

DRAFT Dissertation Prospectus

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Dissertation Overview

The broader goal of my dissertation is to explore existing policies aimed at improving access to, the coverage of, and the efficacy of, government assistance programs. I will do so in three studies. The first measures the impact of a financial incentive that may or may not increase access to fresh produce for SNAP participants. The second investigates if a low-cost, universal nurse home-visiting program can, as a secondary effect, help eligible families receive assistance sooner and/or more frequently. The third aims to continue building the case that in-kind transfer programs, while critical to families coping with poverty, remain insufficient, leaving families living month to month and vulnerable to emergencies.

Chapter Summaries

Chapter 1 is an evaluation of the effectiveness of the Double Up Food Bucks program. “Effectiveness” will be defined by the change in total sales and volume of produce sold within 17 grocery stores that implement Double Up (treatment group), compared to the control group of 15 stores where Double Up was not implemented. A difference-in-differences and regression discontinuity design will be used to measure the size of the effect.

Improving health and food equity of SNAP participants is the broader policy concern. The mechanism is a financial incentive—Double Up Food Bucks—designed to increase fruit and vegetables consumption. A comparison will be made with another financial incentive program called the *Healthy Incentives Pilot* (HIP). I will argue how and why an evaluation of the Double Up program is an important addition to the current literature.

Chapter 2 exploits the random assignment of the Durham Connects program to measure its long term impact on social service applications. Durham Connects (DC) provides free in-home nursing visits to residents of Durham County who have just given birth. It was implemented as an RCT between July 2009 to December 2010. The design treats DC as an information treatment. The DC information treatment (e.g. a nurse contact to ask questions and provide assistance) is expected to lower the learning and barrier costs of low-income families with children when applying for social services.

Chapter 3 aims to build on the work of Schenck-Fontaine et al. (2016). Through surveys,

Schenck-Fontaine et al. (2016) examine how families coping with poverty and economic instability supplement their SNAP benefits with additional assistance from informal and formal resources. In my paper, I hope to build a better understanding of how and when families use emergency resources provided by local-governments and charities. I aim to do this by analyzing food pantry donations data and administrative records of emergency assistance applications.

Chapter 1

An Evaluation of the Double Up Food Bucks program

Motivation

Research Question

How effective is the DUFEB financial incentive at increasing the fresh fruits and vegetables purchased by SNAP shoppers within a grocery store environment?

Hypothesis 1: I expect a slight increase (1 - 2%) in SNAP EBT expenditures on fruits and vegetables (FVs) during the months the DUFEB incentive is active in the experimental stores (Aug - Dec). I expect the effect will fade over time. I expect no significant differences in fruit and vegetable expenditures during the months the incentive is not in effect (Jan - July).

Note that the DUFEB incentive is applied automatically to all SNAP shoppers earning or redeeming DUFEB points (covered in more detail in the Data Section). Therefore, by default, all SNAP shoppers at a DUFEB store are technically “participating”. However, SNAP shoppers should be considered “passive” or “active” participants. “Active participation” would characterize shoppers responding to the DUFEB incentive; “passive participation” would characterize shoppers who continue to shop as usual, despite automatically redeeming points.

I know from prior implementations of the program that participation rates in DUFEB-like incentive programs can be low. In this case, I expect SNAP shoppers to consist of mostly “passive” participants. Combined with the fact that SNAP dollars account for less than 5% of all spending in these stores, I don’t think there is a very large pool of SNAP participants to draw from. As a result, the “active” participants, who respond to the incentive and purchase more fruits and vegetables, will consist of a small fraction of total FV spending. Therefore, simply comparing FV purchases between treatment and control stores would likely fail to find any distributional differences. Instead, to measure the impact of the incentive, I will have to focus on, and compare,

purchases made by the targeted group (SNAP households) in both types of stores.

I don't know if the corporate office, which selected and implemented the DUFEB incentive, clearly communicated or advertised the DUFEB program to store management/staff and customers. I therefore anticipate low awareness of the DUFEB program amongst store staff and shoppers. In turn, I believe the predicted low participation rates to be mostly a function of low awareness, not the DUFEB program itself. I must be clear that this is merely a hunch. I don't think there is a large profit motive behind implementing this program for the retailer. I think it is an opportunity to pretend to be doing some good and to have something which reflects a positive corporate image. A survey of store staff and of some customers to test this hunch would be great.

Hypothesis 2: If measurable, I expect spending increases to occur within the first 3 weeks of each calendar month, when most SNAP benefits are distributed and consumed. I also expect spending with SNAP benefits during the 4th calendar week of each month for all stores to be relatively similar, regardless of DUFEB participation. That is, if I observe any differences in SNAP benefit spending, they will be observed during the 1st, 2nd, and 3rd week of each calendar month, but not the 4th.

Prior research found that SNAP shoppers spend their benefits soon after receiving them, generally in one large shopping trip (Wiig and Smith, 2009; Damon et al., 2013). The grocery stores are located in a state where benefits are disbursed every odd day of the month between the 3rd and 21st, spanning the first 3 weeks of each month. Therefore, by the 4th week, total unspent dollars across all SNAP households will be at a minimum. Since the DUFEB incentive is only triggered by the use of SNAP benefits, many SNAP shoppers will be unable, or unwilling, to make use of DUFEB having already most, if not all, of their benefits for the month.

I expect that, were we to remove the 4th week of each month from all stores, the DUFEB effect size will increase. I do not anticipate to see shoppers behave in strategic saving behavior of DUFEB points (which is quite difficult given the automatic accrual and redemption system) nor do I think FV spending will increase much without the presence of the incentive. More importantly, since I cannot track link purchases to individuals (more on this later), it will be impossible to identify which transactions are made by SNAP shoppers when they are not using their SNAP EBT cards.

Introduction

Chronic conditions like obesity, heart disease, and other metabolic risk factors (stroke, type II diabetes, etc.) are estimated to cost the US health care system between 200 to 400 billion dollars annually (Cawley and Meyerhoefer, 2012; Chatterjee et al., 2014). More importantly, these diseases account for hundreds of thousands of deaths each year. Heart disease alone is the leading cause of death for all persons in the US, with stroke fifth and diabetes seventh (National Center for Health Statistics, 2015). Diet is closely linked to these conditions, particularly obesity and

cardiovascular disease. There is strong evidence that a diet high in (1) vegetables, fruits, nuts, unsaturated oils, fish, and poultry, but low in (2) red and processed meat and sugar-sweetened foods and drinks, helps lower body weight, blood pressure, and the risk of cardiovascular disease (Mente et al., 2009; Nutrition Evidence Library, 2014). Improving the diet of Americans has therefore become an increasing priority for the United States, especially for struggling families that participate in the Supplemental Nutrition Assistance (SNAP) program.

SNAP is a federal aid program administered by the Food and Nutrition Service (FNS), an agency of the U.S. Department of Agriculture (USDA). At 74 billion dollars in FY2015 with roughly 45.8 million participants, it is the largest food assistance program in the US (USDA FNS, 2016b). To be eligible for SNAP, a household must be sufficiently budget constrained that hunger is considered likely without assistance. Eligibility is a function of countable resources, vehicle ownership and value, household size, gross or net monthly income, household composition, and meeting certain work requirements.¹ Some eligibility requirements vary by state, but in general, a family with dependents, less than \$2000 in countable resources, where the adults work at least part-time earning a gross (net) monthly income at or below 130% (100%) of the federal poverty line, is eligible to receive SNAP benefits. Aside from a few restrictions—no alcohol, tobacco, non-food items, read-to-eat meals, or hot foods—households can use SNAP benefits to purchase any foods that will be prepared and consumed at home. Unfortunately, the purchasing patterns of the average SNAP household are not conducive to a healthy diet.

Research on the dietary patterns of households receiving SNAP benefits has found that they are significantly *less* likely to meet USDA dietary guidelines than the average US household and much *more* likely to consume unhealthy foods (Andreyeva et al., 2015; Nguyen and Powell, 2015; Wolfson and Bleich, 2015). A smaller set of research has found that SNAP households, at best, consume the same amount of unhealthy foods (e.g. sugar-sweetened beverages, baked goods, snacks, candy, etc) compared to SNAP-ineligible households (Todd and Ploeg, 2014; Hoynes et al., 2015). In other words, SNAP households consume foods that are less healthy or about the same as SNAP-ineligible households. This is a concerning result given that most US households, regardless of income, already purchase and consume far too much meat and foods rich in sugars and fats, and far too few fruits, vegetables and whole grains (USDA, 2015; Frazão, 1999). However, the purpose of SNAP is to keep struggling families from going hungry, not to ensure they consume the best possible diet. SNAP is designed to act like cash, helping families access more food than they could otherwise do so without assistance (Hoynes et al., 2015). It is therefore not a failing of the SNAP program if benefits are used to purchase unhealthy foods.

The SNAP program could be changed such that it could continue satisfying its role as an anti-hunger program while simultaneously encouraging healthier purchases. Blumenthal et al. (2014) and Leung et al. (2013) both surveyed a field of stakeholders and policy experts in the SNAP program about what they would do to improve the dietary quality of purchases. In both studies, restricting the purchase of unhealthy foods (e.g. sugar-sweetened beverages) and promoting healthy purchases through monetary incentives were the two most popular

¹ For more details, visit <http://www.fns.usda.gov/snap/eligibility>

improvements (i.e. ranked the highest or most often suggested).².

One common suggestion is to restrict the SNAP program to the same set of eligible foods as the Special Supplemental Nutrition Program for Woman, Infants, and Children (WIC) program (Dinour et al., 2007). The WIC program provides food vouchers that limit households to a select group of food products. These food products are specifically selected to ensure women and their children receive nutritious, healthy foods. In other words, the WIC program, by design, places restrictions on food choices by defining a list of *eligible* items, as opposed to the SNAP program, which defines a list of *ineligible* items. Another common, and simpler, suggestion is to expand the existing list of ineligible items (e.g. alcohol) with products that are unambiguously lacking in nutrition and easy to identify, like soda or candy. New York City, for example, attempted to ban the purchase of sugar-sweetened beverages, and the state of Maine attempted to restrict the purchase of sodas, candy, and any other taxable food items (Gundersen, 2015). Both restrictions were overturned by the USDA.

There are problems with “improving” the SNAP program by implementing even greater purchasing restrictions. First, there is no reason to believe that such a restriction would work. The restriction assumes that, under WIC-like requirements, households will substitute healthy foods for unhealthy foods when using SNAP benefits. What would most likely happen is that households would shift to purchasing unhealthy foods with cash. Second, such restrictions would likely lead to a drop in SNAP participation (Gundersen, 2015). Restricting choice is a paternalistic policy that would further stigmatize SNAP participation. It would give the impression that SNAP beneficiaries are assumed to have worse diets and that they cannot be trusted to make healthy food purchases. Participation would also drop due to increased transactions costs of purchasing items with SNAP. Not all stores would clearly mark which items were SNAP eligible nor should participants be expected to remember. The result would be longer, more frustrating shopping trips. Lastly, it is important to remember that for many SNAP recipients, freedom of choice is what makes the SNAP program popular and easy to use (Edin et al., 2013).

The most popular “improvement” was providing a monetary incentive to SNAP participants for purchasing healthy foods (Blumenthal et al., 2014; Leung et al., 2013). Monetary (or financial) incentives, in this context, tend to be a rebate or voucher awarded to SNAP households for using their benefits to buy certain healthful foods, generally mineral-rich and nutrient-dense fruits and vegetables (i.e. leafy greens but not white potatoes). These monetary incentives for buying “targeted” fruits and vegetables (aka TFVs) are exclusive to SNAP participants. Much like a grocery stores loyalty card or a student ID card, retailers can “discriminate on price” (aka “target the incentive”) using SNAP Electronic Benefit Transfer (EBT) cards to identifying eligible participants. Monetary incentives in the food retail environment are popular for two main reason. First, the framing of the “improvement” is positive. Instead of “punishing” SNAP participants through paternal restriction or disincentives (not covered), monetary incentives reward participants for healthy shopping behavior (Gundersen, 2015). Retailers also prefer the

²It should be mentioned that there were other, less popular recommendations, such as modifying how SNAP benefits are distributed and improving nutrition education. For more details, see Blumenthal et al. (2014) and Leung et al. (2013)

positive framing of monetary incentives. For the moment, monetary incentives programs for SNAP participants are not wide spread. Therefore, taking up an incentive program, assuming the cost of implementation isn't too expensive, creates an opportunity for retailers to differentiate themselves from their competitors (Hartmann, 2011). The second reason is a strong theoretical framework established by neoclassical economics supporting incentives as an effective mechanism for changing human behavior. In practice, however, incentives have had mixed results, but there is building evidence that incentives may work in the food retail space.

How, why, and to what effect incentives may encourage SNAP participants to purchase more targeted fruits and vegetables will be discussed in detail below, and is the motivating question behind this paper.

Financial Incentives to Encourage Healthy Food Purchases

Encouraging healthy behavior through financial incentives has a long history. Results are mixed. For example, financial incentives have been shown to help individuals commit to regular exercise, improve dieting, increase weight loss, and to quit smoking, but the intended effect of the financial incentives were often only short-term (see Gneezy et al. (2011) and Cawley (2015) for an overview). Gneezy et al. (2011) also explain, through a review of the literature, that depending on the context and design, incentives can backfire, producing an effect known as “crowd out”. Crowd out occurs when an incentive displaces the intrinsic reward of a behavior (originally defined for “prosocial” behavior, like volunteering or giving blood; see Bénabou and Tirole (2006)). The behavior then becomes dependent on the extrinsic reward. As a result, having shifted from being intrinsically rewarding to extrinsically rewarding, the positive behavior continues only as long as the monetary incentive is provided. More significantly, the intrinsic reward of the behavior does not return once it has been “crowded out”. Therefore, the long-term effect of a monetary incentive can be negative, despite showing positive effects in the short-term. That said, incentives can produce successful long-term results if they are instead used as a mechanism to build good habits. This requires that the incentives be salient and produce immediate feedback without neglecting behavioral findings such as loss aversion and mental accounting (John et al., 2011).

Given the research on incentives, it is reasonable to assume that a monetary incentive for SNAP participants to purchase healthy foods, like fruits and vegetables, may fail or even backfire. Should the act of purchasing healthy foods be intrinsically rewarding to SNAP shoppers, introducing an incentive may produce a “crowd out” effect. However, recent field experiments find that incentives can establish healthy food choice as a habit, possibly overriding any crowd out. Daily incentives encourage children to make healthier food choices in school lunchrooms, who in turn develop positive, long-term food habits (Loewenstein et al., 2016; List and Samek, 2015; Belot et al., 2014). Outside of the school lunchroom environment, List et al. (2015) found that similar habit formation is possible with incentives in a more traditional food retail environment. In their experiment, List et al. (2015) provided an incentive to 222 shoppers (\$1) to use their rewards cards, but then randomly assigned each participant to the control group to

one of three interventions: *information*, *incentive*, or *combination*. The *information* treatment was a flyer with tips on how to prepare fruit and vegetable dishes as well as the health benefits of eating more fruits and veggies. The *incentive* was an additional dollar for every 5 cups of targeted fruits and vegetables (TFVs) purchased. The *combination* treatment group included both. The intervention lasted for 5 months but each group continued to be observed for roughly 6 weeks months after. The *information* intervention had no effect, but the *incentive* and *combination* interventions on average doubled their purchase of fruits and vegetables in comparison to the control group. Most promisingly, the gap persisted with minimal shrinkage for 6 weeks following the end of the intervention. However, there was no follow up after the 6-week post-intervention period. It is therefore possible the gap closed over multiple months (as opposed to multiple weeks).

