses on the sales of carbonated soda. This category represents the majority of SSB sales and is most often associated with high amounts of high fructose corn syrup. In addition, carbonated soda is readily available from a variety of outlets such as grocery stores, gas stations, convenience stores, and vending machines relative to other SSBs products such as sugar-sweetened fruit juices.

Sales tax data is collected from a variety of sources. Detailed state-level soda taxes for each sample year is obtained from Bridging the Gap research program (Bridging The Gap). This resource provides accurate tax information for each state including tax applied on food and soda and including tax exemptions. The soda tax is equal to the sum of the general state sales tax and additional soda specific tax that may be applied at the state or county level. It is equal to the state sales tax only if no additional tax is levied on soda. While almost all states impose a non-zero sales tax (exceptions include Alaska, Delaware, Montana, New Hampshire, and Oregon), several states choose to exempt grocery food which may or may not include carbonated soda.

Counties may choose to impose additional taxes on food, called grocery taxes, which may include carbonated soda. In 2014, 16 states imposed grocery taxes at the state level, county level, or both. While only a handful of counties add a grocery tax to the state sales tax, most county level grocery taxes are imposed in southern states (as shown in Figure 3-3) where obesity seems to be especially prevalent. Due to lack of access to historical data, I use county-level grocery taxes for the year 2014. However, there is generally limited, if any, variation in county taxes over time. In addition, counties may choose to exempt carbonated soda from the grocery tax or exclude carbonated soda from the grocery tax exemption. This information is not available, therefore, I rely on the assumption that carbonated soda is treated the same as grocery food at the county level. I conduct a series of sensitivity checks to determine the strength of this assumption and find nearly identical estimates for the DID model.

Combined grocery tax data are obtained mainly from Tax-Rates.org, augmented with data from Sale-tax.com and state and county departments of taxation websites. There is considerable cross-sectional variation in combined state and county level taxes on grocery food. They ranged from 0% in most of the country to 9% (4% state plus 5% county) in Tuscaloosa County, Alabama in 2014. Moreover, the average grocery tax in counties that do not exempt groceries is about 4.2%. Figure 3-3 shows a map of combined state and county level soda taxes for the year 2014.

Table 3-4 provides summary statistics by cohort for the sample used in this model. From the table, weekly county-level soda sales are considerably higher and median income is slightly higher in treatment counties relative to counties in control states. In addition, counties in the treatment group are substantially more populous than counties in the control group. Counties in the treatment states have an average population size that is about twice the population size of counties in the control states. It is not surprisingly that larger counties comprise the treatment group because they generally have a greater proportion of SNAP beneficiaries. They are also more likely to adopt policies to ease the eligibility criteria because they are more likely to have better access to administrative resources such as biometric technology and ability to accept online applications. Finally, soda taxes are somewhat similar in the two cohorts. Table 3-5 provides descriptive evidence for the influence of participation on soda sales. The third column shows the difference in average weekly county-level soda sales in the treatment and control states before and after the occurrence of the recession. While soda sales increased in both cohorts, treatment states experienced an increase of $4,483 while control states experienced an increase of $1,151. That is, stores in the treatment states experienced a change in soda sales of $3,331 higher than stores in the control states.

V. Empirical Model

The research design discussed above gives rise to the following Difference in Difference specification:

$$SodaSales_{isct} = \varphi Treat_s * Recession_t + \theta MedInc_{ct} + \rho Pop_{ct} + \tau Tax_{ct} + \mu_s + \partial_t + \varepsilon_{isct}$$

where the outcome variable represents weekly county-level sales of carbonated soda for store i located in state s and county c and observed in year t. The variable of interest is the interaction between the variables $Treat_s$ and $Recession_t$ and the coefficient φ determines the effect of treatment on sales of carbonated soda. The variable $Treat_s$ equals 1 if store i is located in a state classified as treatment state according to the willingness index and equals 0 otherwise. The variable $Recession_t$ equals 1 if store i is observed at any time period after January 1, 2008 (the presumed start of the Great Recession) and equals zero otherwise. $MedInc_{ct}$ is a measure of county-level income and Pop_{ct} measures county population for each sample year. The two variables, $MedInc_{ct}$ and Pop_{ct}, are essential for unbiased estimation of the DID model because they control for channels other than SNAP participation through which the Great Recession may influence soda sales. Finally, Tax_{ct} represents combined state and county level soda tax, μ_s and ∂_t represent state and year level fixed effects, and ε_{isct} is the error term.

VI. Results and Discussion

The estimates from the DID model are shown in Table 3-6. Columns I and II of the table contain results from the model estimated using a full sample of county-week observations. Columns III, IV, and V show results from estimation conducted on a subsample of counties with median income less than $45,533, the average for counties in the full sample. Columns I through IV include results from models that use state and year level fixed effects while the results in column V include county and year-level fixed effects.

I start with a parsimonious model (column I) that includes income and population as covariates but not soda tax. The coefficient shows no effect of SNAP participation on soda sales. Column II includes soda tax as an additional explanatory variable. The magnitude and significant of the coefficient does not change much leading to the conclusion that soda tax has little to no effect on the relationship between SNAP participation and soda sales. The main shortcoming of the first two specifications is that they consider soda sales in all counties in the country. Because treatment occurs at the state-level, the effects of the recession on each county within a state might be heterogeneous. To target counties that had the highest exposure to treatment, I restrict the sample to include only low-income counties. A county is defined as low-income if the median income in that county falls below the average median income of the full sample which is $45,533. While this is a somewhat arbitrary threshold, results are robust to different measures of low-income. Columns III, IV, and V show results from the model estimated on this restricted sample. As expected, the model in column III has a highly significant estimate of treatment on soda sales. SNAP participation leads to an increase of

$1,355 in weekly county-level soda sales in treatment counties relative to control counties. The inclusion of soda tax attenuates the estimate towards zero and inflates the standard error leading to a lower level of statistical significance as shown in column IV. Column V adds county-level fixed effects instead of the state-level fixed effects used in previous specifications. This drastically inflates the standard errors of the estimate making it insignificant at the 10% confidence level. This provides evidence that county-level unobservable factors influence the effect of SNAP on soda sales. The full results for all specifications are given in Table 3-7.

The effect of income and population is worth noting. Income invariably exerts a downward bias on the estimates because treatment is defined as states that adopted policies to expand SNAP participation. These states likely experienced greater income declines from the recession than the rest of the country. Adding county-level median income removes the confounding effect of income and increases the magnitude of φ. Population, on the other hand, has the opposite effect. Controlling for county-level population changes leads to a sharp decline in the magnitude of the coefficient. This is expected because in times of economic hardships, low-income households may migrate to states that provide more generous welfare benefits relative to their current state of residence. While mobility of low-income households is restricted, several Metropolitan Statistical Areas (MSAs) in the US span multiple states. Within-MSA interstate migration is comparably simple and economical. As a result, aggregate county-level carbonated soda may increase in treatment states simply due to a greater proportion of migrants. Excluding population as a covariate will, therefore, inflate the effect of SNAP participation on soda sales. Results show that controlling for population does have a tangible effect on the magnitude of φ which is an indication of interstate migration during recession.

While the estimated effect of $1,355 may initially seem extraordinarily high, a back-of-the-envelope calculation proves that is not the case. I use estimates of annual county-level SNAP benefits and annual state-level SNAP participation estimates from the SNAP Data System of USDA's Economic Research Service to compare changes in soda consumption to changes in SNAP benefits. The calculation is shown in Table 3-11 in section VIII. A 1% increase in weekly county-level SNAP benefits between 2008 and 2012 was accompanied by a 0.08% increase in consumption of soda over the same period. In addition, Table 3-12 presents the differences in SNAP benefits between the two cohorts post-recession relative to pre-recession. The difference between average weekly county-level SNAP benefits disbursed in the treatment and control group increased by about $144,942 in the period after the recession. The Food and Nutrition Service (FNS) of the USDA reports that SNAP households spent about 5.4% of their total food expenditure on soft-drinks and 9.3% of their food expenditure on SSBs in 2011 (Garasky *et al*., 2016). As a result, the increase in benefits is expected to increase soda sales in the treatment states relative to control states by about $7,827 (5.4% of $144,942) and total SSB consumption by about $13,480 (9.3% of $144,942). Relative to these numbers, the $1,355 estimate obtained from the DID model is modest.

As a test for robustness, I estimate the specifications included in Table 3-6 using log per capita sales of carbonated soda instead of total county sales. The results are shown in Table 3-8. The preferred specification (column III) shows that SNAP participation leads to a 0.5% increase in per capita sales in the treatment counties relative to the control counties. However, this increase is not statistically significant. Coefficients from other specifications are highly insignificant as well. These results imply that while the effect of SNAP participation is substantial on total county sales, the effect on per-capita sales is too small for statistical significance.

I conduct a formal test of the parallel trends assumption by including leads (pre-recession interactions) and lags (post-recession interactions) in the DID specification discussed above. I closely follow the methodology of Autor (2003) which is described in detail in that paper. The results are shown in Table 3-9. The first column poses total weekly county-aggregated sales of carbonated soda as the outcome variable and the second column estimates the model on per-capita weekly county-aggregated sales. The results in column 1 provide strong evidence for the validity of the parallel trends assumption. Compared to the base year 2006 interaction, the first lead variable shows an insignificant coefficient. In other words, prior to the occurrence of the Great Recession of 2008, there is no significant difference between the total soda sales of the treatment states relative to control states. However, following the start of the recession the difference becomes statistically significant, indicating a clear divergence in soda sales. This divergence persists over time but eventually dissipates. The validity of parallel trends assumption is less convincing for per capita sales. The first lead variable shows a statistical difference in the per capita soda sales between the two cohorts relative to the base year 2006. This, however, does not completely negate the research design. The coefficients on lag variables depict a clear jump in the difference between the two cohorts immediately following the occurrence of the recession. This difference widens in the following years and weakens short after. While pre-recession trends are not completely parallel in the two cohorts, the diverging trend can partially be attributed to SNAP participation. The estimates of the regression on per capita sales, therefore, are likely overstated and should be interpreted with that caveat in mind.

To remove the confounding effect of seasonal variation in carbonated soda consumption, I estimate the DID model with the inclusion of week fixed effects. This variation may also arise due to differences in monthly SNAP benefit disbursement cycles, weather patterns, sports seasons, and other unobservable factors. If these baseline differences effect states differently, not accounting for them will bias the DID estimator. Table 3-10 shows results on total and per-capita sales of the DID with the inclusion of week fixed effects. The variable of interest is statistically significant in each column and the magnitude shows a much larger impact of SNAP participation on soda consumption. This leads to the conclusion that seasonal effects introduce a downward bias on the estimates and, therefore, need to be accounted for.

A. Soda Tax

To further explore the effect of tax on the relationship between SNAP participation and soda consumption, I estimate two additional specifications of the model. The results of these specifications are shown in columns VI and VII in Table 3-7. In column VI, the DID model is estimated on a subsample of states with zero county-level grocery taxes. The sample contains stores in areas where there are no local taxes on soda and the estimates reflect the impact of state-level soda taxes only. The results show an insignificant estimate of $1,695 for the interaction term. Column VII shows results from a triple difference model that interacts the tax variable with treatment and recession indicators. The estimate of the triple interaction term shows the effect of the combined soda tax on the relationship between treatment (SNAP participation) and soda sales. In other words, it depicts that a one percentage point increase in the combined soda tax will lead to a decrease of about $92 on the effect of SNAP participation on soda sales in the treatment group relative to the control group. The sign of the coefficient is the opposite of what we would expect but the estimate is highly insignificant.

The DID estimates show that soda taxes play little to no role in the relationship between SNAP participation and soda sales. Two major factors might explain this result. First, literature has shown sales taxes (taxes applied at the cash register) are not as salient as other types of taxes such as excise taxes (Chetty *et al.*, 2009; Zheng *et al*., 2013; Chen *et al*., 2015). As a result, even when consumers receive a sales tax exemption through SNAP, their demand for soda does not change by a significant amount. Second, the combined sales tax causes only a marginal change in the price of soda. There is substantial county-level variation in the tax, however, most counties and states do not impose a "disfavored" tax on soda. That is, soda is generally subject to the same amount of sales tax as other items (food or non-food) and no soda-specific tax is imposed. Consequently, SNAP participation may not generate a large enough price trade-off to have a tangible effect on consumption. As a result, the tax exemption only partially explains the increase in soda sales for the treatment group and the impact of SNAP participation on soda sales can be attributed to positive income shock from benefits. The effect of income is particularly strong, especially when low-income counties are considered as shown in columns III and IV in Table 3-7.

An important implication of this result is that policy-makers cannot rely on soda taxes to discourage consumption by low-income households. Since soda sales are relatively unresponsive to sales taxes, eliminating the tax exemption will have only a minor effect. Other policy interventions such as removing carbonated soda from the list of SNAP-eligible items may be more effective in encouraging households to make healthy eating choices. More work is required to determine the extent to which the SNAP restriction inhibits purchases of certain food items and how the removal of this restriction may influence sales of carbonated soda. However, this study provides initial insights into the efficacy of different policies to combat excessive consumption of SSBs by low-income households.

VII. Conclusion

I estimate a Difference In Difference model to determine the impact of SNAP participation on consumption of carbonated soda employing store-level data from Nielsen RetailScan. I create a willingness index based on state-level adoption of policies to ease the SNAP eligibility criteria in the wake of the Great Recession of 2008. Stores are assigned to the treatment group if they reside in states that were high on the willingness index and to the control group if they reside in states lower on the willingness index. I use the occurrence of the Great Recession of 2008 as a natural experiment to identify the effect of treatment on sales of carbonated soda. The results show that SNAP participation increases weekly county-level soda consumption by about $1,355 in low-income counties but exhibits no statistically significant effect in high-income counties. State and local soda taxes elicit a very small effect on the relationship between SNAP and soda consumption. Therefore, the majority of the increase can be attributed to positive income shock from the SNAP in-kind transfer.

Note: “Calculated (or Derived) based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.”

VIII. Tables

Table 3-1. State-Level Policy Option Descriptions

Policy	**Description**
BBCE	The State uses broad-based categorical eligibility to increase or eliminate the asset test and/or to increase the gross income limit for virtually all SNAP applicants.
Call Centers	The State operates call centers, and whether or not call centers service the entire State or select regions within the State.
Combined Application Project	The State operates a Combined Application Project for recipients of Supplemental Security Income (SSI), so that SSI recipients are able to use a streamlined SNAP application process.
Short Recertification Period	The proportion of SNAP units with earnings with 1-3 month recertification periods.
DQ for Noncompliance	The State disqualifies SNAP applicants or recipients who fail to perform actions required by other means-tested programs, primarily Temporary Assistance for Needy Families (TANF).
Initial Telephone Interview	The State has been granted a waiver to use a telephone interview in lieu of a face-to-face interview at initial certification, without having to document household hardship.
Fingerprint Requirement	The State requires fingerprinting of SNAP applicants.
Noncitizen Adult Eligibility	All legal noncitizen adults (age 18-64) who satisfy other SNAP eligibility requirements are eligible for Federal SNAP benefits or State-funded food assistance.
Online Application	The State allows households to submit a SNAP application online.
Outreach Spending	The sum of Federal, State, and grant outreach spending in nominal dollars ($1,000s).
Simplified Reporting	For households with earnings, the State uses the simplified reporting option that reduces requirements for reporting changes in household circumstances.
Vehicle Exclusion	The State excludes all vehicles in the household from the SNAP asset test.