The design, food environment, and target of the incentive in each of these experiments is important. First, the incentive in these experiments is designed to be salient and immediate. In the school lunchroom experiments, the children are aware of the incentive and receive the reward (e.g. a small token) immediately after selecting the healthy food item. Likewise, the shoppers received their additional \$1 reward for every 5 cups of TFVs at checkout. One distinction between the designs is frequency. The children are exposed to the incentive every school day in the lunchroom experiments. The shoppers, on the other hand, were exposed as frequently or as infrequently as they chose. This distinction is important, as the latter better reflects the experience of shoppers using the SNAP benefits. Second, the food environment is important because it determines what choices are available. The children have a finite set of options in the school lunchroom and they also have no outside option (besides not eating lunch). The children optimize on a relatively small set of choices and, for the duration of the intervention, the incentive always existed. Food retail environments are drastically different. There are numerous competing food choices and generally other outside options.³ It is substantially more difficult for the shopper to optimize over such a large set of choices. Last, and most obviously, one set of studies targets children, the other adults. A priori, we would expect a monetary incentive to affect children differently than adults. The fact that habit formation through incentives appears possible for both target groups is promising.

Research where SNAP participants are the target group is nascent. The USDA's Food and Nutrition Services (FNS) ran the first large scale randomized control trial investigating the impact of a financial incentive for targeted fruits and vegetables in 2011. The experiment was called the Healthy Incentives Pilot (HIP). HIP is the precursor to every incentive program currently being funding by the USDA. It also provides the data for the few papers recently published on incentives for SNAP participants.

³It should be noted that this is not always the case. In List et al. (2015), for example, the store that was selected for the experiment was one of the few places local shoppers could find fresh produce. The store itself was located in one of Chicago's poorer neighborhoods.

The Healthy Incentives Pilot

A brief overview of the Healthy Incentives Pilot is necessary to provide context to, and contrast with, more recent financial incentive programs.

The USDA's Food and Nutrition Services designed the Healthy Incentives Pilot. The pilot was funded by the Food, Conservation, and Energy Act of 2008 to test whether financial incentives would increase consumption of targeted fruits and vegetables (TFVs). SNAP participants were the target group.

HIP was designed as a large scale randomized control trial (RCT). FNS partnered with the Massachusetts Department of Transitional Assistance to implement HIP. The pilot lasted from early 2011 to the end of 2012. The population included all 55,095 SNAP participants in Hampden County, MA. Hampden County is the poorest county in Massachusetts and has the highest rates of obesity and other diet-related chronic illness (e.g. type 2 diabetes).

Of the 55,095 SNAP participants, 7,500 were randomly assigned to the treatment group. The remainder fell into the control group. The treatment was a 30 cent (or 30%) rebate on every dollar spent on TFVs. The rebate was capped at \$60 per month. To receive the rebate, selected SNAP participants had to use their EBT cards at participating retailers. The rebate, which was returned to their EBT account, could then be used on any food item. That is, the rebate could only be earned buying TFVs, but could be redeemed buying any SNAP eligible food item. Most HIP participants spent about \$12 a month on TFVs, earning an average of \$3.65 per month in rebates—drastically lower than the \$60 per month rebate cap.

The evaluation was conducted using 24-hour dietary recall surveys. A total of 5,000 participants were selected to be surveyed, even split between treatment and control (2,500 HIP, 2,500 non-HIP). The first survey was conducted prior to the start of the pilot. This established a baseline. The second survey occurred 4 to 6 months into the pilot and the third survey occurred 9 to 11 months in. (The variation, e.g. 4 to 6 months, was due to the treatment being implemented in 3 waves of 2500.)

The evaluation found that the 30% rebate led to about a 26% increase in consumption of TFVs. This was equivalent to about 0.24 cups of TFVs. Roughly 60% of the increase was due to increased vegetable consumption and 40% due to increased fruit consumption. The effect, in absolute terms (0.24 cups), seems small. But a 0.87 price elasticity, relative to other results in the literature, is quite high—0.7 and 0.48, on average, for fruits and vegetables, respectively (Andreyeva et al., 2010).

Despite some limitations and technical problems—underreporting on the 24-hour recall survey and system glitches early in the pilot (see pages 60 and 208-210 of Bartlett et al. (2014))—HIP was considered to be an overall success (Klerman et al., 2014; Olsho et al., 2016). It implemented one of the largest, most complex RCTs to isolate how incentives can increase household consumption of TFVs. It also provided a feasible model for nationwide expansion (assuming cost reductions due to economies of scale; see An (2015)).

HIP also provides a framework for understanding how a financial incentive, expanded dramatically in one geographic area, could improve TFV consumption. But, as noted in the final HIP report, one of the most prominent retailers in Hampden County chose not to participate (page 61, Bartlett et al. (2014)). Its third-party processor decided it was too difficult and too costly to implement the financial incentive on its point-of-sale technology. This strategic behavior by the retailer, which had a significant presence in Hampden County, impacted where participants could use the incentive.

Most financial incentive programs work at the local level, expanding non-randomly. We should anticipate certain retailers (firms) to behave strategically when participating in any of these incentive programs. Likewise, we should anticipate voluntary (non-random) self-selection by SNAP beneficiaries into these financial incentives programs. To this end, more research is needed to understand the impact of incentive programs under *real-world* conditions. HIP provided evidence that incentive programs can work, but barring state-wide or nation-wide adoption of point-of-sale financial incentives, we should expect growth to occur organically under non-experimental conditions.

An example of such a financial incentive program for SNAP participants is the Double Up Food Bucks program (DUFb or Double Up). The non-random expansion and impact of this financial incentives program will remain the focus of this paper

The Double Up Food Bucks Program

The success of HIP paved the way for the Food Insecurity Nutrition Initiative (FINI), established by section 4208(b) of the Agricultural Act of 2014 (aka 2014 Farm Bill). FINI—a 100-million-dollar initiative—in turn piloted numerous non-profit financial incentive programs aimed at improving the diets of SNAP participants.

Of specific interest is Double Up Food Bucks (DUFb or Double Up), an incentives-based program funded by FINI. In 2009, the non-profit organization Fair Food Network (FFN) launched the Double Up Food Bucks program in Detroit, Michigan. The intention of the program was to get more low-income families visiting and participating in local Detroit farmer's markets. The mechanism for increasing participation was a dollar-for-dollar match of locally grown fruit and vegetable purchases. This subsidy was accessible only to low-income families receiving SNAP benefits, who could exchange up to \$20 of their benefits for a wooden token that could be used on up to \$40 worth of locally grown produce.

The DUFb program was considered successful given it had expanded to more than 150 farmer's markets in 2014 from just 5 farmer's markets in 2009. SNAP benefits have been used more than 200,000 times to purchase fresh produce, with more than 10,000 first time SNAP customers visiting farmer's markets in 2013 alone (Network, 2014). The program is considered by Fair Food Network to be a "three-fold" win given that the program helps local low-income families buy more fresh produce, provides new customers for local farmer's, and stimulates the local food economy. Relative to farmer's markets in other states, DUFb did seem to be bringing

in substantially more SNAP dollars (\$1.7 million in Michigan versus \$307,000 in Illinois, the second largest).

A 5.17 million dollar FINI grant was awarded to Fair Food Network to help it pilot three adjustments to the Double Up Food Buck program (USDA NIFA, 2015). First, FFN needs to test DUFEB as a year-round program in select locations instead of the current seasonal format. Second, shift away from the token system to providing DUFEB electronically at point-of-sale. Third, the DUFEB needs to expand from farmer's markets into other retail environments, like supermarkets and grocery stores.

Successful expansion into supermarkets and grocery stores is critical. Approximately 80% of all SNAP benefits in 2015 were used in supermarkets or super stores (USDA FNS, 2016a). Less than 1% percent of SNAP benefits were used at local farmer's markets. The amount of SNAP benefits used in local farmer's markets has increased since 2009, but no where near the growth necessary to reach the type of stores most frequented by low-income families. If localized financial incentive programs like DUFEB are going to be considered one of the USDA's many tools to increase food access and combat obesity, then they must be successfully implemented and scaled across supermarkets and grocery stores. Most importantly, incentive programs like DUFEB must prove they are effective in changing purchasing habits within supermarket/grocery store food environments.

Double Up Food Bucks vs the Healthy Incentives Pilot

There are notable differences between DUFEB and HIP that make the evaluation of DUFEB more difficult. In short, HIP was implemented as an RCT. DUFEB implementation is not. Let's explore in greater detail.

HIP had substantially more participating stores, all within the same county (Hampden County, MA). DUFEB has fewer participating stores, spread across many different counties, and across many different grocery store chains. Therefore, the probability of a SNAP shopper in Hampden County having walked into a HIP participating store was much higher than a SNAP shopper walking into any DUFEB participating retailer.

The incentive delivery mechanisms also differ. First, all SNAP beneficiaries who shop at a DUFEB participating store receive the benefit automatically. In other words, SNAP households that patron a store with DUFEB receive the incentive regardless of their intentions or awareness of the DUFEB incentive. Therefore, evaluating DUFEB has the added difficulty of identifying which shoppers are optimizing in response to DUFEB, as opposed to shopping normally. In contrast, SNAP households assigned to the HIP treatment group were made aware of incentive and were eligible to use it (even if they didn't quite understand how the incentive program worked — see Bartlett et al. (2014)). Households in the control group were not aware of the incentive and were not eligible to use it. And because participants were assigned, HIP evaluators could identify treated participants from control participants.

Second, the DUF� financial incentive is substantially larger but more restrictive. The DUF� incentive is a dollar-for-dollar match of locally grown produce purchases capped at \$20 per day. The matched dollars are accrued as points on a store loyalty card. Existing points are then automatically redeemed as dollars on *any* fresh produce purchases, not just locally grown produce. In comparison, the HIP financial incentive was a return of 30 cents per dollar spent on TFVs which could be spent on *any* food item. That is, the DUF� incentive doubled the purchasing power of every dollars spent on TFVs *only for more TFVs*; the HIP incentive increased the purchasing power of every dollars spent on TFVs by 30% *for any SNAP eligible food item*.

Finally, the experimental design of HIP allowed researchers to form a causal interpretation of their results; the average treatment effect is the same as the average treatment effect on the treated. Any difference in the purchase and consumption of TFV between the treatment and control groups could therefore be attributed to the incentive. This is not the case for DUF�. However, HIP implementation is the exception. How DUF�, and similar financial incentive programs are implemented, is the norm. The contribution of this paper will be evaluating and understanding the impact of DUF�, given that DUF� and similar programs are implemented in the “real-world” (non-experimental conditions)

Evaluating Double Up Food Bucks in Non-experimental Conditions

DUF�’s expansion and implementation into supermarkets and grocery stores did not follow an experimental design. Fair Food Network searched for local partners in the Detroit area willing to participate in DUF�. Not all grocery stores, especially the smaller independent stores, had the capacity to implement the point-of-sale technology necessary for the incentive—even if FFN offered to help cover the upgrade costs. The result is a self-selected group of stores participating in DUF�. This, in some ways, parallels what occurred in HIP, where one of the largest retailers decided integrating their point-of-sale systems to include the incentive was too expensive. This type of strategic firm behavior is important to consider, even if complicates the evaluation of an incentive program like DUF�.

In the real world, stores seek to maximize profits and will opt to participate only if they expect to profit. Similarly, individuals will self-select into participating; participation is optional and more likely to occur with well-informed and motivated SNAP shoppers. Selection, in this case, is a feature, not a flaw, of such incentive programs when implemented by non-profits or policy makers. The evidence, thanks to HIP, exists that incentives can lead to an increase in consumption. The goal of this paper is therefore to accurately measure the effect of the DUF� on TFV purchases while taking the selection into account. That effect can then be extrapolated forward, albeit weakly, using the results of HIP, to measure changes in consumption.

Fair Food Network started testing and gathering data from grocery stores implementing DUF� in 2014. One of FFN’s largest partners, a Michigan grocery retail and distribution company, piloted the program in 2 of its stores in 2014. The company has since expanded to 5 stores in 2015 and then to 17 of 62 stores in 2016. Rapid scaling was possible due to the point-of-sale

technology used by the company to implement DUFb across its stores. It provides, to date, the best case study of a firm strategically scaling DUFb across numerous grocery stores that span different geographic areas and populations.

All transaction data from 2014 - 2016 will be provided for every store that has, at any point, participated in DUFb. These data are complete (i.e. no records have been removed) and at the item level. A complete set of data will also be provided from another 15 stores where DUFb was not implemented.

Currently, no research exists evaluating DUFb, or similar incentive programs, using a complete set of store transaction data. HIP, for example, only had transactions records for SNAP EBT cards. Transactions, should a different tender be used by the same individual, could not be observed. Therefore, these data provide an unprecedented opportunity to analyze how the DUFb financial incentive performs under real-world conditions. This paper will be, to the best of my knowledge, the first to perform an evaluation of a financial incentive, targeted at SNAP participants, using a complete set of data, from multiple stores, across multiple years, and collected under non-experimental conditions.

Concept in a Plot

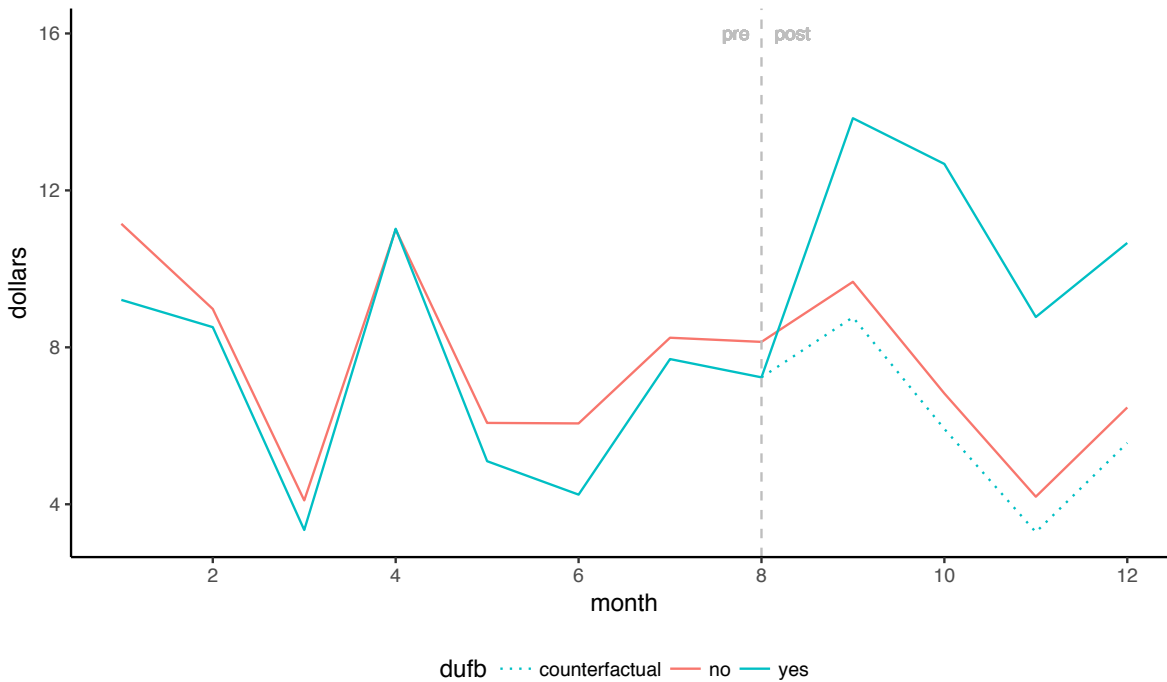


Figure 1.1: Example of Hypothetical Result (Fake Data)

What I am hoping to find is displayed in Figure 1.1. Note that the data is fake and the time interval is at the monthly level (I plan to use daily data). The point of the graph is to emphasize that I expect to find a jump in dollars spent on fruits and vegetables in the experimental (treated) stores once the DUFb program begins in August. While I intend to use a difference-in-difference-in-differences (DDD) model as part of my analysis, I display a difference-in-differences (DD) to more easily highlight the effect of interest.