Source: Economic Research Service (ERS), U.S. Department of Agriculture (USDA). SNAP Policy Database, 2013

Table 3-2(a). Factor Analysis on State-Policy Options: Correlations

	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.65	0.58	0.53	0.53
Factor2	1.07	0.46	0.34	0.87
Factor3	0.61	0.16	0.19	1.06
Factor4	0.45	0.05	0.14	1.21
Factor5	0.40	0.13	0.13	1.33
Factor6	0.27	0.38	0.09	1.42
Factor7	-0.11	0.04	-0.04	1.38
Factor8	-0.15	0.06	-0.05	1.34
Factor9	-0.21	0.04	-0.07	1.27
Factor10	-0.25	0.03	-0.08	1.19
Factor11	-0.28	0.03	-0.09	1.10
Factor12	-0.31	.	-0.10	1.00

Table 3-2(b). Factor Analysis on State-Policy Options: Factor Loadings

	Factor1	Factor2	Uniqueness
BBCE	0.50	0.21	0.71
Call Centers	0.44	-0.24	0.75
Combined Application Project	0.36	0.07	0.87
Short Recertification Period	-0.37	0.38	0.72
DQ for Noncompliance	-0.13	0.25	0.92
Initial Telephone Interview	0.18	-0.20	0.92
Fingerprinting Requirement	0.35	0.39	0.72
Noncitizen Adult Eligibility	0.27	0.22	0.88
Online Application	0.50	-0.15	0.73
Outreach Spending	0.53	0.39	0.57
Simplified Reporting	0.25	-0.58	0.60
Vehicle Exclusion	0.33	0.01	0.89

Table 3-3. SNAP Participation Growth and Carbonated Soda Sales by Cohort, 2008 to 2012

Treatment States	SNAP Participation	Soda Sales	Control States	SNAP Participation	Soda Sales
Washington	91%	4%	Wyoming	52%	16%
New York	58%	7%	South Dakota	65%	28%
Texas	59%	2%	Oklahoma	47%	36%
Wisconsin	98%	34%	Idaho	133%	5%
California	79%	-9%	New Hampshire	84%	7%
Pennsylvania	51%	4%	Arkansas	33%	19%
Massachusetts	70%	7%	New Mexico	83%	16%
Arizona	79%	-10%	North Carolina	76%	3%
Tennessee	45%	8%	Alabama	59%	6%
Maryland	99%	-3%	Missouri	35%	23%
Florida	130%	-1%	Montana	57%	6%
Oregon	74%	4%	Colorado	94%	8%
Delaware	99%	-1%	Nevada	146%	-6%
South Carolina	47%	8%	Vermont	73%	5%
West Virginia	25%	23%	Kentucky	34%	20%
Virginia	68%	4%	Minnesota	83%	-1%
Indiana	46%	9%	Mississippi	48%	10%
Georgia	87%	11%	Nebraska	46%	17%
Connecticut	79%	13%	Louisiana	20%	-6%
Utah	106%	21%	Illinois	44%	-8%
Michigan	46%	11%	New Jersey	89%	1%
Iowa	58%	9%	Kansas	62%	17%
Maine	46%	6%	District of Columbia	58%	18%
Ohio	57%	14%	Rhode Island	104%	1%
			North Dakota	21%	50%

Source: SNAP Participation Rates obtained from Economic Research Service (ERS), U.S. Department of Agriculture (USDA). Supplemental Nutrition Assistance Program (SNAP) Data System. Soda sales calculated based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

Table 3-4. Summary Statistics by Cohort

	Treatment	Control
Weekly Soda Sales	$50,005	$27,518
Median Income	$46,022	$43,595
Population	152,975	78,727
Mean Soda Tax	4.2%	3.9%
Mean Soda Tax if Positive	5.4%	5.0%

Table 3-5. Change in Average Weekly County-Level Soda Sales by Cohort

	Pre-recession	Post-recession	Difference
Treatment	$46,399	$50,881	$4,483
Control	$26,581	$27,732	$1,151
Difference	$19,818	$23,149	$3,331

Table 3-6. Difference-In-Difference Estimates on Weekly Carbonated Soda Sales

	(I)	(II)	(III)	(IV)	(V)
Treatment*Recession ($)	1668	1599	1355***	1133*	1837
	(1132)	(1141.74)	(491)	(676)	(2421)
Income	Yes	Yes	Yes	Yes	Yes
Population	Yes	Yes	Yes	Yes	Yes
Tax	No	Yes	No	Yes	Yes
Observations	1,167,492	1,167,296	699,201	699,005	699,005

* p<0.10, ** p<0.05, *** p<0.01

Note 1: Standard errors for all specifications are multi-way clustered by state and year

Note 2: Specifications in columns (I) through (IV) include state and year fixed effects while column (V) includes county and year fixed effects.

Table 3-7. Difference-In-Difference Estimates on Weekly Carbonated Soda Sales (Full)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Treat*Recession ($)	1668	1599	1355***	1133*	1837	1695	2150
	(1132)	(1141.74)	(491)	(676)	(2421)	(1404)	(2141)
Median Household Income	0.362**	0.362**	0.891***	0.890***	0.507**	0.237	0.202
	(0.15)	(0.15)	(0.3)	(0.29)	(0.2)	(0.188)	(0.171)
Population	0.337***	0.337***	0.242***	0.242***	0.244***	0.322***	0.334***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.05)	(0.021)	(0.023)
Tax	-	626	-	1626	-216	-1174	836
	-	(780)	-	(1070)	(475)	(1179)	(723)
Treat*Soda Tax	-	-	-	-	-	-	395
	-	-	-	-	-	-	(1301)
Tax*Recession	-	-	-	-	-	-	31.2
	-	-	-	-	-	-	(229)
Treat*Tax* Recession	-	-	-	-	-	-	-92
	-	-	-	-	-	-	(430)
	-	-	-	-	-		
Constant	27122***	29689***	34590***	41345***	11365**	-4809	-5489
	(4098)	(5403)	(8479)	(10094)	(5043)	(7912)	(6479)
Observations	1,167,492	1,167,296	699,201	699,005	699,005	730,708	1,167,296

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Note 1: Standard errors for all specifications are multi-way clustered by state and year

Note 2: All specifications include state and year fixed effects with the exception of column (V) which includes county and year fixed effects

Table 3-8. Difference-In-Difference Estimates on Log Per-Capita Sales of Carbonated Soda

	(I)	(II)	(III)	(IV)	(V)
Treat*Recession	0.011	0.011	0.005	0.005	-0.077
	(0.07)	(0.06)	(0.07)	(0.07)	(0.17)
Median Household Income	0.018***	0.018***	0.021***	0.021***	0.015***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Tax	-	0.001	-	0.007	-0.047
	-	(0.02)	-	(0.03)	(0.02)
Constant	3.423***	3.414***	3.209***	3.131***	4.888***
	(0.13)	(0.29)	(0.23)	(0.38)	(0.34)
Observations	1,167,492	1,167,296	699,201	699,005	699,005

* p<0.10, ** p<0.05, *** p<0.01

Note 1: Standard errors for all specifications are multi-way clustered by state and year

Note 2: All specifications include state and year fixed effects with the exception of column (V) which includes county and year fixed effects

Table 3-9. Difference-In-Difference Model on Weekly Carbonated Soda Sales with Leads and Lags (Base Level: 2006)

	Total Sales	**Per-Capita Sales**
2007*Treat	1106	14.53**
	(1013)	(7.29)
2008*Treat	1909*	21.79***
	(1129)	(7.04)
2009*Treat	2233**	25.87***
	(1123)	(8.33)
2010*Treat	1764**	28.46***
	(784)	(8.77)
2011*Treat	2111***	20.99**
	(622)	(8.18)
2012*Treat	1589**	14.24**
	(668)	(6.76)
2013*Treat	886	8.564
	(837)	(8.40)
Median Household Income	0.394**	0.244***
	(161)	(0.68)
Population	0.337***	-
	(20)	-
Tax	1709	1.50
	(1088)	(5.32)
Constant	-46738***	1.70
	(12176)	(60.52)
Observations	1,167,492	1,167,492

* p<0.10, ** p<0.05, *** p<0.01

Note 1: Standard errors for all specifications are multi-way clustered by state and year

Note 2: All specifications include state and year fixed effects

Table 3-10. Difference-In-Difference Estimates on Weekly Carbonated Soda Sales with Week Fixed Effects

	Total Sales	Per-Capita Sales
Treat*Recession	3613**	0.271***
	(1611)	(0.07)
Median Household Income	0.393**	0.018***
	(161)	(0.00)
Population	0.337***	-
	-0.02	-
Tax	1638	0.002
	(1112)	(0.03)
Constant	-42479***	3.7***
	(12087)	(0.36)
Observations	1,167,492	1,167,296

* p<0.10, ** p<0.05, *** p<0.01

Note 1: Standard errors for all specifications are multi-way clustered by state and year

Note 2: All specifications include state and week fixed effects

Table 3-11. Average Weekly County-Level Change in Carbonated Soda Sales Relative to SNAP Benefits

	Pre-recession	Post-recession	Difference	Percentage Change
SNAP benefits	$187,558	$347,145	$159,587	85.1%
Soda sales	$38,054	$40,779	$2,726	7.16%
Percentage change in soda sales relative to 1% increase in SNAP benefits				0.08%

Note: SNAP benefit data is obtained from the SNAP Data System of the Economic Research Service, USDA. Soda sales are estimated from Neilsen RetailScan Dataset.