Assume that the DD displayed is isolating on the subpopulation of SNAP transactions observed. Then the dotted green line beginning at month 8 would represent the gap under the “parallel trends” assumption. The difference between the solid green line and the dotted green line represents the increase in dollars spent that I hope to identify.

Data Description

These data come from a large grocery distributor and retailer serving multiple grocery chains. Three years of data will be made available, 2014 through 2016. To my understanding, this includes months where the DUFBI incentive is active (Aug 1 to Dec 31) and inactive (Jan 1 to July 31) across all stores. These data are transaction level data and will include (at least) store number, register, transaction ID, date and time of purchase, payment type, item, dollars, and quantity.

Double Up implementation was considered for a single grocery chain. The chain has more than 60 stores, 17 of which were selected as “treatment” stores (with Double Up). Of the remaining stores, data is being made available from an additional 15 to serve as “controls”. The quotes here signify that these terms will be used as shorthand, but the terminology is somewhat misleading. The use of “treatment” and “control” could lead one to think store assignment was random. It was not.

How the DUFBI Incentive is Implemented

The DUFBI incentive can differ in implementation. Three different implementations have been observed: earn/redeem DUFBI points via loyalty card, single-use paper coupon, and immediate discount. The earn/redeem DUFBI point system is unique to the retailer that provided these data. For information on the other two DUFBI implementations, see (Margaret Schnuck, 2016).

The DUFBI implementation for this particular grocery store chain is a point system. SNAP shoppers can *earn* points by buying locally grown produce using their SNAP EBT card and their loyalty card. The loyalty card is required because it is used to store and track earned DUFBI points. Each dollar spent buying locally grown produce earns a DUFBI point. SNAP shoppers are eligible to receive up to \$20 dollars worth of DUFBI points (20 points) per day. Earned points are not reflected immediately on loyalty cards. They are redeemable the day after.

Points can be redeemed on *any* eligible produce (excludes frozen and canned fruits and vegetables). Any form of payment can be used when redeeming points; it is not necessary to use a SNAP EBT card to redeem points.

There are four important details about this implementation of the DUFBI incentive. I already mentioned the first but it is worth reiterating: earned points take a day to be processed on a loyalty card. This forces SNAP shoppers to delay the reward of the DUFBI incentive earned by at least a day. While perhaps a technological necessity (it takes time to process and reflect earned points on loyalty card accounts), this delays the transactional utility that could potentially be earned by the SNAP shopper (Thaler, 1985). I expect that delaying the transactional utility reduces the “pleasure” and effectiveness window of the DUFBI incentive. SNAP shoppers tend to spend benefits in one large shopping trip soon after receiving monthly benefits. These shopping trips therefore correspond to the single largest opportunity to earn DUFBI points. Unless the

shoppers returns to the store frequently to buy fresh produce, the “reward” of redeeming points.

Second, the incentive alternates between earning and redeeming states. A loyalty card with a DUFEB point balance of zero is in an “earning” state. However, once DUFEB points are earned by buying *locally* grown fresh produce, the card switches to a “redeeming” state; loyalty cards with a point balance greater than zero will redeem until the point balance is once again zero. This removes the possibility of strategically “banking” earned points to be redeemed all at once (say for a holiday shopping trip). Should I purchase \$10 dollars of local produce and earn 10 points, the next time I purchase *any* produce (even local produce), my purchases will be redeemed from the point balance until the 10 points are gone.

Third, the points *earned* are not communicated to the shopper at the moment of sale (Family Fare, 2016). In other words, the fact that shoppers are earning points is *not salient*. There is no feedback connecting the purchase of fresh healthy produce to the fact that the shopper is earning points. Currently available points (those processed in prior shopping trips) are printed at the bottom of each receipt, and can even be checked on-line or on in-store kiosks. But no feedback or information is shared to the shopper during the current sale. Earning points, at least, ends up being like any other shopping trip. I would argue this is more a con than a pro. Certainly a bell shouldn’t ring when SNAP shoppers earn points. One of the great consequences of moving to an EBT card is that the potential stigma of using food stamps has greatly diminished. But shoppers could benefit from some sort of feedback that is informative without producing a spotlighting effect. For example, shoppers could be told, “You saved \$4.50 today and you also earned 5 DUFEB points”.⁴

The fourth, and most important point, is the automatic earning and redeeming of DUFEB points. This implies the incentive works only if individuals choose to actively participate in the program. This is distinct to standard experimental procedure where individuals are assigned to the treatment or control group and then choose to participate (or not).

What is a “participant” for this DUFEB implementation?

How a participant responds to assignment is generally referred to as *compliance* (Angrist and Pischke, 2008).⁵ But in this case, it is the stores, not the individual shoppers, that have been “assigned” to a treatment or control group. Stores, if assigned to the treatment group by the retail chain, are “compliers” by default; the DUFEB incentive is implemented on store’s point-of-sale (POS) system. Some stores (4) behaved somewhat like “always-takers”, having asked to participate in DUFEB, but most store (13) are “compliers”.⁶

⁴I need to confirm that this does not happen. Considering the points earned don’t appear on receipt, I do not see how the clerk know to inform the customer. Does it appear on the machine?

⁵Participants can be further categorized into “compliers”, “never-takers”, “always-takers”, and “defiers”. These categorizations provide useful terminology but are not relevant in the context of the DUFEB incentive.

⁶I must note that, while this creates some worries of “self-selection” by stores, I think this bias can be handled by a model that includes a store-level fixed-effect.

How, then, does one think about SNAP shopper participation in the DUFEB program if it is stores that are ultimately assigned to the DUFEB program? SNAP shoppers have the option to benefit from the program without ever being “assigned” to any treatment group. A shopper’s active participation in DUFEB is therefore driven by another type of self-selection. I imagine use of the DUFEB incentive depends on a series of latent variables corresponding to individual shoppers, stores, and the retail chain. For example, demographics, price sensitivity, food preferences, health consciousness are all latent variables that could affect shopper DUFEB activity. Other latent variables include how effectively the retail chain markets the DUFEB program to management of participating stores and how effectively this information is relayed by stores to individual shoppers. Management’s enthusiasm for the program is likewise a latent retail chain and store-level variable.

Automatic redemption of the DUFEB points also complicates identifying individual participation. Automatic redemption of DUFEB “points” means I cannot identify which SNAP transactions are responding to the incentive versus “shopping as usual”. That is, I will observe many SNAP transactions earning or redeeming DUFEB points for fruits and vegetables that are oblivious to the existence of the incentive. I will also observe individuals who have chosen to actively participate in the program. In aggregate, however, I assume that any increase in the total amount of fruit and vegetables purchases in DUFEB stores can be attributed to the incentive. This is where having purchasing data from the non-DUFEB stores is important. The non-DUFEB stores will help improve estimation by controlling for any changes in fruit and purchases that may occur for reasons other than the DUFEB incentive e.g. seasonal or macroeconomic conditions.

Purchases Cannot Be Linked to Individuals (No Loyalty Card Data)

One important variable that will not be made available is a variable for loyalty card numbers. The company’s use of loyalty cards across its many chains was an exciting prospect. Previous transaction data from smaller independent grocery chains had no way linking purchases to a single unique identifier over time because these smaller chains did not have advanced point-of-sale systems.

In earlier conversations with the company, it was understood that loyalty cards would be made available. However, months into working with the company, I was informed that this was no longer possible. Per the company’s legal department, the company cannot share any personal information about their customers. Unfortunately for us, in the loyalty card contract signed by customers, the loyalty card number itself is considered personal information, meaning loyalty card numbers fall under the same legal category as phone numbers and home addresses.

DUFB Incentive Inconsistency Across Years

The retail company informed us that the way the DUFB incentive worked in 2016 is distinct from 2014 and 2015. The DUFB incentive in 2016 worked by earning points for each dollar spent on *locally grown* fresh produce. (Recall that each point is equal to one dollar.) Points are then redeemed automatically on *any* fresh produce. However, in 2014 and 2015, the incentive was the *opposite*. In those two years, the DUFB incentive worked by earning points on *any* fresh produce, automatically redeeming points on *locally grown* fresh produce.

This is important because *locally grown* fresh produce is a much smaller subset of the *any* fresh produce. Therefore, in years 2014 and 2015, shoppers could easily earn points but had a constrained set of produce on which to redeem points. In any case, estimates of the incentive for the year 2015 cannot be compared to estimates in the year 2016.

Limited Dependent Variable

It is very likely that for any recorded visit to the cashier—what I call a “transaction”—a customer does not purchase fresh fruits or vegetables (FV). If I split a customer’s items purchased during a transaction into a few general categories (e.g. dairy, candy, meat, etc.) and aggregated expenditure over these categories, I will observe a non-trivial amount of zeros. More importantly, these are “true” zeros aka *corner solutions*. That is, these zeros are not substitutes for missing data or representing negative values but the result of a utility-maximizing choice.

These concerns are covered in greater detail in the Methods Section.

Other Information

Past Experience with Similar Data

This is not my first experience working with transaction data. At this point, I have more than 3 years working with transaction data. Furthermore, this is not my first experience with transaction data where (1) DUFB was implemented and (2) transactions were not linked to individuals.

I performed an analysis in April of 2016 for FFN using 5 months of transaction data from 3 small Detroit-area grocery stores. Figure 1.2 was produced with those data. It was easy to distinguish when SNAP benefits were being used in those data. Likewise, it was easy to tell when transaction made use of the DUFB incentive (either an issuing of DUFB or a redemption). A simple aggregation could determine the total amount of dollars spent per some unit time (*day* was the smallest possible unit of time). I expected data for my prospectus will be very similar. The empirical models in the next section were developed under these expectations of the data.

SNAP Spending is Cyclical

In some prior work, I've observed that SNAP spending is cyclical, peaking in the 2nd week. This is due to the state's monthly SNAP benefits transfer schedule. Benefits are distributed every odd day of the month between the 3rd and 21st. Each day maps to the digits 0 through 9. SNAP participants receive their benefits once a month on the day corresponding to the last digit of their SNAP ID number. For example, ID numbers that end in 0 receive their benefits on the 3rd of each month. SNAP EBT benefits are spent quickly. As a result, there are always fewer SNAP purchases during the 4th week of the month. And fewer SNAP benefits means fewer transaction capable of receiving the DUFBI incentive. I'm not yet sure what impact this will have on my analysis this time around, but I thought it important and interesting to point out and consider.

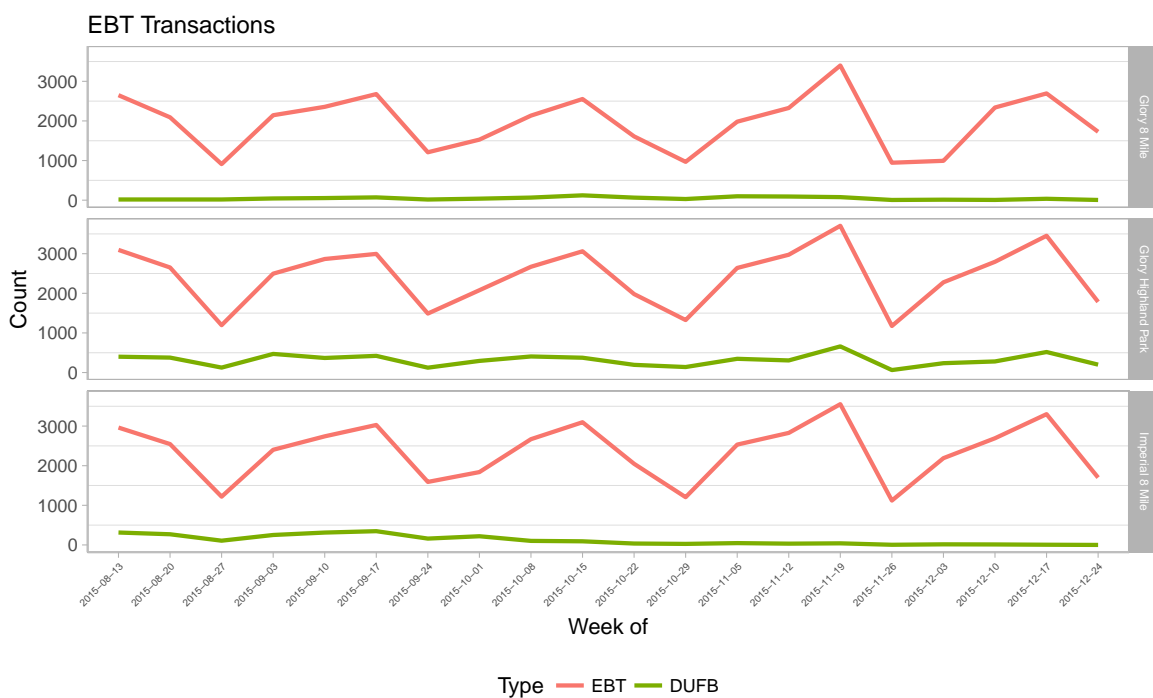


Figure 1.2: Example of how SNAP EBT benefits are spent in a predictable, week-to-week, cycle. It is the result of how benefits are distributed (uniformly across the first 3 weeks) and of how most SNAP participants spend their benefits (quickly and soon after being received). The red line is the count of transactions where SNAP EBT benefits were used as tender. Ignore the green line.

The week-to-week cyclical pattern of SNAP EBT spending can be observed in Figure 1.2. (Note that these are from a different data source and different store chain, but from the same US state.) At the start of the each month, SNAP EBT transactions (red line) increase until peaking at the second week. The count then declines steadily through the 4th week before once again spiking during the 1st week of the following month. (Ignore the green line; these are DUFBI counts from a different data set.)

Supply Chain Concerns

One concern I had was if local supply of produce differed geographically across the state where the stores are located. The company representative told me that should not be a factor because all stores are supplied from the same warehouse. Therefore, in theory, each store should have the same local produce. I plan to visit the stores on a later date to confirm that this is actually the case.

Overview of Store Selection and Expansion

How the 17 “treatment” stores and 15 “control” stores were selected in 2016 is important. First and foremost, selection was *not* random. Stores were either selected by the company (13 of 17) or self-selected into Double Up (4 of 17). Second, the 15 control stores were selected *after* the selection of the 17 treatment stores. Data from all remaining stores was requested but the request was denied; only 15 stores had been approved by the company’s management. Finally, and most importantly, the selection criteria for the 17 treatment stores is *observable*. The implications of this will be covered in more detail in the Methods section.

Selection and Expansion of Double Up Stores

The first 2 stores were piloted with Double Up in 2014. Both were in geographically distinct areas (these will be referred to as “Node 0” and “Node 1”). There was a small expansion adding 3 more stores in 2015. The 3 stores were selected because they were geographically close to the 2 original pilot stores (2 close to Node 0, 1 close to Node 1). The 5 stores are referred to as the “core”. The location of these 5 stores, separated in two clusters, established the geographic constraints that were then used to determine most of the additional stores in 2016.

Double Up was expanded to 12 more stores in 2016, totaling 17. Of those 12, 6 were selected due to their proximity to the 5 core stores, their SNAP EBT⁷ sales figures, and similarity in surrounding demographics (high population density, more African-American). In other words, 9 of the 17 stores—excluding the initial 2 pilot stores—were selected on a set of *observable* characteristics. The remaining 6 stores were not.

Of the remaining 6 stores, 4 asked if they could be included in the program. These stores *self-selected* into Double Up, making these stores fundamentally distinct. They were considered, and then included, only because they fell within the “Top 50”. The final 2 stores were selected by the company for “strategic business decision”. The best interpretation of this is that the company thought that Double Up would provide a competitive edge to the 2 included stores given some internal calculus. How the company came to this decision is *unknown* and therefore *unobserved*.

⁷Electronic Benefit Transfer.

Table 1.1: Year by Year Store Selection. Stores 1 and 2 represent the initial 2014 pilot stores.

| Store | 2014 | 2015 | 2016 |
|-------|-------|----------|---------------|
| 1 | pilot | pilot | pilot |
| 2 | pilot | pilot | pilot |
| 3 | | assigned | assigned |
| 4 | | assigned | assigned |
| 5 | | assigned | assigned |
| 6 | | | assigned |
| 7 | | | assigned |
| 8 | | | assigned |
| 9 | | | assigned |
| 10 | | | assigned |
| 11 | | | assigned |
| 12 | | | self-selected |
| 13 | | | self-selected |
| 14 | | | self-selected |
| 15 | | | self-selected |
| 16 | | | unobserved |
| 17 | | | unobserved |

Table 1.1 helps understand the year by year expansion of Double Up. Stores are classified as either assigned, self-selected, or unobserved. To be assigned means a store's participation in Double Up was determined (assigned) by the company; self-selected means the store asked the company to participate; unobserved means that the company selected the store to participate in Double Up but for unknown and unobserved reasons. Numbers were assigned to each store for easy reference but otherwise have no meaningful interpretation.

Expansion on Observables

An example expansion on *observables* (using fake data) can be seen in Figure 1.3. In the top frame, one can see two blue dots. These blue dots simulate the first two pilot stores in 2014. The left blue dot is Node 0 and the right blue dot is Node 1. The gray zones represent areas of higher population density. Dark gray is considered *urban*, defined as having a population density of 1500 persons or more per square mile. The light gray are small towns and cities, more densely populated than very rural areas, but could not be considered *urban*. The expansion in 2015 (middle frame) proceeds to the stores closest to the original pilot stores. The expansion continues to 6 more stores in 2016 (bottom frame) away from the nodes but also along areas of higher population density.

Not conveyed in Figure 1.3 is that the 2015 and 2016 expansions also move through stores that happen to be “highly ranked”—that is, have relatively higher SNAP EBT sales.⁸ Also not conveyed is the fact that there is a strong correlation between geography, population density, racial composition, and SNAP EBT sales. The 2015 expansion to the most nearby stores also meant that it was an expansion to stores with high SNAP EBT sales in densely populated, African-American neighborhoods. The 2016 Double Up expansion was more explicit given that set of feasible stores substantially increases as one moves away from each node. Double Up stores were thus specifically selected not just by geographic proximity, but also by SNAP EBT sales ranking and demographic compositions similar to the initial 2014 stores.

Expansion Data

Data for about each store was built by merging 4 different sources. The core data came from the grocery retailer directly, which provided a list of stores participating in DUFB from 2014 - 2016. The grocery retailer also provided a list of stores ranked by EBT sales as a fraction of total store sales and the size (square footage) of each store. Demographic and socioeconomic data came from the Data Science Toolkit API⁹ (DSTK) and the American Communities Survey API¹⁰ (ACS). The DSTK API provides access to US Census data from 2000 at the *census block* level and the ACS API provides data spanning 2010 - 2014 at the *zip code* level. Lastly, data was extract by mining the Family Fare¹¹ website.

Matching was done with the ACS data. The ACS zip code data was preferred because it provided income and housing data. Zip code level demographics are sufficiently descriptive; stores are evenly distributed across zip codes. Specifically, 58 stores are spread across 58 zip codes and 4 stores split between 2 zip codes (60 zip codes and 62 stores).¹²

Ideally, prior to matching, demographic data from the neighborhoods surrounding the store, who shopped at the store, and how the store was performing, its size, and goods made available would be known. Unfortunately, most of the publicly available data was not store-specific. The only store-specific data came either from the retail parent company directly or from mining the website.

Selection of Control Stores

Ideally, all remaining stores would have been available to use as a control group but the company only approved that data be released for 15 stores. This left the added—and incredibly

⁸All stores within the chain were ranked by SNAP EBT sales as a percentage of total sales.

⁹<http://www.datasciencetoolkit.org/>

¹⁰<http://www.census.gov/data/developers/data-sets/acs-survey-5-year-data.html>

¹¹<https://www.shopfamilyfare.com/store-locator>

¹²I must also admit that my spatial and geocoding skills improved drastically in the months following the matching process. At the time, I did not know how to determine census blocks from lat/long coordinates, relying on the DSTK API that did the conversion. The downside is that it returned 2010 data. I’m confident I could do it now, but I still think it is not worth the effort given the US Census Data excludes income data.

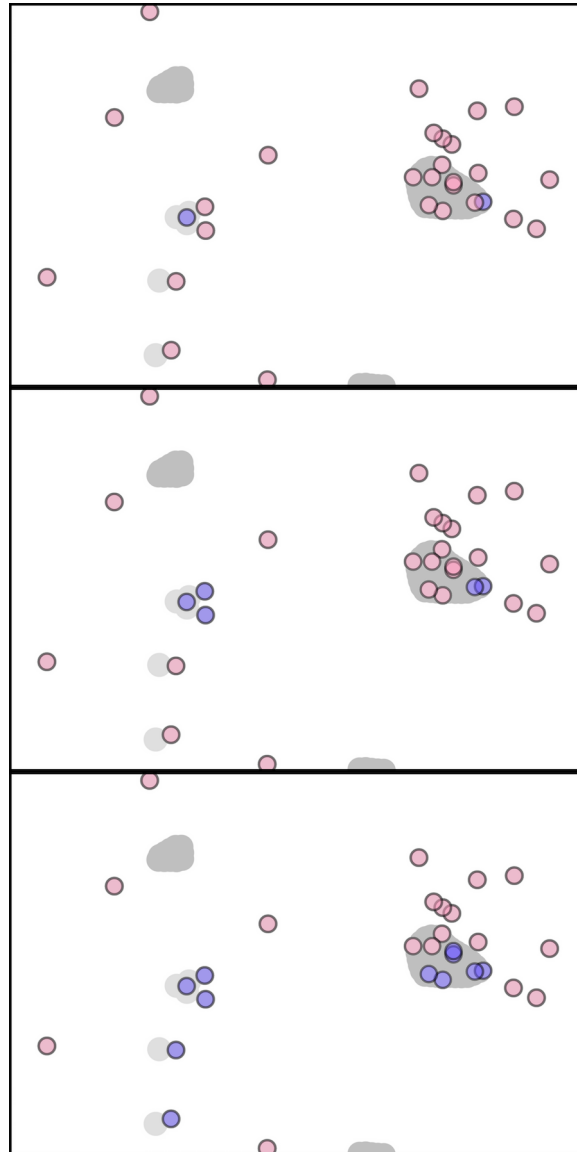


Figure 1.3: Example expansion over time from 2014 to 2016 (top to bottom) using fake data. Blue dots denote stores with Double Up, pink dots denote without. Gray sectors denote higher population density. The initial nodes can be seen in the top (2014) frame.

important—step of selecting the control stores since the company approved, but did not explicitly select, the 15 stores.

Selecting the control stores proceeded in two steps. First, stores that either self-selected or were selected using some unobservable criteria were matched using *Coarsened Exact Matching* (CEM) (Iacus et al., 2011). Second, stores assigned Double Up were pooled with nearby control stores and then scored using a linear probability model. Each step is explained in detail.

Step 1: Coarsened Exact Matching

The 6 stores classified as self-selected or unobserved (stores 12 through 17; see Table 1.1) were compared against all possible control stores for matches. Matching was done across 5 dimensions: race, income, population density, store attributes, store EBT sales. One variable per dimension was selected: percentage of population that is African-American (zip code level); people per square mile (zip code level); median income for people who have received SNAP or similar assistance (zip code level); the number of associates employed in each store; and the percentage of total stores sales attributed to EBT/SNAP.

Of the 6 stores (stores 12 - 17), only 3 produced viable matches. However, each of the 3 matched stores had matched to more than one control stores. The closest stores, by driving distance, were selected as the tie-breaker for each matched store. Stores were sufficiently far apart, with very sparsely populated areas between, that “spill-over” was considered unlikely. That is, it is considered unlikely that a shopper near a store without Double Up would opt to drive 30 or more minutes to shop at the store *with* Double Up.

This left 12 stores to be allotted to the control group and 3 treatment stores to be effectively discarded.

Step 2: Scoring via Linear Probability Model

Assignment to treatment and control can be perfectly determined since we know and observe the criteria used for assignment: geographic distance from an initial store (node), SNAP EBT sales rank, and demographics—specifically population density and percentage African-American.¹³ A scoring function was created by fitting a linear probability model to all stores within 140 kilometers of the two initial pilot stores.

$$\begin{aligned} s &= P(\widehat{\mathbf{D}} = 1 | \mathbf{X}, \mathbf{N}) \\ &= \mathbf{X}\hat{\beta} + \hat{\alpha}\mathbf{N} + (\mathbf{X} \odot \mathbf{N}) \hat{\gamma} \end{aligned}$$

s are the fitted values of the estimated linear probability model; $\mathbf{D} \in \{0, 1\}$ is a $n \times 1$ vector of store assignments to Double Up; \mathbf{X} is an $n \times k$ matrix of normalized observable covariates that determine assignment; $\mathbf{N} \in \{0, 1\}$ is an $n \times 1$ dummy vector denoting the closest pilot store aka “Node”, where 0 is Node 0 and 1 is Node 1. \odot represents element-wise multiplication aka “Hadamard product”.

¹³It should be noted that the company did not explicitly say population and race were part of the selection criteria. Instead, they said something along the lines of “stores serving a similar population as the original stores.”

Stores were sorted by the fitted values of the model, \hat{s} . There is perfect separation between Double Up stores and those without (see Figure 1.4). Therefore, the top 11 stores by score value are all Double Up stores. The next 12 stores by score value are then allotted to the control group.

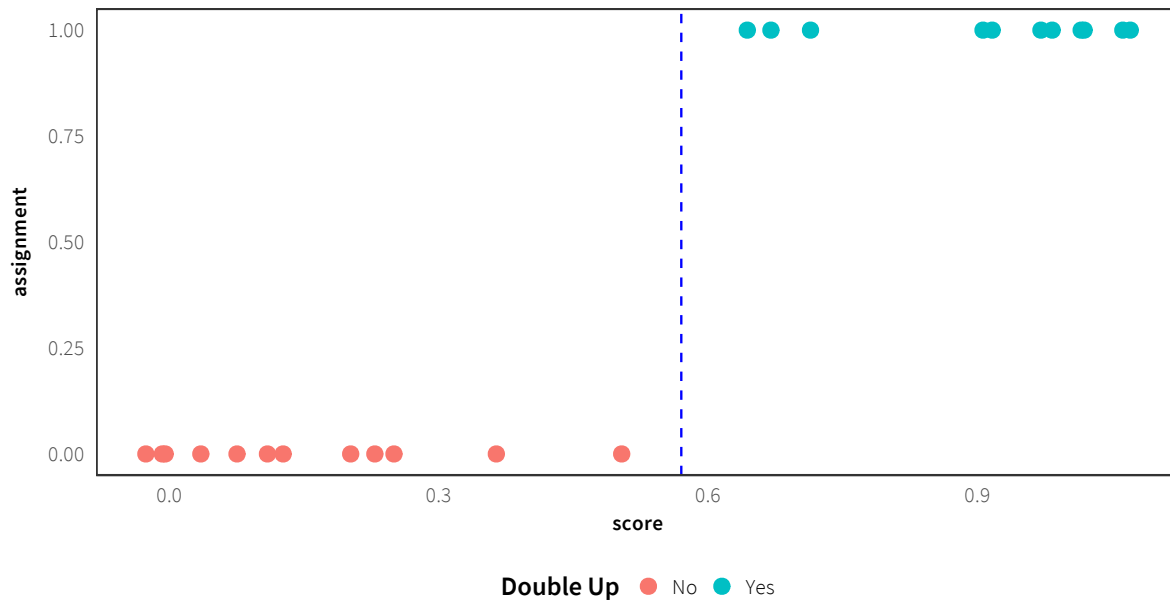


Figure 1.4: Store Score vs Double Up Assignment

Motivation for Matching

Not all treated stores will be matched to a control. As mentioned, this is due to the nature of how the 17 treated stores were selected. The parent company intentionally selected stores with some of the highest EBT (aka SNAP Electronic Benefit Transfer (EBT) Card) sales that were also within relatively similar geographic locations. This reduced the burden of advertising and implementing DUFb for The parent company. The unfortunate downside of this implementation is that it effectively removed any likely matches for treated stores located in the most Urban areas (e.g. Grand Rapids and Battle Creek).

Here is an example to illustrate why it is infeasible to matching all treated stores and instead expand selection algorithmically on observables. If we calculate the percentage of the population by *zip code* that is African American then split the data into treatment and control groups, we get the following:

```
#> Difference in Means (Treated - Control) = 7.848600
#>
#> Population, % Black (Treated, Top 10):
```

```
#> [1] 26.060929 21.945444 19.790582 18.880000 18.688795 14.693513 11.857163
#> [8] 8.531952 5.644237 5.644237

#>
#> Population, % Black (Control, Top 10):

#> [1] 8.575720 8.141256 7.271242 5.057010 4.613969 4.374678 3.256329
#> [8] 2.955071 2.676733 2.593660
```

What these results tell us is how potentially distinct the populations are within the zip codes containing the treated stores. Sorting population percentages in descending order, no good match exists within the control stores for the top 7 treated stores. One variable is the simplest case; matching only gets more difficult as one brings in more variables to match.

Considering the separation between some of the treated stores and all of the control stores, it was prudent to rethink the store selection and matching strategy.

It must be noted that matching is not a necessary step during every design phase. It is, in large part, a way to hedge against the possibility that merely selecting the next top 15 stores by EBT sales could sour the estimates. Matching a smaller set of treatment stores against a larger pool of controls can often produce estimates less sensitive to even the smallest changes in some model specifications (Imbens and Rubin, 2015). However, other models and tools (like regression) are in relatively unperturbed by a lack of design-phase matching, but still benefit from having a larger sample size (Angrist and Pischke, 2008).