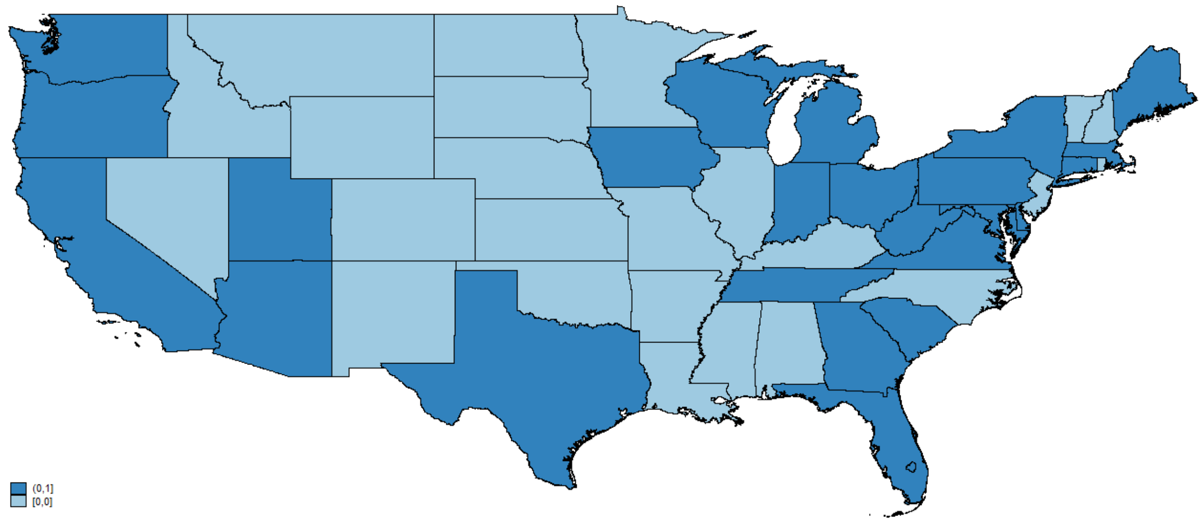
Table 3-12. Change in Average Weekly County-Level SNAP Benefits by Cohort

	Pre-recession	Post-recession	Difference
Treatment	$253,285	$482,896	$229,610
Control	$116,960	$201,629	$84,668
Difference	$136,325	$281,267	$144,942

Note: All estimates are obtained from the SNAP Data System of the Economic Research Service, USDA

IX. Figures

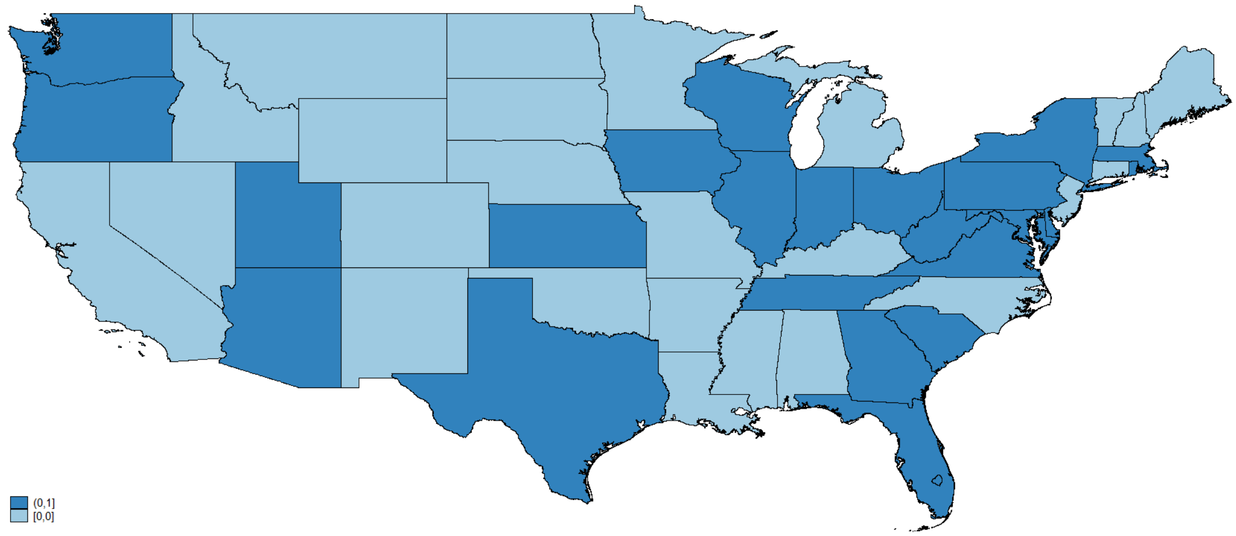
Figure 3-1: Treatment and Control States by Index of Willingness, 2008, Factor 1 only



Note: Dark-colored states are more willing (treatment) states and light-colored states are less willing (control) states.

Source: Economic Research Service (ERS), U.S. Department of Agriculture (USDA). SNAP Policy Database, 2013

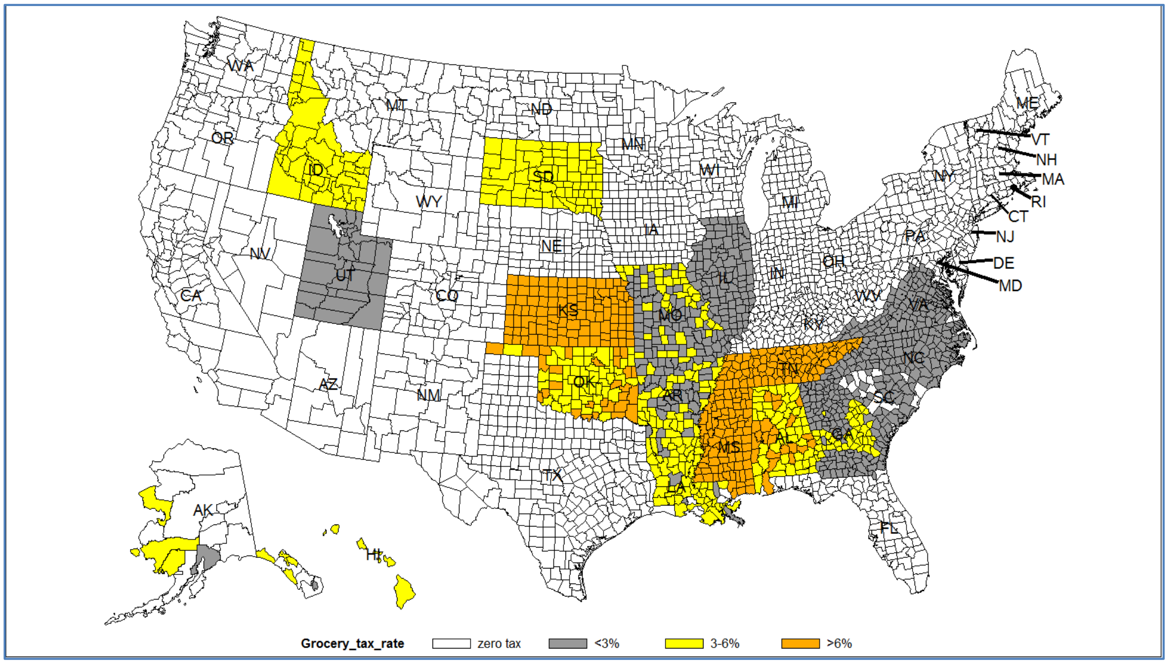
Figure 3-2: Treatment and Control States by Index of Willingness, 2008, Using Factor 1 and Factor 2



Note: Dark-colored states are more willing (treatment) states and light-colored states are less willing (control) states.