Matching Details

Like most data-dependent endeavors, the most tedious part of matching the stores was obtaining enough variables. Once enough data were obtained, variables were selected on how best they captured data from the following dimensions:

- Demographics (e.g. race)
- Income/wealth
- Population density (e.g. urban vs rural)
- Store attributes
- Store EBT sales

One may assume that more variables makes matching easier. This is only true insofar as it provides one with a large pool of options. It is still necessary to carefully select how many variables one is using because matching becomes more and more difficult with each added variable used. This is especially true with a small sample size.

The matching covariates that were finally selected are:

- `pct_black`: Percentage of population that is black (zip code level)
- `dens_pop`: The population density (people per square mile, zip code level)

Table 1.2: CEM Match Matrix

| | G0 | G1 |
|-----------|----|----|
| All | 44 | 17 |
| Matched | 14 | 3 |
| Unmatched | 30 | 14 |

- `income_p50_snap_yes` : Median income for people who have received SNAP or similar assistance (zip code level)
- `store_n_associates` : The number of associates employed in each store.
- `ebt_sales_pct` : Percentage of total stores sales attributed to EBT/SNAP.

Results of Match

G0 represents the “control” group and G1 represents the “treated” group. One can observe that 3 “treated” stores were matched to 14 “control” stores. Each of the 3 treated stores was matched to its closest control store by driving distance.

Covariate Cut-points

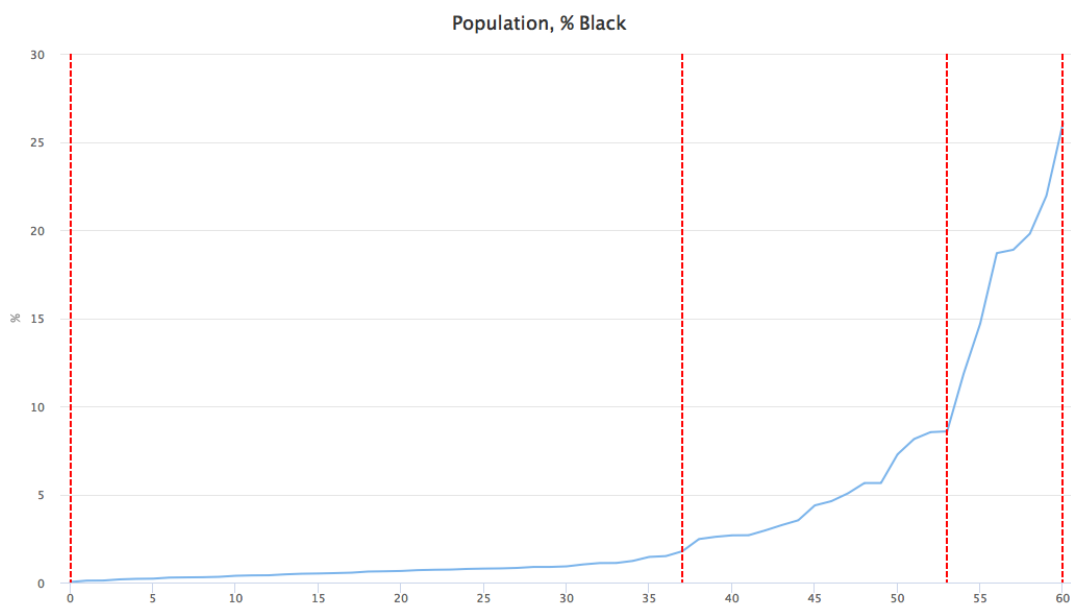
The CEM procedure depends heavily on the “cut-points” selected for each variable. This is akin to setting the cut-off points when turning a continuous variable into a categorical variable. For example, when converting income values from dollars into low- middle- and high-income groups, at least 4 cut-points are required (2 of which are the maximum and minimum). What the other 2 cut-points are will greatly affect the match. This leads to the question, for example, should the cut-points be 25000 and 100000 or perhaps the median and the top 10%?

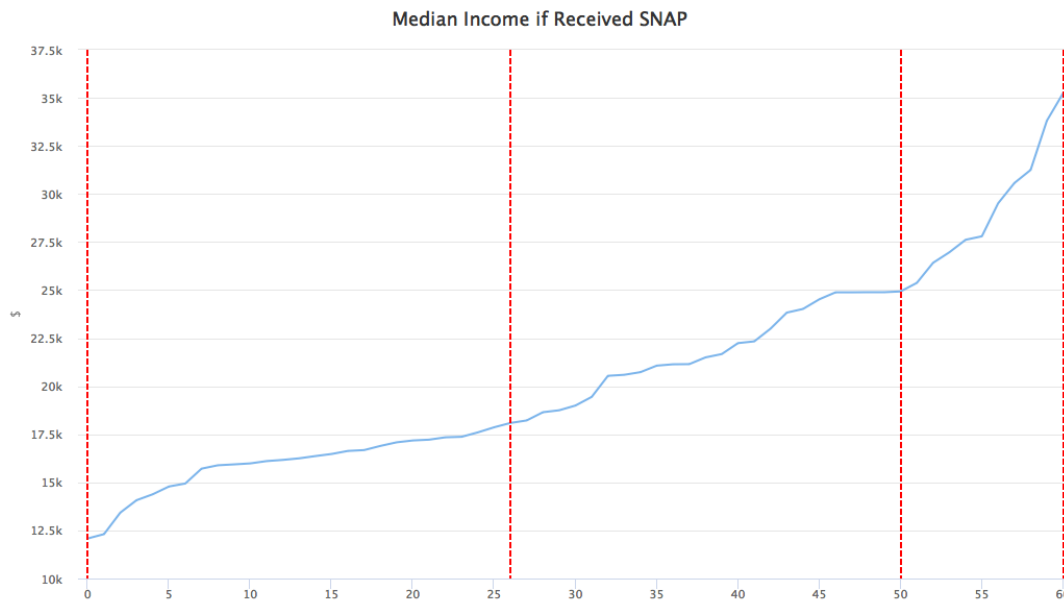
For the matches produced, the following cut-points were created.

```
#> $pct_black
#> [1] 0 2 10 40
#>
#> $dens_pop
#> [1] 0 200 1000 5000
#>
#> $ebt_sales_pct
#> [1] 0.00 1.65 3.00 5.00
#>
#> $store_n_associates
#> [1] 20 40 60 80 130
#>
#> $income_p50_snap_yes
#> [1] 12000 18000 25000 40000
```

Understanding why is best explained using a visualization. Below are graphs of the variables `pct_black` and `income_p50_snap_yes` with their corresponding cut-points. The aim of each cut-point is to balance the creation of reasonably sized partitions while still marking obvious shifts in the underlying distribution.

For example, in the first plot (`pct_black`), there are clearly points where the slope dramatically increases — and then spikes — in the percentage of African Americans. But in the second plot, the slope is more gradual, so the partitioning is aimed more at getting relatively balanced groups.





Methods

Set up

Recall the research question of interest—whether the DUFBI incentive increases spending on fresh fruits and vegetables (FV) within stores participating in the program. The outcome variable, in this case, is total spending on FV.

I've considered other possible values for the outcome variable. For example, the proportion of dollars spent per transaction or the total ounces of FV purchased. Each added an extra layer of complication. Using proportion of expenditure per given transaction would vary wildly, particularly with small transactions, and would create two mass points at zero and one (no FV purchased and only FV purchased). Total ounces depends on the variable and quality of the data. I cannot be sure the data received will contain counts or ounces for fresh fruits. Fresh fruits generally do not have UPC values. Dollars spent (expenditures) on FV gets to the heart of the question and is the data guaranteed to be in the data.

Unfortunately, using the total expenditure of FV is complicated by 3 problems.

1. Purchases not linked to customers.
2. Outcome Variable with non-trivial amount of zeros (corner solutions).
3. Consumers maximize across multiple product types.

The first problem is not specific to the outcome variable. The inability to link purchases to individuals means I cannot use Panel Data Methods at the customer level; I will be unable to look at how customers behavior changes over-time and cannot control for unobserved customer heterogeneity. I'm instead limited to methods for repeated cross-sections over-time.

The second and third problems are directly related to the preferred outcome variable. I anticipate a non-trivial amount of zeros because I expect to observed a large fraction of transaction where no FVs are never purchased. Likewise, FV expenditures are often a part of a basket of goods. Just as I anticipate a non-trivial amount of zeros, I also anticipate that FVs are not purchased independently of other goods. When spending their money, consumers optimize expenditure across a large set of options. This optimization is also complicated by the first problem (cannot link) but I will go into more details later.

Methods Overview

Difference-in-Difference-in-Differences

I want to measure the difference in SNAP EBT dollars being spent or redeemed on fresh produce. If the incentive is working, then I should see an increase in SNAP EBT dollars spending on fresh produce within stores implementing the DUFBI incentive. I do not think it is enough to assume the DUFBI incentive, if effective, will be measurable without considering heterogeneity. That is, if a store's implementation of DUFBI affects individual behavior, the effect could be hard to measure if measured across the entire distribution of FV purchases, instead of the subset of SNAP EBT dollars spent.

The Difference-in-Difference-in-Differences (DDD) regression is a fitting framework if I expect the SNAP population that patrons DUFBI (experimental) stores to be systematically different from the SNAP population that patrons the non-DUFBI (non-experimental) stores.¹⁴ Differencing along time, store experimental group, and the type of transaction (SNAP or not) will reasonably capture any systematic differences.

This is unfortunately complicated given that I cannot link transaction to individuals. But I can tell if a purchase was made with SNAP EBT dollars or that it redeemed DUFBI points. This is enough to split transactions into SNAP/DUFBI-redeemed versus other standard transactions. This provides a way of grouping to perform a DDD.

Any model like DDD that is estimate via OLS, however, ignores the second and third problems. I think it is prudent to consider consumer choice behavior and the mechanisms that generate zero-expenditures. Numerous demand models exist for cross-sectional data that, with a few assumptions (like each transaction represents a distinct individual), may better estimate the impact of the DUFBI incentive than straight OLS.

There is a vast literature on consumer purchasing behavior aka choice models (see Train (2009)

¹⁴See Wooldridge (2010) for more details. I'm assuming familiarity with the DDD model.

for an introductory overview). Multiple-discrete choice models, in particular, have become popular given the increased availability of transaction-level (scanner) data (Dubé, 2004; Hendel, 1999). Multiple-discrete choice models, however, are too product-specific. It is not important for me to model which brand and quality of bananas or carrots were purchased. What is important to me is how much was spent on bananas, carrots, and other fruits and vegetable types versus other non-FV types. Remember, my outcome variable is expenditure on *total* FV spending. I'm far more concerned about whether or not consumers are observed buying *any* FV than I am with the exact types. That said, expenditure on non-FV is also important. *Therefore, what is needed are model framework flexible enough to handle a continuous outcome variable with a non-trivial amount of zeros (corner solutions) and multiple types of goods.*

Continuous Outcome Variables and Corner Solutions

Corner solutions for expenditures can occur for various reasons. Pudney (1989) covers three of the most likely mechanisms producing “true” zeros in cross-sectional data. The first is that the data was gathered in too short a period of time for the purchase to occur. This problem is far more common in cross-sectional data of infrequently purchased goods (i.e. durable goods like cars or refrigerators). The second is due to a supply side factor the customer has no control over. For example, there could be a shortage of FVs or none are available. Imagine searching for FV purchases in collection of convenience store data. Many zeros would exist because some convenience stores do not sell FVs. The third zero results from a customer's decision as a function of prices, preferences, and income constraints. A zero is perhaps observed because FVs are too expensive and the customer can get larger quantities of other, equally or more preferred, foods for the same price.

I expect first mechanism could apply to food purchases under specific circumstances. If data are left disaggregated or the period of observation is shrunk substantially, zeros for FVs will exist due to infrequency of purchase. For example, customers that make frequent trips to the store may not always buy FVs. A cross-section of data from one day may have a non-zero FV value for the customer but zero the next. The third mechanism applies very naturally to the grocery store environment (classical utility theory). The second will require further verification. I do not expect to find out that there were shortages of FVs in the stores observed, but I could be wrong.

Humphreys (2013) and Carlevaro et al. (2016) discuss cross sectional models that accommodate corner solutions—Tobit, *Two-Part*, and *Hurdle* models, specifically.¹⁵ The classic “corner solution” regression model is the Tobit model. Corner solutions are utility maximizing and no assumptions are made about the decision not to purchase/consume. In contrast to the Tobit model, the decision to participate in consumption is explicitly formulated in the Two-Part and Hurdle models. Participation is the “first hurdle”, the amount purchased/consumed is the “second hurdle”.

In the “Naive” Two-Part model, the decision to buy is estimate separately and sequentially from

¹⁵Wooldridge (2010) does not appear to differentiate between “Two-Part” models and “Hurdle” models. I will use it following Humphreys (2013) language, which does.

how much (amount) to buy; Probit is used to estimate the decision-to-buy process and OLS is used to estimate the amount purchased. The Double Hurdle model estimates both these decision simultaneously via maximum likelihood. The full Double Hurdle model allows for correlation between the error terms in the decision and amount/consumption equations (Jones, 1992). Imposing the assumption that unobservable factors between the decision and amount decisions are uncorrelated reduces the full “Jones” Double Hurdle to the “Cragg” model (Cragg, 1971).

It is unclear to me if Two-Part or the Double Hurdle models that formalize “participation” are necessary when considering FV purchases. This makes more intuitive sense for something like cigarette or alcohol consumption, where zero-expenditure can be the result of abstention or price/income constraints.¹⁶ There are, after all, consumers who will never consume cigarettes or alcohol, even if free (abstention). But I’m not sure if an abstention mechanism is reasonable when considering FV purchases. Do consumers really opt out (or abstain) from buying FVs altogether?

An infrequency of purchase mechanism for FVs, however, seems more reasonable. Deaton and Irish (1984) introduced this mechanism as an expansion to the Tobit model. This Double Hurdle has been used to model infrequent purchases of butter, pork, and prepared meals (Yen and Su, 1995; Su and Yen, 1996; Newman et al., 2003). I find it reasonable to expect that, for any given daily cross-section of data, some of the zeros observed will be due to infrequent purchase of FVs.

It’s worth noting the general increased popularity of Hurdle models as alternatives to Tobit, and other related models, like Adjusted Tobit and Heckit models. There is a long existing debate over which models perform better, with most of the criticism falling on Tobit. Monte Carlo comparison under different error distributions and exclusion restrictions find Hurdle models consistently out performing Tobit and Heckit models, both in model fit and coefficient bias (Hay et al., 1987; Manning et al., 1987). Monte Carlo studies have also been used to defend both approaches, encouraging a more flexible, case-by-case approach on choosing the appropriate model (Leung and Yu, 1996; Dow and Norton, 2003; Madden, 2008). But applied work in the applied social science, like health care expenditure and consumer purchases, generally tend to favor use of Hurdle models over Tobit or Heckit models (Yen, 1993; Smith and Brame, 2003; Stewart, 2013).

Multiple Goods

The limitation of Tobit and other hurdle models is the estimated demand of a single good. Ideally, expenditure on different types of goods better captures the decisions and purchasing behavior of customers within a grocery store. That is, instead of collapsing all expenditure on FVs into one outcome variable, the model would allow for customers to optimize across *multiple* goods of different types, while also allowing corner solutions. Multiple discrete choice models allow the purchase of multiple types of goods, but do not capture the intensive margin (the amount) of the good purchase/consumed.

¹⁶See García and Labeaga (1996) and Aristei et al. (2008) for abstention-style hurdles.