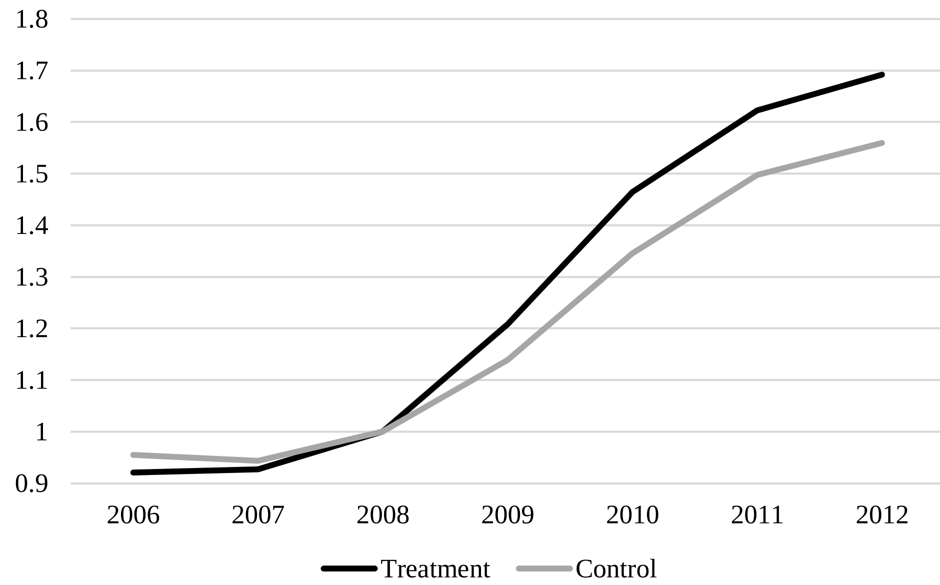
Source: Economic Research Service (ERS), U.S. Department of Agriculture (USDA). SNAP Policy Database, 2013

Figure 3-3: Combined State and Local Grocery Tax by County, 2014



Sources: tax-rates.org, www.sale-tax.com, and state and local departments of taxation.

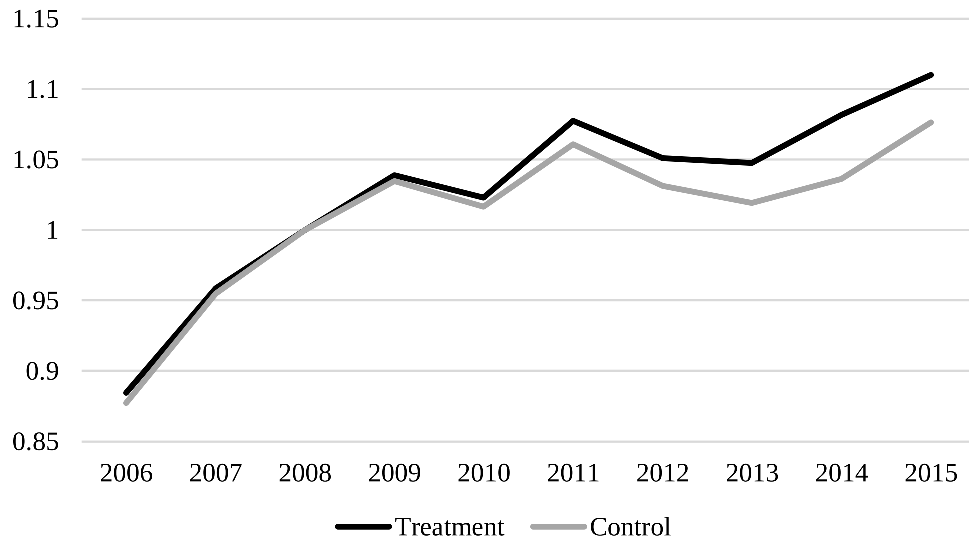
Figure 3-4: SNAP Participation by Cohort Indexed to 2008, 2006 to 2012



Note: A complete list of states in the treatment and control group is given in Table 1.

Source: Economic Research Service (ERS), U.S. Department of Agriculture (USDA). Supplemental Nutrition Assistance Program (SNAP) Data System

Figure 3-5: Weekly Carbonated Soda Sales by Cohort Indexed to 2008, 2006 to 2015



Note: A complete list of states in the treatment and control group is given in Table 3-3. Source: Calculated based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

CHAPTER 4: HABIT FORMATION IN US DEMAND FOR DIETARY FAT

I estimate habit formation to dietary fat in two categories of common food products: ground meat and milk. Each product in the category shows fat content on the front packaging which alleviates the issue of nutrient misinformation at the grocery store shelf. This allows for comparison to be made across products with different fat contents. I construct a dynamic AIDS model using scanner-generated purchases during the period 2004 to 2014 obtained from Nielsen Consumer Panel Dataset. Results show strong habit formation to all products in the two categories. However, there is only sparse evidence of a positive association between habit formation and dietary fat for ground meat products and no evidence for fluid milk products. This leads to the conclusion that dietary fat, as a nutrient, does not exhibit significant habit formation even though products containing dietary fat might be habitual. Habit formation parameters coupled with elasticity estimates provide support for a tax on saturated fat as a possible obesity-targeting policy intervention.

I. Introduction

Obesity has reached epidemic proportions in the US. Statistics from the National Health and Nutrition Examination Survey (NHANES) show that between 2009 and 2010, more than 1 in 3 adults are considered to be obese. The prevalence of childhood obesity is especially alarming as more than 1 in 6 children and adolescents aged 6 to 19 are considered obese (National Institute of Health, 2012). A wide range of detrimental health outcomes is associated with obesity including diabetes, cardiovascular diseases, and cancer. In addition, children are considered especially vulnerable to health issues arising from obesity because it not only leads to abnormalities such as earlier puberty, type 2 diabetes, and metabolic syndrome (Biro and Wien, 2010) but also leads to greater likelihood of obesity as an adult (Serdula *et al.*, 1993).

While numerous explanations and policy recommendations have been offered for such a high rate of obesity in the country, there are only few factors that have consensus among researchers. Traditionally, obesity has been attributed to lack of access to healthy food, cognitive disposition, food acquisition cycles, etc. However, in recent years economists have started to consider the time-dependence of energy-dense nutrients, such as sugar and saturated fat, as a possible explanation. If unhealthy nutrients have addictive properties then households might not alter consumption patterns despite interventions such as participation in SNAP. Becker and Murphy (1988) have developed a theory of "rational addiction" which predicts that households may choose to consume habit forming goods even with full knowledge of their addictive properties because this consumption pattern maximizes their discounted utility.

The purpose of this study is to determine whether households form a habit of consuming dietary fat. Dietary fat is fat obtained from food consumption as opposed to fat naturally produced in the human body to aid in normal bodily functions. While dietary fat is an important nutrient, there is considerable evidence to show that excess consumption is a significant contributor to obesity (Bray and Popkin, 1998; Golay and Bobbioni, 1997; Astrup, 2005, Bray *et al*., 2004). This is not surprising because fat is the most energy-dense nutrient found in food (9 calories per gram compared to 4 calories per gram in carbohydrates and protein). In addition, food products contain multiple types of fat (for example, saturated, polyunsaturated, and monounsaturated) with varying thresholds for overconsumption, which makes it difficult for consumers to distinguish harmful calories from nutritious ones.