Dubin and McFadden (1984) construct a *discrete-continuous* model where consumers can select from multiple goods/options but that they are mutually exclusive, perfect substitutes. The *discrete* component of the model captures the decision to buy a non-zero amount; the *continuous* part captures the amount purchased/consumed/utility acquired. The mutually exclusive, perfect substitute condition, however, means that one cannot be observed buying/consuming more than one good/option.

For any observed trip to the store, zero-expenditure in FV implies non-zero expenditure for some non-FV. Ignoring this seems unwise and I plan, at a minimum, to implement a model optimize along two dimensions—FV and non-FV. The best model I’ve found is the *multiple discrete-continuous model extreme value (MDCEV)* model introduced by Bhat (2005). MDCEV is an extension of the Kuhn-Tucker based model developed by Wales and Woodland (1983). MDCEV allows non-zero consumption across multiple goods. Kim et al. (2002) solved the intractability of the Wales and Woodland (1983) model. Bhat (2005) simplified both to be more realistically applicable.

In the next subsection, I will formally introduce the different modeling structures I intend to use in my paper. I will first introduce the DDD framework where estimation via OLS is sufficient. I then expand from OLS to Tobit and other Hurdle models before expanding into the more complex MDCEV model. The share goal, across all models, is the best possible measurement of the impact the DUFBI incentive has on fruit and vegetable expenditures between participating and non-participating stores.

Difference-in-Difference-in-Differences (DDD)

I observe transaction $i = 1, \dots, L$ in store $j = 1, \dots, N$ across $t = 1, \dots, T$ days. Let y_{ijt} be total FV expenditures for transaction i in store j on day t . The DDD regression is

$$\begin{aligned} y_{ijt} = & \alpha_0 + \alpha_1 dE_j + \alpha_2 dS_i + \alpha_3 dE_j \cdot dS_i \\ & + \theta_1 dP_t + \theta_2 dP_t \cdot dE_j + \theta_3 dP_t \cdot dS_i \\ & + \delta dE_j \cdot dS_i \cdot dP_t + \mathbf{x}'_{ijt} \boldsymbol{\beta} + \lambda_t + \epsilon_{ijt} \end{aligned}$$

where dE_j represents store assignment to experimental group, dS_i represents a SNAP or SNAP related transaction (target group), and dP_t represent the treatment period, August - December. λ_t captures daily (time) effects and \mathbf{x}'_{ijt} is a vector of observable characteristics about transaction i in store j on day t . The coefficient of interest is δ . ϵ_{ijt} are idiosyncratic errors at the transaction level.

Again, I do not observed individuals, only transactions. Yet I think it reasonable to assume that the structure of daily transaction data more closely resembles that of repeated cross-sections than of panel data. Assuming it was possible to link individuals to purchases and build panel

data. The same individual would likely be observed *sporadically* within in a given month. That is, were this to be panel of the same N individual shoppers across T total days, many—if not most—of those days would have missing data. There would certainly be shoppers observed multiple times per week, but I expect such shoppers to be rare. I certainly would not expect to have a balanced panel and no shopper would be observed all 365 days.

I therefore find it reasonable to treat each day of observed data as a single independent cross-section of L transactions generated by an unknown $N \leq L$ individuals across J many stores. Aligned sequentially, these form a repeated cross-sections over-time. Each transaction also falls naturally into a cluster—the store where it occurred—that is time-invariant and determined prior to the data being collected.

The model DDD model above can be improved by introducing store effects. These effectively capture experimental assignment and all other time-invariant store-level characteristics. The dE dummy, for example, drops out. The notation can also be cleaned up by condensing the others dummies, emphasizing only variation. The spruced up model is

$$y_{ijt} = \gamma_j + \lambda_t + \phi_0 D_i + \phi_1 D_{ij} + \phi_2 D_{it} + \phi_3 D_{jt} + \delta_t D_{ijt} + \mathbf{x}'_{ijt} \boldsymbol{\beta} + \epsilon_{ijt} \quad (1.1)$$

where γ_j now represents store effects, $dS_i \equiv D_i$, and the remaining dummy variables D_{ij} , D_{jt} , D_{it} , D_{ijt} represent the dimensions along which they vary— i transaction type (SNAP or not), j store experiment group, and t day during DUFEB treatment period (August - December). To capture more detail than just the average, δ_t is allowed to vary by day.

Unobserved Effects

I still do not know what the transaction characteristic variables will be and hence do not know what variables go into \mathbf{x}'_{ijt} . I do know, however, that without panel data, I have no methods for dealing with unobserved individual effects. That is, some unobserved individual effect c_i likely exists such that $e_{ijt} = c_i + u_{ijt}$ where $\exists t \ni E[\mathbf{x}'_{ijt} c_i] \neq 0$. In short, my estimates will be biased due to an omitted variables problem.

I'm am still thinking about how I can capture part of the unobserved individual effect c_i . I am open to suggestions.

Tobit and other Hurdle Models

Calculating fruit and vegetable expenditures, y_{ijt} , for each transaction will result with a non-trivial amount of zeros. These zeros are not “censored” values in the Heckman selection problem sense. They are genuine zeros aka “corner solution”. But the mechanisms behind the zeros is unknown.

Tobit Model

The Tobit model is agnostic to the economic mechanism generating corner solutions. It is the basic approach when little else is known other than the decision not to purchase fruits and vegetables is resulting in zero-expenditures. The basic structure is

$$\begin{aligned} y^* &= x'\beta + u \\ y &= \max(0, y^*) \end{aligned}$$

where y^* is a latent variable and y is observed. Tobit can be generalized beyond requiring homoskedastic error terms but requires normality. This is important because error terms in repeated cross sectional data are assumed independent *not* identically distributed. In other words, heteroskedastic. Other than error term specifications, any additive and linear-in-parameters regression can be estimated using Tobit. In other words, I can set y^* equal to equation (1.1).

For details on the likelihood functions, see Amemiya (1984).

Hurdle and (Naive) Two-Part Models

Hurdle models generally have two parts (i.e. “Double” Hurdle)—a decision-to-buy (participate) and the amount to purchase (consumption) (Jones, 1989). Let $I^* \in 0, 1$ indicate the decision to purchase fruits and vegetables and y^* be the amount of dollars spent. Both are latent variables. Let y be observed expenditures. Formally,

$$\begin{aligned} I^* &= z'\gamma + v \\ y^* &= x'\beta + u \\ y &= I^* \times \max(0, y^*) \end{aligned}$$

$$\begin{aligned} (u, v) &\sim N(0, \Omega) \\ \Omega &= \begin{pmatrix} \sigma_u^2 & \sigma_{uv} \\ \sigma_{uv} & \sigma_v^2 \end{pmatrix} \end{aligned}$$

The Jones (1989) “Full” Double Hurdle model and the Cragg (1971) have the same framework. The distinction is that in the Cragg model assumes no correlation between u and v (i.e. $\sigma_{uv} = 0$). The likelihood function for the Cragg model is, in other words, a simplification of the Jones model. Formally, the Jones model is

$$\begin{aligned} L &= \prod_0 \left[1 - \Phi \left(\frac{z'\gamma}{\sigma_v}, \frac{x'\beta}{\sigma_u}, \rho \right) \right] \times \\ &\quad \prod_+ \Phi \left[\frac{\left(\frac{z'\gamma}{\sigma_v} + \rho(y^* - x'\beta) \right)}{(\sqrt{1 - \rho^2})} \right] \frac{1}{\sigma_u} \phi \left(\frac{y^* - x'\beta}{\sigma_u} \right) \end{aligned}$$

Once again, setting the DDD to be y^* is not a problem. The main problem is determining the participation equation I^* . What factors variables participation i.e. the decision-to-buy fruits

and vegetables? Variables about individual characteristics would certainly be helpful here but that isn't possible. There is clearly some mechanism driving consumers to buy or not buy fruits and vegetables. The likeliest candidate is data on *other* products purchased within a given transaction. The existence of complimentary goods (e.g. olive oil, meats, etc) may increase the likelihood of observing FV purchases within the same trip. The size of the shopping basket likely increases overall chances of FV purchases. Likely day of the week or week of the month, since government benefits and pay schedules may increase the chances of shopping trips in aggregate.

I anticipate estimate both the Jones and Cragg model as a robustness check. But I do not expect $Cov(\sigma_u, \sigma_v) = 0$ given I cannot capture individual effects. Unobserved individual effects likely affect both participation and consumption. In both equations, individual effects are absorbed by the error terms, making them correlated by construction.

I will also estimate a “Naive” Two-Part model, where the participation and consumptions equations are estimate independently from the other (Probit + OLS). Again, just another comparison point.

Multiple Discrete-Continuous Extreme Value Models

The Bhat (2005) Multiple Discrete-Continuous Extreme Value (MDCEV) framework allows for choice along a vector of non-mutually exclusive goods. Non-negative consumption is allowed in across all goods.

I will attempt to use a later iteration of the MDCEV model from Bhat (2008). The distinction that interest me is that the Bhat (2008) model allows for price variation across goods and explicitly formulates the Kuhn-Tucker constraints using expenditures. The econometric model is as follows.

Utility from purchasing vector of goods $(x) = (x_1, x_2, \dots, x_k)$ is defined as

$$\begin{aligned}\tilde{U} &= \sum_k \frac{\gamma_k}{\alpha_k^*} \psi(z_k, \epsilon_k) \left[\left(\frac{y_k}{\gamma_k p_k} + 1 \right)^{\alpha_k} - 1 \right] \\ \psi(z_k, \epsilon_k) &= \exp(z_k' \beta + \epsilon_k) \\ \sum_k p_k &= Y\end{aligned}$$

where z_k is a vector of attribute variables about product k and of the consumer, y_k is expenditure on product/good k , p_k is the price, and Y is total expenditure on basket of goods (x) . ϵ_k are idiosyncratic shocks with an extreme-value distribution. To understand the role of ψ_k , α_k and γ_k , see Bhat (2008) for details.

Using the first good as a reference group, the KT conditions that solve the optimal expenditure problem (the Lagrangian above) are

$$\begin{aligned}
V_k^* + \sigma \epsilon_k &= V_1^* + \sigma \epsilon_1 \text{ if } y_k^* > 0 (k = 2, 3, \dots, K) \\
V_k^* + \sigma \epsilon_k &< V_1^* + \sigma \epsilon_1 \text{ if } y_k^* = 0 (k = 2, 3, \dots, K), \text{ where} \\
V_k^* &= \sigma z_k' \beta + \sigma (\alpha_k - 1) \ln \left(\frac{y_k}{\gamma_k p_k} + 1 \right) - \ln p_k
\end{aligned}$$

where V_k is identified only when α_k or γ_k is fixed (both terms estimate related “satiation” behaviors). See Bhat (2008) (equations 18 and 19) for the Jacobian and closed form expression for the probability of spending y_k^* . Example likelihood function to solve the equation for $i = 1, \dots, L$ transaction (or N individuals) in a given cross-section can be found in Bhat (2005) (equation 18) and Bhat and Sen (2006) (equation 8).

Expected Challenges with this Model

Despite the theoretical advantages of the MDCEV framework (i.e. optimization over multiple goods allowing corner solutions), there are a few challenges I anticipate with using the MDCEV framework.

The first is a concern about prices. The most effective way to incorporate price variation is to make the basket of available goods equal to the full universe of observed products. This would likely be huge. The MDCEV framework is flexible enough to do it, but my fear is that it will lead to some difficulties in interpretation. In reality, however, I don’t care as much about expenditure at the product level as much as I do about expenditure on particular types. That is, I care more about spending on FVs versus non-FVs. Therefore, at the simplest level, my vector of possible goods would be just 2. However, how would I price FV versus non-FV? I could construct a price index for just those two groups but it would combine far too many distinct food types to be reasonable. Moving towards something like having between 20 to 40 general food categories seems like better approach. For example, Harding and Lovenheim (2014) estimate the prices for 33 different product groups by using the Stone price index, which depends only on observable price values.

The second concern is programming related. There are no available packages that implement the MDCEV package. I would have to adapt the GAUSS code provided by Bhat on his website in order to get the model running. This isn’t a concern about being able to do it as much as the amount of time it would require to learn/understand GAUSS in order to implement it in R or Python.¹⁷

Regression Discontinuity (RD)

Work in Progress

¹⁷It looks like some folks at the company Mobility Analytics¹⁸ have started, which is very promising.

I will also perform a secondary Regression Discontinuity (RD) Design analysis.

In the Store Selection section, I discussed the construction of the score function $s = P(\mathbf{D} = 1 | \mathbf{X}, \mathbf{N})$. The score of each store can be determined via observable data, $s_j = P(D_j = 1 | \mathbf{x}_j, n_j)$. These scores, when ordered, produced perfect separation between experimental stores and control stores (see Figure 1.5).

An RD design requires a *running variable* where, above some value c , the probability of being assigned to the experimental group is 1. Assume I make the score function s my running variable such that $D_j = 1[s_j \geq c]$.

In my case, assignment D_j is determined by s_j by construction. Recall that s_j is a function estimated on observable covariates. These are the same observable covariates the company used to determine assignment for a subset of stores. I used a linear probability model to estimate the score function and the estimated model perfectly predicted assignment. I then ordered stores by their score value and selected the next 12 unassigned stores.

This problem is that I do not actually know c . I only know that $c \in (0.50, 0.64)$. The light gray band in Figure 1.5 displays the possible values of c . The problem, in essence, is that I do not have—and never will have—enough stores, so I’m lacking density around where the separation occurs.

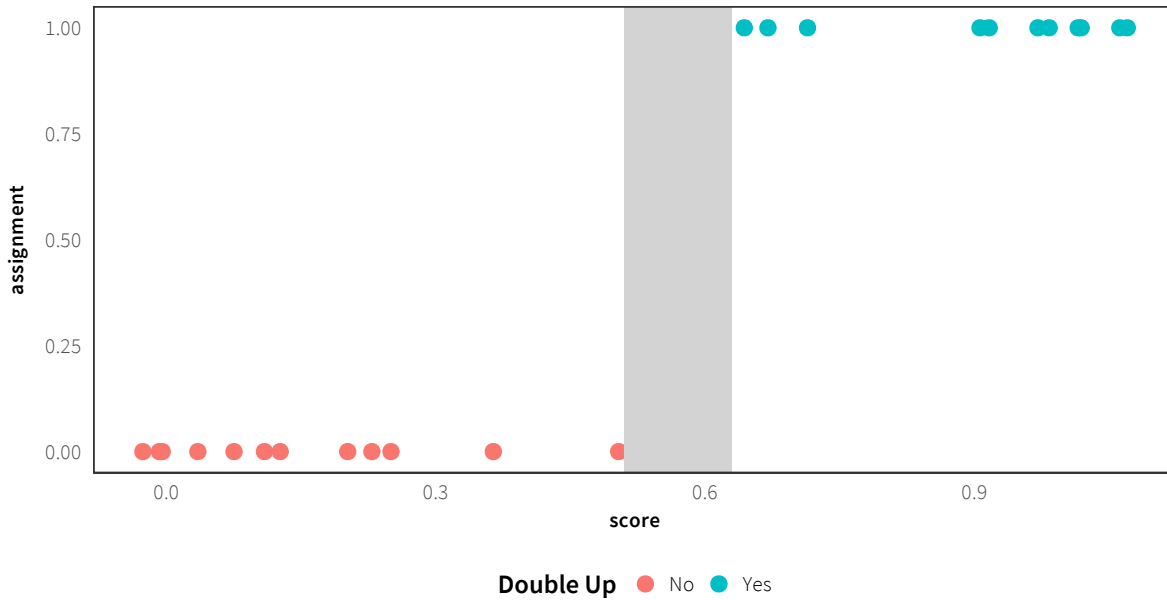


Figure 1.5: Store Score vs Double Up Assignment with Uncertainty Band (light gray)

I propose to estimate the RD design using various values of c . The perpetual gap means any model estimate to the left or right of some $c_0 \in (0.50, 0.64)$ will have to be extrapolated up to c_0 .

Set-up

The outcome of variable, as before, is *the total daily amount of dollars spent on fruits and vegetables per store transaction*. I decided on using days as the unit of observation to increase the sample amount of data for estimating. I expect there to be enough transactions per day for this to be possible. The time frame will be August - December (months 8 - 12) of 2016, when the DUFBI incentive is in place. Only SNAP transactions will be considered and transactions will be pooled. Given that stores may vary in sales volume sold, I may divide by total SNAP dollars spent so that the outcome variable is instead a proportion. In total, there will be 11 treated (experimental) stores and 12 control stores.

Let y_{jt} represent the outcome variable where $j = 1, \dots, N$ denotes stores across $t = 1, \dots, T$. Let c denote the cutoff; s_j the score computed for store j ; and D_j the assignment variable. Each draw (or row) of data for store j is a vector (y_{jt}, s_j, D_j) corresponding to a single day. λ_t are time effects and u_{jt} is an idiosyncratic store level error term.

The RD model I propose follows the setup of Lee and Lemieux (2010) (section 4.3):

$$y_{jt} = \alpha + \lambda_t + \rho D_j + \gamma(s_j - c) + \delta D_j(s_j - c) + u_{jt}$$

Expected Results

Plotting RD data and observing a visual gap is standard. The first thing I would do is plot the outcome variable of interest—total daily (fraction of) SNAP dollars spent on fruits and vegetables—against the running variable s_j . A total of $N \times T$ (23×153) data points exists; each value of s_j , $j = 1, \dots, 23$ will contain $T = 153$ points.

The graph produced will have more gaps compared to conventional RD graphs. In more conventional RD graphs, each point represents a single value for a single person (e.g. score on an exam), producing more points along the running variable axis. I do not have enough stores to produce enough s_j values for this to be possible. Instead, this RD design plots multiple points per stores, creating a distribution such that the mean (or median) value (with some confidence interval) becomes the fitted values of interest. Estimation wise, this distinction changes very little; $E[y_{jt}|s_j, D_j]$ effectively fits a mean value to each different store. But graphically, what matters in my RD is the overlap between distributions before and after the cut-off point.

Chapter 2

The Durham Connects RCT and Applications for Social Services

Motivation

Research Question

Did assignment to the Durham Connects (DC) RCT impact a family's future probability of applying for social services? That is, for families assigned to DC during the trial period, I want to see if the intervention (nurse home-visit) increased the probability of applying for social services *sooner* and/or overall.

Hypothesis: I expect to observe a larger proportion of families, randomly assigned to the Durham Connects program, requesting social services. This would include social services like the Supplemental Nutrition and Assistance Program (SNAP), Temporary Assistance for Needy Families, Child Care Subsidies, and Medicaid.

My hypothesis is that the information and nurse contact provided to DC families decreased the complexity of applying and navigating the social safety net. As a result, I expected DC families will be observed applying for social services sooner and/or more frequently, not because they are, on average, in greater need of assistance, but because they have been informed and encouraged to seek out available resources.

The RCT design of the Durham Connects program allows me to make certain assumptions with reasonable confidence. Without these assumption, my research question would be difficult to answer.

The first assumption is that random assignment resulted in relatively balanced groups. Eligibility for social services is a function of income and demographics, and I'm assuming these are, on average, the same between the treatment and control groups. I have no way to test balance along income, but I can attempt to check balance along race/ethnicity using first and last names.

The second assumption is a high compliance rate. I'm assuming that vast majority of families assigned to DC accept and commit to the nurse home-visit. This assumption should be easy to verify. Compliance is important because any effect the nurse home-visit may have on social service application is going to be driven by the complying population. The nurse is who assesses the mother and child's health and home environment. These assessments, in turn, determines follow-up visits, educational resources, recommendations to programs, and, if needed, referrals—the mechanisms that I believe reduce learning and administrative costs.

The last assumption, related to the first, is valid model identification. Assignment to DC is random. It is, by construction, exogenous to observable and unobservable variables. It is also easy to defend the idea that assignment to DC has a direct impact on recommendations and referrals by nurse home-visitors. Assuming valid model identification is very reasonable given such a good instrument.

Introduction

Not all individuals that are eligible for social services apply to receive them. The proportion of those eligible for a social service that are actually receiving the service is known as the “take-up” rate. Ideally, given complete information about eligibility and the existence of social service programs—and zero costs in apply for, or receiving, government assistance—the take-up rate would be 100%. To do otherwise would be to “leave money on the table”—a violation of neoclassical economic theory. In the United States and across the globe, however, most social service programs never reach a full take-up rate.

Explanations for low take-up rates are numerous. Economists, for example, developed models of social stigma to explain an individual's decision for not applying for government assistance (Moffitt, 1983). “Stigma” broadly encompasses any cost that reduces the total utility acquired from receiving government assistance. Stigma and available benefits can vary across individuals. Those that acquire insufficient net benefits once the costs of stigma are included would therefore, reasonably, choose not to apply for government assistance. That is, the take-up rates can fall below 100% within any set of eligible individuals when the costs of stigma outweigh those of the benefit. Stigma can also be extended to include other standard costs, like transaction costs or search costs.

Low take-up rates can also be explained by relaxing standard neoclassical assumptions, like complete information. If one instead assumes that most individuals have *incomplete* information about existing social services programs and corresponding eligibility requirements, then lower take-up rates are unsurprising. Eligibility requirements, for example, are dynamic. Families and individuals can fall in or out of eligibility given a change in policy, leaving families with an outdated understanding of requirements. For example, following welfare reform in 1996, federal requirements shifted for programs like Medicaid, Supplemental Security Income (SSI), and cash assistance (renamed to Temporary Assistance for Needy Families or TANF).

Welfare reform also gave more power to states to determine eligibility standards. Dissemination and implementation of these new eligibility requirements was not instantaneous and the confusion lead to a reduction in take-up rates for some programs (Stuber and Kronebusch, 2004). Shifting requirements aside, many families that are eligible for social service programs can be misinformed or confused. It can be difficult to navigate the application process when requesting government assistance. Information about programs and their eligibility requirements is diffuse and complicated. We do not expect everyone to fully grasp how to complete their taxes without assistance or making errors. Likewise, we should not expect families coping with poverty to be fully informed about benefit levels or the application process of every existing social service program.

Behavioral economics offers other compelling reasons for low take-up rates. Status quo bias, for example, is a common task-completion deterrent (Kahneman et al., 1991). Simple inertia means that most people will procrastinate. This can keep any person from completing things like applications, making doctors appointments, or even folding laundry. Bounded rationality and the human tendency to use heuristics for decision making also reduce take-up rates. Often, individuals assume, based on some rule-of-thumb, that they must not be eligible. If this assumption is never challenged, either by seeking out information or having it provided, then they will never discover otherwise. Time-inconsistent preferences also present a challenge for take-up rates. Hyperbolic discounting implies that humans will favor putting off any decision where gains are felt far in the future but losses are felt almost immediately. In applying for government assistance, future benefits are discounted heavily while the short-term cost of applying are not (Currie, 2006).

A simpler explanation for low take-up rates is the existence intentional bureaucracy. Governments purposefully make the application process burdensome and confusing to deter applications. The take-up rate of TANF, for example, has plummeted since the federal government overhauled welfare in 1996 (Ribar, 2014). TANF gave enormous leeway to states on how to distribute TANF dollars with little oversight. As a result, over the last 20 years states have shifted away from using TANF dollars for its intended purpose of providing cash assistance to needy families. On average, 26 percent of TANF dollars go towards provided basic cash assistance (Schott et al., 2015). This drop in TANF take-up rates has coincided with increasingly strict TANF eligibility requirements. This is particularly true in state and local governments with a long history of racial animus towards minorities and the “undeserving” poor, like in the deep south (Keiser et al., 2004). North Carolina, for example, added a drug testing requirement to its TANF program known as “Work First” (Lynn Bonner, 2016). These requirements tend to disproportionately affect minority families because they are more likely to be sanctioned by local caseworkers for failing to meet requirements compared to white families (Monnat, 2010). This both increase the cost of acquiring TANF benefits *and* increases the chances of losing access to an already difficult-to-acquire benefit. All in all, take-up rates for some social service programs can be low because state and local governments are actively increasing the costs for applying and maintaining benefits.¹

¹ It is important to note that there is also research showing application complexity always punishes the poor.

Low take-up rates should concern policy makers. The positive impact many government programs have on quality of life is well researched. For example, passage of the Affordable Care Act gave states the option to expand Medicaid coverage. This increased the pool of who was eligible for Medicaid. For those previously without health insurance, Medicaid coverage increased self-reported health status, lowered rates of depression, and reduced financial strain and poverty (Baicker et al., 2013; Sommers et al., 2012; Sommers and Oellerich, 2013). Families that participate in the Supplemental Nutrition Assistance Program (SNAP) increase the nutritional value of their diet and free up cash for use on other priorities, like health care (Bartfeld et al., 2015; Sonik, 2016; Miller and Morrissey, 2017). Increased use of the Earned Income Tax Credit (EITC) increases cash on hand, improves educational outcomes for children, and improves labor market outcomes for adults (Grogger, 2003; Bhargava and Manoli, 2012; Dahl and Lochner, 2012). Lastly, eligible families that participate in the Special Supplemental Nutrition Program for Woman, Infants, and Children (WIC) program see improved child health outcomes when compared to eligible non-participating families (Bitler and Currie, 2005). Therefore, considering the positive impact of most government assistance programs, it should be a priority to champion any low-cost policy changes that increase take-up rates.

In the next section, I will introduce the Durham Connects (DC) program and how I believe it may help increase requests for social service programs. Note that increasing requests for social services is not equivalent to increasing take-up. A request for service, however, is a necessary first step for any eligible participant to receive benefits. Increased requests, therefore, serve as a proxy for increased take-up rates.

The Durham Connects Randomized Control Trial

The Durham Connects² (DC) program is a postnatal nurse home-visiting program designed to be universal, short-term, and less intensive than other nurse home-visiting programs like Healthy Families America and Nurse-Family Partnership. The DC program, in brief, aims to celebrate with new mothers, support and connect them with community resources, and then follow-up if necessary.

Before expanding, a randomized control trial (RCT) of the DC program was implemented from July 1, 2009 to December 31, 2010 to determine its efficacy. The RCT included 4777 births from two Durham hospitals. These two hospitals account for a vast majority of birth in Durham County. The randomization procedure assigned all babies born on even days to the DC program. Babies born on odd days were assigned to the control group, and were not invited to receive a DC home visit.

For those assigned to the treatment group, soon after birth, a DC program liaison at the hospital

When applying for federal student aid, which is open to all families, increased complexity burdens poor families the most. This further implies that the poor are also those most likely to benefit from targeting marketing and educational assistance. See Dynarski and Scott-Clayton (2006) and Bertrand et al. (2006) for more.

²<https://www.durhamconnects.org/about/>

scheduled a home-visit by a registered nurse with the infant's family. The initial home-visit was generally scheduled about 3 weeks following the birth. During the initial home-visit, the nurse assessed and rated 12 factor along 4 domains of family support: health of the mother and child, the safety of the home environment, planning care for the infant, and general wellbeing of the parent(s). Each of the 12 factors received a rating between 1 and 4 from the home-visiting Nurse. Each number represented varying levels of need and risk:

- 1 - No risk/needs. General supportive guidance provided.
- 2 - Low risk/needs. Concerns can be addressed by education and in-home demonstrations during visit.
- 3 - Moderate or high risk/needs. Family are linked with community resources best suited to support risk areas.
- 4 - Urgent needs. Immediate intervention required.

Follow-up visits were scheduled as necessary. Generally, the more support a family needs, the more follow-up visits would occur.

Prior research has used the RCT to evaluate some aspects of DC. Notably, Dodge et al. (2013) found that the DC nurse home-visiting program reduced emergency medical care costs and increase health outcomes for both mother and child. Furthermore, the DC program was found to be cost-effective, saving an estimated 3 dollars in medical costs for every dollar spent on implementation. In short, DC was impressively successful at improving the physical health and mental health of mother and child.

I'm interested in exploiting the randomized assignment to measure what I would consider a secondary effect of the nurse home-visiting program. An essential part of the program was establishing a link between DC families and Durham Social Services (DSS) to "facilitate the ... ease of access to and knowledge about eligible services" (O'Donnell and Wright, 2015). I hypothesize that by providing a trusted contact (the nurse), educational resources, and a link to local social services, a secondary effect of the DC program was that participants had a higher take-up rate of social services than non-participants.

The nurse-patient relationship is key to the success of the DC program. The days and weeks following a new birth are periods of high need for both mother and child (Organization and others, 2013; Evans et al., 2001). High need for postnatal/postpartum support means new mothers and families are more willing to accept help when offered—especially from nurses and nurse-centered programs. Patients, generally, view nurses favorably, but interactions tend to be viewed more positively when they occur outside the hospital/clinic environment (Jansson et al., 2002). Likewise, perceptions about community health programs tends to be more positive when they are known to be organized and conducted by nurses (Kneipp et al., 2009). Nurses that assist in home-visiting program for new mothers, in particular, tend to be viewed very positively by their patients—as both a professional expert and friend (Landy et al., 2012).

While initial DC home-visit may be brief in some cases (e.g. rating is 1), new mothers requiring the most support and resources are visited more than once. Nurses are most involved with families that receive factors rated 3 or 4. In these instances, families are *referred* to Durham

Social Services for help. That is, DSS is made aware that the family is in need of a specific type of support and, with the help of the nurse, links up with the family directly. This is distinct to families with factors of only 1 and/or 2. For these families, nurses only *recommend* community services and resources. The option to utilize the resources is then left to the family.

In both cases, however, notice that the nurse is, in one way or another, reducing the costs associated with applying for social services. At a minimum, the nurse reduces the *search* costs for families by provided information for resources. At a maximum, the nurse works connect families with DSS directly to determine eligible services. In the latter case, the nurse, in partnership with DSS, also lowers the *transaction cost* of applying.

I should pause to specify what it meant for a family to be “connected with DSS”. It is my understanding that this means a family was put in contact with, or place “on the radar” of, a specific DSS worker assigned to assist DC families (name omitted). The degree, and success, to which this worker was involved in assisting families apply for services would have had a significant impact take-up rates. I have yet to interview this person, but I plan on doing so.