In an effort to combat obesity, in recent years policymakers have begun to explore ways to curb fat consumption. A policy quickly gaining traction is the imposition of a Pigouvian tax on fatty foods akin to a tax on tobacco, alcohol, and sugar. In October 2011, Denmark became the first country in the world to pass a “fat tax”, which was levied on food items exceeding 2.3% saturated fat content. Although the tax was rescinded shortly afterwards, it galvanized substantial interest into whether it can be a valid policy intervention in the US. Although there is no history of a fat tax in the US, other Pigouvian taxes like a tobacco tax have shown remarkable results.

I consider two categories of grocery products that are widely used in American households; fresh ground meat and milk. Products in both categories are differentiated by level of fat content specified directly on the package and therefore households are aware of the nutritional properties of their purchase. For example, ground beef may be labeled as “80% lean, 20% fat” while milk products may contain one percent or two percent fat. This study empirically tests the hypothesis that households that consistently purchase products with high fat content develop a habit which has a non-trivial effect on future household utility derived from that product. I construct a dynamic Almost Ideal Demand System (AIDS) model to estimate the magnitude of habit formation to each product in the fresh ground meat and milk categories. The relevance of the hypothesis is that if the strength of habit formation is positively associated with fat content then price shocks will do little to sway household expenditure towards healthier options. Results show strong habit formation to all products in the two categories. In addition, results show some evidence of a positive link between habit formation parameters and fat content in the ground meat category but no discernible relationship in the milk category. Habit formation parameters coupled with elasticity estimates provide support for a tax on saturated fat as a possible obesity-targeting policy intervention.

The rest of this paper is organized as follows. Section II provides a review of literature in this area. Section III develops the conceptual dynamic AIDS model used to test the above hypothesis. Section IV outlines the empirical framework. Section V describes the dataset used and provides summary statistics. Section VI reports results from empirical estimation. Section VII discusses policy relevance and possible areas of improvement for future research. Section VIII concludes and is followed by a group of tables in section IX.

II. Literature Review

Habit formation has been extensively studied in literature on multiple categories of goods, including food (Carrasco *et al.*, 2005; Heien and Durham, 1991; Dynan, 2000; Khare and Inman, 2006), transportation (Carrasco *et al.*, 2005; Heien and Durham, 1991), services (Carrasco *et al.*, 2005), alcohol, tobacco, and clothing (Heien and Durham, 1991). The most common method of estimating habit formation is to exploit time-series variation in large datasets to observe the dependence of current consumption on consumption in previous periods. However, a few researchers such as Bruijn *et al.* (2008) and Heien and Durham (1991) have utilized cross-sectional datasets to estimate the magnitude of habit formation as well. Heien and Durham (1991) find that cross-sectional estimates tend to be much smaller, albeit highly significant, relative to time-series estimates.

Habit formation to products in the food category has been the focus of many previous studies but only a handful are directed at meat and milk products. Among literature that looks into habit forming properties of milk, Briz et al. (1998) employ the Prais-Houthakker demand model to show that milk consumption in Spain is heavily influenced by habit persistence. Zhen et al. (2011) use a dynamic AIDS model on a group of beverages such as milk, Sugar-Sweetened Beverages (SSBs), bottled water, and coffee and find that low-fat milk is the most habit-forming beverage. Whole milk also exhibits a high degree of habit formation in their analysis and ranks among the top three most habitual beverages. Similar studies can be found on the habit-formation properties of meat. For example, Capps (1989) use data from a Houston retail food firm to show that habits are evident in the consumption of steak, chicken, pork chops, ham, and pork loin.

Supplementing this strand of literature is a small collection of studies that examine the addictive properties of dietary fat. A recent study by Bruijn *et al.* (2008) depicts that saturated fat is associated with habit formation. The main shortcoming of this paper, however, is that it relies on cross-sectional data and therefore largely ignores the possible confounding influence of household preferences over time. Furthermore, fat content is self-reported by participants, which might lead to bias. Richards et al. (2007) consider the consumption of snack foods to determine rational addiction to macronutrients. Their results show strong habit formation to fat. However, the study is conducted on a sample of only 30 households and is not generalizable. Therefore, there is a clear lack of comprehensive evidence of habit formation to dietary fat in literature.

The results of this study shed some light on the potential success of a fat tax. Some research has been devoted to the efficacy of a tax on saturated fat but it is largely constricted by lack of data due to sparse adoption of the policy. Smed et al. (2007) analyze the potential of targeted price change and show that it is effective in reducing demand for saturated fat among individuals in “lower social classes” (p. 627) and among young individuals in Denmark. Chouinard et al. (2007) simulate the effects of a fat tax on demand for dairy products and find that the short run effect of a 10% fat tax would reduce fat consumption by less than 1%. This area of literature is largely inconclusive in determining the magnitude of a tax on fat consumption. Neither of the two studies mentioned take habit formation into account.

To the best of my knowledge, this study is the first to measure habit formation for dietary fat in fresh meat and milk products using household-level panel data. It will add to existing literature by enhancing our understanding of the addictive properties of dietary fat. While other studies have provided elasticity estimates for products analyzed in this paper, they largely ignore the influence of habit formation on household responsiveness to price changes. Moreover, I estimate demand over an 11 year period while other studies generally consider shorter periods of time. Hence, I provide a more complete picture of the link between habit formation and dietary fat. Finally, this study provides more granular estimates because it groups products into more specific categories relative to other studies (for example, ground meat versus all meat products).

III. Conceptual Model

I closely follow the conceptual framework of the dynamic AIDS model laid out in Zhen et al. (2011) and apply it to fresh ground meat products and milk purchased in grocery stores. For the sake of simplicity, I depart from Zhen et al.'s (2011) approach by excluding the durability parameter. Durability refers to the idea that purchases in current period have a positive influence on future utility. Even though perishable items such as fresh ground meat and milk are not considered durable, Zhen et al. argue that they could still exhibit nonzero durability by reflecting both the physical trait as well as consumer preference of the product (2011, p. 178). In other words, despite physical depletion the perishable item may exert an influence on future consumption by altering current household preference. However, I defer to the argument put forth by Muellbauer and Pashardes (1992) that the habit formation parameter is capable of capturing both habit formation and durability. Foregoing the inclusion of durability lends substantial computational simplicity to the dynamic AIDS and allows for a more straightforward interpretation of the habit formation parameters.

A two-stage process is modeled for the representative consumer who allots total income between a product category (ground meat and milk) and the numeraire good (all other goods) in the first stage, and chooses between different products in each category in the second stage. Assuming a myopic consumer (one who ignores the effects of current purchases on future utility), Zhen et al.'s (2011) demand system is given by:

(1) $q_{it} = \left\{a_i + \sum_{j=1}^{J} \gamma_{ij} \mathrm{ln} p_{jt} + \beta_i [ln\bar{x} - \mathrm{ln}a(p_t)]\right\} \left(\frac{\bar{x}_t}{p_{it}}\right) + \varphi_i Z_{it-1} - d_i Z_{it-1}$

(2) $ln\overline{x_t} = a_m + \beta_m \ln(hhinc_t) + \gamma_m lna(p_t)$

(3) $lna(p_t) = a_0 + \sum_{i=1}^{n} a_i lnp_{it} + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} lnp_{it} lnp_{jt}$

(4) $a_i = a_{i0} + X_{it} + R_{mt} + Q_t$

where q_{it} represents expenditure on product i at time t, p_{jt} is a vector of all prices in the product group, Z_i is the service provided by the flow of good in period t, group expenditure is given by $\bar{x} = \sum_{i=1}^{n} p_{it} Z_{it}^{*}$, and $\mathrm{ln}a(p_t)$ is the price index of the product groups shown in equation (3). In equation (4) the parameter a_i is augmented into household-level demographic variables X_i, binary variables each for Nielsen market R_{mt}, and quarters Q_t in the year. The coefficients φ_i and d_i capture habit formation and durability respectively. Theoretically, φ_i is expected to have a negative sign because habit formation is meant to decrease current utility as consumers get conditioned to a stock of utility from past consumption. Conversely, d_i is expected to be positive because durability will increase current utility as the service flow from previous periods will carry over to the current period. As mentioned above I do not incorporate durability in the AIDS model and therefore estimate the equation without the component $d_i Z_{it-1}$.

Equation (2) represents the first-stage decision of the household to allocate expenditure to the product group relative to the numeraire good. The first-stage budget allocation is a function of $hhinc_t$, which represents per capita household income, and the price index of all products in the group, $lna(p_t)$. For a full discussion and derivation of the dynamic AIDS model refer to Zhen et al. (2011).

IV. Empirical Model

Each major product within the ground meat and fluid milk category is included in the AIDS model. Product types in the ground meat category include beef, turkey, chicken, and pork. Beef and turkey products are classified by fat content using a threshold of 20% fat. For example, ground beef is characterized as high fat beef if the product is specified as having 25% fat or being 75% lean. Chicken and pork are combined to create one product type due to limited purchases of both. The chicken/pork product type is not classified by high or low fat since neither category exhibits sufficient variation in fat content. The milk category includes products classified by 1% fat, 0.5% fat, 1.5% fat, 2% fat, whole milk, and fat free milk. Whole milk contains approximately 3.25% fat and is therefore the highest fat product in this category. Fat-free milk can contain up to 0.5% fat. For the sake of simplicity and because 1.5% and 0.5% fat products represent a negligible share of total milk expenditure, I combine these two products with 1% fat product type. These classifications result in five product types in the ground meat category and four product types in the milk category. The AIDS model is estimated separately for each of the two categories.

The biggest challenge to estimating dynamic AIDS is addressing the issue of zero purchases. That is, within a market, year, and month, the total expenditure for a product in the ground milk or meat category may be zero. This may be an indication of sequential decision-making such that the household must decide whether to purchase the product first, followed by the decision of how much to purchase. Since there may be unobserved factors that influence the household's first decision, the model may suffer from selection bias if zero purchases are left unaddressed. I follow Zhen et al.'s (2011) synthetic household approach by averaging monthly purchases to create a representative household within each market-year. In other words, a synthetic household represents all households in a particular market in a particular year. Zhen et al. (2011) include poverty status as factor to group individual households into a synthetic household. However, for the categories of products considered in this study, a higher level of aggregation is required to eliminate zero purchases. The resulting data includes 836 synthetic households in the ground meat sample and 1,672 synthetic households in the milk sample.

The Fisher price index is used to determine prices for products in each category. Prices and quantities are averaged over market, brand, poverty status, and month. In other words, prices for each brand in a month faced by a synthetic household of a certain poverty status are averaged to create the Fisher price index. Poverty status is used to capture the possibility that low-income households typically shop in different market sub-sections relative to high-income households. The Fisher price index is a transformation of the Laspeyres price index and the Paasche price index and is calculated by comparing average market-brand-month-poverty status prices with national averages. Missing prices are inferred by prediction using coefficients estimated from the regression of product price on year, month, market, and brand.

To simplify estimation, I reduce brand parameters by condensing brands with small market shares into a category-specific composite brand. The composite brand includes all brands with less than 1% market share in their respective category. All major brands are included separately. Demographics include dummy variables for each Nielsen market, household size, race, income, gender of household head, and quarter in which the household is observed. These variables are averaged over all households represented by the synthetic household to assign continuous measures of each demographic.

V. Data

Two samples are generated from data obtained from Nielsen's Consumer Panel survey. Nielsen provides a large nationally representative scanner panel dataset of household level purchases for 40,000 to 60,000 households per year dispersed across the country. A tremendous amount of detail is available for each purchase including the date of the shopping trip, store location, average weekly prices, quantities purchased, etc. Household demographics include income, composition, presence of children, gender and employment status of the household head, race of the household head, and geography at the three digit zip-code level. Nielsen samples households across 52 major markets that cover most of the country.

The dataset covers a range of different food and non-food products, each characterized by a unique Universal Product Code (UPC). Product attributes include brand, size of package, promotional status, and additional characteristics for some products such as flavor and nutritional value. Products in the ground meat and milk category include full information on fat content for each UPC. I use all purchases available in the Nielsen Consumer Panel dataset during the years 2004 to 2014. This results in a sample of 10,024 monthly purchases in the ground meat category and a sample of 19,972 monthly purchases in the milk category at the synthetic household level.

Table 4-1 shows average monthly synthetic household-level expenditure and quantity of purchases in the two categories. The first two columns depict values for full samples of each category. The next two depict values for lower income households that have income less than the median income ($56,650) of the full sample. The first panel of the table shows that lower-income households have a stronger preference for chicken and pork in the ground meat category and a weaker preference for both types of turkey products. Comparison for milk products is given in the second panel. On average, low income households consume less of all types of milk.

Tables 4-2(a) and 4-2(b) show summary statistics for variables in each category. In the ground meat sample (table 4-2(a)), the two ground beef products have the highest share of total category expenditure per month, followed by low-fat turkey. High fat turkey and chicken & pork products constitute a very small proportion of monthly expenditure. On average, synthetic households spend an aggregate of $586 on the five ground meat categories included in this model per month. Average household size is 2.57 individuals, the sample includes about 10% of households that are black, mean annual income per synthetic household is just under $58,000, and about 78% of households have male heads. Table 4-2(b) shows summary statistics for variables in the milk category.

Among milk products, the largest budget share is attributed to 2% fat milk, followed by whole milk and fat-free milk. Monthly expenditure per synthetic household on the milk category is considerably higher than that of the ground meat category. Annual household income for the milk sample is approximately $43,000 per annum which represents a non-trivial difference from the ground meat sample. This is not surprising given that milk is a more common household food and the category is more broadly defined (including almost all milk products) relative to meat. In addition, milk is generally available to households of all income strata and is a more affordable source of nutrition relative to ground meat.

VI. Results

The habit formation parameters for each product category estimated from the dynamic AIDS model are shown in Table 4-3. The first panel of the table shows results for all five products in the ground meat category and the second panel shows results for the four products included in the milk category. Each product exhibits strong habit formation as given by the significance level of the estimates.

The results show there is a clear positive association between dietary fat content and strength of habit formation, although the effect is invariably small. For the ground meat category, there is little variation in habit formation across products. As expected, among ground beef and ground turkey products, high fat products are slightly more habit forming than low fat products. The combined product “chicken & pork” shows the weakest level of habit persistence. This is also expected because the product is likely the least fat content product relative to others in the category. Ground chicken is generally the leanest type of meat. Recall that chicken and pork products were grouped together to represent one product due to lack of sufficient observations for each individual product. However, the combined product reflects substantially greater number of purchases of chicken products than pork products. Therefore, the habit formation parameter for this product is likely driven by ground chicken rather than ground pork. While the habit formation parameters in this category are positively correlated with fat content, high fat products are only marginally more habit forming than low fat products.

With the exception of fat-free milk, milk products generally exhibit a positive relationship between fat content and level of habit formation as well. Whole milk has a higher degree of habit formation relative to 2% milk, which has a higher degree of habit formation relative to 1% milk. The lowest fat content product (fat-free milk) unexpectedly has a larger habit formation parameter relative to 1% and 2% milk. However, the parameters for all other milk products are consistent with expectations and provide strong evidence for the habit forming properties of saturated fat. In addition, there is little variation in habit formation parameters between products which indicates that fat content has only a modest impact on habit formation.

Table 4-4 shows long run unconditional own-price and cross-price elasticities. For the ground meat category, all own-price elasticities are negative and statistically significant. Ground chicken and pork demand seems to be the most sensitive and ground low-fat turkey demand is the least sensitive to own-price effects. The magnitude of the elasticities is consistent with the results of Capps (1989) who estimated own-price elasticities for several beef, chicken, and pork products (including ground meat) in the range of -0.6557 and -1.2737. Furthermore, ground beef products and ground chicken and pork products consistently show negative cross-price elasticity indicating complementarity with other products. High-fat ground turkey, on the other hand, is largely considered a substitute for other products in the category.

In the same vein, all own-price elasticities of milk products are negative and all are statistically significant with the exception of fat-free milk. The estimates for these products are much less elastic relative to -1.59 for whole milk and -2.17 for low-fat milk obtained by Zhen et al. (2011). A possible explanation for this discrepancy might be that Zhen et al. (2011) aggregate all fluid milk products into two products while I estimate elasticities for four different milk products. Among cross-price elasticities, almost all that are statistically significant are negative. This is, again, an indication that milk products within the category are generally complementary to each other.

VII. Discussion

The results show that while ground meat and milk products are very habitual, high fat products are only slightly more habit forming than lower fat products. In the milk category, not only are habit formation parameters much smaller, the coefficient on fat-free milk is inconsistent with expectations. This might be due to a number of reasons. First, there is substantially greater variation in the fat content level of ground meat products. Recall, products were labeled as “high fat” if they contained 20% fat or greater. Fat content in ground meat products ranges from 1% (99% lean) to 40% (60% lean). The broad range in ground meat products provides a clear distinction between what consumers may consider high fat versus low fat. For products in the milk category, however, the fat content range is relatively narrow. The highest fat product (whole milk) contains only 3.25% fat while the lowest fat product (fat-free milk) can contain up to 0.5% fat. Due to the lack of variation in fat content in milk, the habit forming properties of fat may not be fully realized. Second, fat-free milk might be considered a specialty product that may appeal to unobservable traits of consumers. If these traits influence demand for fat-free milk differently relative to other products in the category, the habit formation parameter will be biased. Overall, due to such small magnitude of coefficients habit formation is likely insufficient to drastically influence demand for dietary fat.

This result has immense policy implications. Because the influence of habit on consumption behavior is small, household demand is likely more responsive to a targeted tax on saturated fat. In addition, certain products such as high fat turkey are substitutable with lower fat products such as chicken and pork and low fat turkey. In these cases, a tax on saturated fat might have the intended consequence of shifting household consumption to lower fat products. However, tax policy should be designed with the consideration that other high-fat products (for example, ground beef) are complementary to low-fat products. In such cases, price increases might fail to achieve the desired consumption shift because consumers will forego purchases of low-fat products as well. Additional work is required in this area to determine the potential efficacy of a fat tax in the US. However, the results of this model lend credence to the fat tax as a viable policy option.

Some shortcomings of the analysis are worth mentioning. First, to circumvent the problem of zero purchases I use a synthetic household approach. This led to the aggregation of purchases for each market-year and this censoring might have led to substantial loss of information. Second, due to lack of observations and variation in fat content, chicken and pork in the ground meat category were amalgamated into one product. This inhibits the measurement of each individual product's habit formation parameter and elasticities which may have proven useful for the analysis. Third, for the sake of computational simplicity I chose not to model durability in the dynamic AIDS model. Literature provides sufficient support for this decision. However, there is an argument that durability might exist for food products. Therefore, future studies may provide more insight by estimating the durability parameter in a demand system.

VIII. Conclusion

I estimate a dynamic AIDS model to estimate habit formation to dietary fat. I consider two categories of products that explicitly state fat content information on the label thus eliminating any prospect for misinformation in nutritional value. The ground meat category includes high fat beef, low fat beef, high fat turkey, low fat turkey, and chicken and pork products. Products are characterized high fat if they contain at least 20% fat. The milk category includes fat-free, 1% fat, 2% fat, and whole milk products. The dynamic AIDS model is estimated separately for ground beef and milk categories. Results show strong habit formation to each product in the two categories. In addition, there is a clear positive association between fat content and strength of habit formation. However, evidence of habit formation to dietary fat is weak as indicated by the magnitude of habit formation parameters. This provides evidence that while dietary fat may be an addictive nutrient, a tax on saturated fat might be effective in reducing household demand for high fat products.

Note: "Calculated (or Derived) based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business."

IX. Tables

Table 4-1. Average Monthly Expenditure and Quantity by Synthetic Household

	Full Sample		Households with Income in the 50% Percentile	
	Quantity	**Expenditure**	**Quantity**	**Expenditure**
Ground Meat:				
Beef: High Fat	52	$261	48	$248
Beef: Low Fat	48	$236	38	$182
Turkey: High Fat	13	$35	3	$10
Turkey: Low Fat	48	$184	10	$25
Chicken & Pork	5	$21	28	$101
Milk:				
Fat Free	252	$662	103	$264
1% Fat	165	$441	58	$154
2% Fat	340	$919	156	$426
Whole Milk	173	$473	99	$277

Table 4-2(a). Summary Statistics of Sample: Ground Meat Category

	Mean	Std. Dev.
Budget Shares		
Beef: High Fat	0.35	0.17
Beef: Low Fat	0.34	0.16
Turkey: High Fat	0.02	0.03
Turkey: Low Fat	0.29	0.20
Chicken & Pork	0.01	0.02
Monthly Expenditure on Category by Synthetic HH	$586	$501
Household size	2.57	0.16
Percentage of population that is black	9.8%	8.01
Annual Income per Synthetic HH	$57,857	$8,193
Percentage of HH heads that are male	78%	4.32

Table 4-2(b). Summary Statistics of Sample: Milk Category

	Mean	Std. Dev.
Budget Shares		
1% Fat Milk	0.16	0.13
2% Fat Milk	0.39	0.17
Whole Milk	0.22	0.16
Fat-free Milk	0.22	0.15
Monthly Expenditure on Category by Synthetic HH	$2,454	$2,316
Household size	2.48	0.24
Percentage of population that is black	8.7%	6.3
Annual Income per Synthetic HH	$42,959	$22,978
Percentage of HH heads that are male	71%	10.21

Table 4-3. Habit Formation Parameter Estimates

	φ_i	Standard Errors
Ground Meat		
Beef: High Fat	0.496***	(0.0052)
Beef: Low Fat	0.484***	(0.0051)
Turkey: High Fat	0.553***	(0.0069)
Turkey: Low Fat	0.495***	(0.0051)
Chicken & Pork	0.375***	(0.0189)
Milk		
1% Fat	0.060***	(0.0065)
2% Fat	0.067***	(0.0059)
Whole	0.073***	(0.0061)
Fat-free	0.069***	(0.0168)

*** p<0.01, **p<0.05, *p<0.1

Table 4-4. Long Run Unconditional Own and Cross-Price Elasticities

Ground Meat	Beef: High Fat	Beef: Low Fat	Turkey: High Fat	Turkey: Low Fat	Chicken & Pork
Beef: High Fat	-.899***	-.044***	-.005**	-.064***	-.002**
Beef: Low Fat	-.033***	-.727***	-.008***	-.222***	-0.005***
Turkey: High Fat	-.010*	.042***	-.968***	.038***	.023***
Turkey: Low Fat	-.057***	-.209***	-.003	-.703***	.008***
Chicken & Pork	.068	-.582***	-.056***	-.487***	-1.28***
Milk	1% Fat	2% Fat	Whole	Fat-free	
1% Fat	-0.732***	-.067***	-.1538***	-.065**	
2% Fat	-.056***	-.576***	-.219***	-.146***	
Whole	-.144***	-.203***	-.448***	.175***	
Fat-free	-.058***	-0.14***	.170***	-0.623***	

*** p<0.01, **p<0.05, *p<0.1

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VITA

SHAHEER BURNEY

EDUCATION

M.S., Economics, University of Kentucky, Lexington, KY — Dec. 2014

M.B.A., University of Louisville, Louisville, KY — Sept. 2011

B.A., Economics & Mathematics, Hanover College, Hanover, IN — May 2010

PROFESSIONAL POSITIONS

Postdoctoral Fellow, Zwick Center for Food and Resource Policy, Department of Agricultural and Resource Economics, University of Connecticut, Storrs, CT. May 2017 – Present

Graduate Research Assistant, Department of Agricultural Economics, University of Kentucky, Lexington, KY. Aug. 2012 – Apr. 2017

Visiting Researcher, Department of Agricultural and Resource Economics, University of California – Berkeley. Aug. 2015 to Dec. 2015

Research Assistant, University of Louisville, Department of Economics, Louisville, KY Nov. 2011 – July 2012