Concept in a Plot

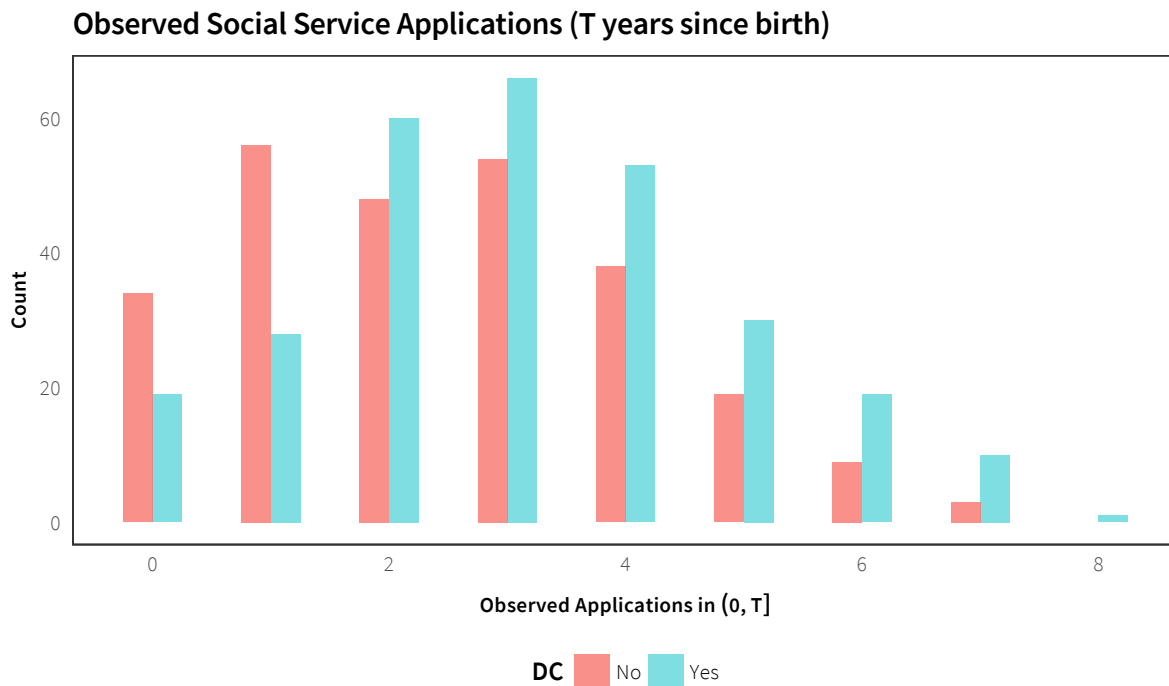


Figure 2.1: Example of Hypothetical Result (Fake Data)

Figure 2.1 represents what I would ideally observe in the data should my hypothesis prove correct. Unit of analysis is aggregated counts of observed applications (requests) per person between time 0 and T (T is some fixed unit of time, perhaps 1 or 2 years). Time 0 is the date of birth for the baby that is (or is not) assigned to the Durham Connects RCT.

The histogram of green bars represents counts for parents that were randomly assigned to DC. Red bars are those assigned to the control. Should my hypothesis prove correct, then I would see, in aggregate per person, more requests for services families that were assigned to DC.

Note that these distributional comparisons are not the best way to test any hypothesis with what is event data. I also do not expect to see so many applications per person. In fact, what I really care about is if DC increase the likelihood of applying at all. But that graph looks far less interesting.

Data

This paper will depend on two sources of data. The first data source is Durham Social Services (DSS). DSS has generously provided administrative records to determine what services were applied for and by whom. The second data source is the Center for Child and Family Health at Duke University (CCFH). CCFH has already collected the short-form birth records of all children born during the RCT. While these data are public record, access to CCFH's data would drastically reduce the burden of acquiring these data.

For example, were I not to use CCFH's data, I would have to request the short-form birth records, wait to receive them, and then manually input the records data into a spreadsheet (the birth certificate comes as digital copies of the paper certificate). That would take an incredibly long time. Furthermore, CCFH was able to verify if the short-form birth records received contained any errors. This is because they have access to their own records collected during the RCT. Six errors were found and corrected. I would not be able to do the same corrections on my own.

Administrative Records

Durham Social Services provided the Durham Children's Data Center (DCDC) with access to their administrative records. The pertinent data within the collection provided is known as the *Scheduler* data. This is a database that logs all requests for social services assistance from the DSS.

I do not yet have explicit permission to write about what is in these data. That said, I do not think I'm revealing anything obvious by noting that the *Scheduler* data contains name, age, service requested, and date of request. These 4 variables are sufficient to explain my methodological approach. I have access to multiple years of data but still need to verify if I have all that is available.

Short-form Birth Certificate Data

Short-form birth certificates are public record. It is possible, for example, to request birth records directly from the North Carolina Department of Health and Human Services³. Collecting all recorded births in Durham County from the 2 largest hospitals would take a considerable amount of time. Fortunately, the CCFH already collected and corrected the short-form birth certificate data.

Short-form birth certificate includes sufficient information to identify which families were randomly assigned to Durham Connects. It also provides enough information to identify parents

³<http://vitalrecords.nc.gov/order.htm>

should they appear in other administrative records that contain name and date-of-birth. Specifically, the child's date-of-birth, the child's name, the mother's maiden name, and the father's name (if present).

These four pieces of information are enough to search and tag when the parents of a child born during the DC RCT applied for services. The child's date of birth is all that is required to determine assignment status.

Matching Strategy

An important step will be to link the two datasets. This will likely be done by matching on the names of the parents and dates of birth. Fuzzy matching procedures for character strings exists in R and Stata. I do not think this will too difficult or computationally intensive as the set of names that need to be searched for is quite small (about 5000).

IRB and Permissions

Currently, I am in the process of submitting an IRB request to access the CCFH's database contain the digitized and curated public short-form birth records.

I am also waiting to hear if I have permission from the director of Durham Social Services to link these two data sets. I have no reason to believe the director will not approve. It is just a matter of having an opportunity to sit down and explain the idea and what it entails. The meeting is anticipated to occur in late March.

Methods

Methods for this paper are greatly simplified by the fact that assignment to Durham Connects was *random*. This immediately provides an instrument where, by design, the exclusion restriction is true (always exogenous) given almost any outcome variable of interest. For this study, I am interested Durham Social Services *applications*, which will serve as a proxy for take-up rate. Requesting (applying for) government assistance does not guarantee receipt of benefits. But it is a necessary step for any eligible individual/family to apply.

A Simple Model of Social Service Demand

A simple economic model helps illustrate how I believe the Durham Connects program may help increase take-up.

Assume all individuals equally value government benefits and incur the same costs when applying for benefits. Individuals, however, have different characteristics. These characteristics determine both eligibility and size of benefits. Let's also assume complete information, rationality, and that errors when applying are non-existent.

Individual i with characteristics vector \mathbf{x}_i will apply for government assistance only if the *net benefit* amount is greater than zero. That is,

$$r_i = \begin{cases} 1 & \text{if } NB(\mathbf{x}_i, c) > 0 \\ 0 & \text{if } NB(\mathbf{x}_i, c) \leq 0 \end{cases}$$

$$NB(\mathbf{x}_i) = B(\mathbf{x}_i) - c$$

where r_i is the decision to apply for benefits; $NB(\mathbf{x}_i, c)$ is the net benefit; $B(\mathbf{x}_i)$ is the benefit amount as a function of individual characteristics, \mathbf{x}_i ; and c is the cost of applying. Eligible individuals have a value $B_i > 0$. Note that for convenience, $B_i \equiv B(\mathbf{x}_i)$ and $NB(\mathbf{x}_i, c) \equiv NB_i$

My hypothesis is that the Durham Connects program reduces the cost of applying. In this simple model, assume that the DC program drops the cost of applying down to some $\tilde{c} < c$. Let $d_i = 1$ represent assignment to DC. Before assignment, each individual is eligible for net benefits

$$\begin{aligned} NB_i|_{d_i=1} &= NB_{i1} = B_i - \tilde{c} \\ NB_i|_{d_i=0} &= NB_{i0} = B_i - c \end{aligned}$$

such that $NB_{i1} > NB_{i0}$ for all individuals. This implies,

$$P(r_i = 1|d_i = 1) \geq P(r_i = 1|d_i = 0)$$

In words, if assignment to DC reduces the costs of applying, then the probability of applying for all individuals must either increase or stay the same. Under this framework, this would imply that there must exist a population of eligible individuals ($B_i > 0$) such that $NB_{i1} > 0$ but $NB_{i0} < 0$. All other individuals are either ineligible ($B_i \leq 0$) or their application decision remain unchanged after assignment ($B_i > 0$ but $NB_{i1} > NB_{i0} > 0$ or $NB_{i0} < NB_{i1} \leq 0$).

In reality, the cost of applying is also a function of (both observed and unobserved) individual characteristics. But the model, even with simple costs, still helps to illustrate why I believe the DC program may lead to higher observed counts within the treated group.

Analytical Framework

I plan to use the local average treatment effects (LATE) framework to measure changes in the timing and volume of applications to Durham Social Services (Angrist and Pischke, 2008). I

can be quite—but not totally—confident that, whatever the measured difference between the two subpopulations, it was driven solely by *compliers*. I say “quite” because there are still some assumption that need to be made that would be costly to verify. I’ll expand on this later in the section.

In this context, *compliers* are assigned to the treatment (Durham Connects) and do not back out from the nurse home-visit. *Non-compliers* are families with a child born on an even day that opted out of DC or a child born on an odd day that found a way into DC. *Never-takers* are families that would never accept a home-visit and *always-takers* are families that found a way to participate in Durham Connects.

I expect never-takers to have existed but do not know if there were any always-takers. Until I find evidence otherwise, I will assume no always-takers. Likewise, I need check and see if any families with children born on odds days found a way into DC. If this happened, I’m assuming records exists and I can remove them from the analysis. I will also need to check how many families with children born on even days opted out of DC. I believe this did occur but I don’t know the opt-out rate. However, I’m sure CCFH has this data and will provide it once the IRB is approved.

If I observe any differences in the *timing* or *volume* of applications between the treatment and control group, I can be reasonably confident that the effect will come from the complying population. This is because only the complying population should have received a nurse home-visitor. Any observed differences would then be a function of the recommendations and referrals generated by the nurse assessments. If the treated group is found to have earlier application times or higher application rates, then I would expect recommendation and referrals helped reduce the cost of applying. If no differences are found, then the assessments either generate few recommendations and referrals or the recommendations and referrals were ineffective. That is, referrals or recommendations provided no new information, opportunities, or reduced costs to eligible families.

I want to elaborate on what I mean by the *timing* and *volume* of applications. That an eligible family choose to apply for a service would affected that family’s application *volume*. But also important was the *timing* of the application. That a family applied earlier than they would have otherwise is important. As mentioned, hyperbolic discounting and status quo bias push humans to procrastinate. I could count the number of applications submitted within a fixed window (say, 2 years) between the two groups and find no differences. Lost in this comparison, however, would be the *timing* of the applications. That is, if the treated group happened to submit the same amount of applications as the control group, but did so *sooner* than the control, that difference would be missed.

To this end, I propose using two analytical approaches. The first is a simple Probit model. For the outcome variable, I determine which families with children born during the RCT were observed during some fixed period of time. I will then pool all families and regress whether or not they were observed on vector of observed characteristics, eligibility, assignment group, and other variables, like distance from the DSS office.

This first approach is mostly to determine if there is really a “there” there. It is inelegant and ignores some very important aspects of the application process. For example, this totally ignores that eligibility for social services is dynamic. For example, families receive SNAP benefits during a fixed number of months known as a “certification period”. But families can have discontinuous certification periods if they lose eligibility or fail to renew. This model, however, is useful if I make the assumption that dynamic movement in and out of certification is similar between the two groups. That is, I’m assuming the two groups are balance in both observable and unobservable character, such as eligibility, even over time.

The second model will be a Cox proportional hazard (Cox PH) models for recurrent events. These event models explicitly account for time and counts. I must admit, though, that these recurrent event models are relatively new to me but I understand the basics enough to get how to structure the data. (I can certainly see that there is a relationship between Poisson regression and any hazard model.) I’m still deciding what type of Cox PH model suits this study (see Chapters 7 and 8 of Aalen et al. (2008)).

Poisson Regression Model with Pooled Data

Assume I’ve collected data for some fixed interval of time T and know the complete population of RCT individuals, N . Any individual observed applying for assistance is tagged $y_i = 1$. Those never observed are tagged $y_i = 0$. I’m assuming that the treated and control groups are balanced along both observed and unobserved characteristics. The probit model is as follows:

$$w^* = \mathbf{x}'\boldsymbol{\beta} + \delta D + u, \quad u \sim N(0, \sigma^2)$$

$$P(y = 1|\mathbf{x}, D) = \Phi\left(\frac{\mathbf{x}'\boldsymbol{\beta} + \delta D}{\sigma}\right), \quad y = \begin{cases} 1 & \text{if } w^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\star E[u|D] = 0 \star$$

The emphasis on $E[u|D] = 0$ is to reiterate that assignment, D , was random, and is therefore *exogenous*. What I care to find out is the difference in probability of observing *any* social service application given D . Furthermore, my hypothesis is that it leads to an *increase*, such that

$$E[y|\mathbf{x}, D = 1] - [y|\mathbf{x}, D = 0] > 0$$

$$\Rightarrow E\left[\Phi\left(\frac{\mathbf{x}'\boldsymbol{\beta} + \delta}{\sigma}\right) - \Phi\left(\frac{\mathbf{x}'\boldsymbol{\beta}}{\sigma}\right)\right] > 0$$

Of course, since $E[u|D] = 0$, the average treatment effect (ATE) is sufficient (and without bias)

Stratified Cox Proportional Hazard Model

TDB.

Next Steps

Data

- Get IRB approval for short-form certificate data
- Get approval from Michael Becketts to link datasets

Methods

- Research Stratified Cox Proportional Hazard Model

Chapter 3

The SNAP Benefit Cycle and the Demand for Emergency Assistance

Motivation

Research Question

Do requests for local-government emergency assistance increase towards the end of a household's SNAP benefit cycle?

Hypothesis: I expect, on average, an increase in demand for emergency assistance towards the last 2 weeks of the month following SNAP benefit transfers. That is, I expect to reject the null hypothesis that request for formal assistance from SNAP households are randomly distributed between transfer dates.

Formal assistance refers to any assistance—cash, goods—from a government program, non-profit, or charity. In this paper, however, I focus on *emergency* formal assistance, where households apply for one-time (nonrecurring) assistance. I also include an analysis of aggregated food pantry data. This type of assistance can be recurring but when and how it is utilized by households is also enlightening.

I plan to answer the question above in two ways. The first exploits the random nature of North Carolina's SNAP transfer schedule. Households are assigned a monthly transfer date based on the last digit of the head of household's social security number. Using administrative records, I can determine a households transfer date then check to see if, and when, any household member applied for emergency assistance. I can then build a discrete-time hazard model for each individual where the start time is a household's transfer date and the event of interest is date of application for emergency assistance.

The second approach uses food pantry data. These data cannot capture individual level variation in SNAP transfer dates. It can only capture aggregate trends observed within normal

monthly calendar cycles. However, I anticipate that demand for food pantry assistance will increase, in aggregate, during the 4th week of every calendar month, through the 1st. SNAP benefits are transferred from the 1st through 3rd week of each month. Most households will have had access to SNAP benefits for at least 2 weeks by the 4th week of each month. If most SNAP household consume their SNAP benefits quickly, then overlapping demand for additional food assistance will be highest during the 4th week through part of the 1st.

Introduction

Cash assistance to needy families fell dramatically after 1996—the year welfare reform replaced Aid to Families with Dependent Children (AFDC) with Temporary Assistance for Needy Families (TANF). TANF profoundly changed how states prioritize and spend government welfare dollars. The result has been a gutting of traditional cash assistance programs over the last 20 years (CBPP, 2016). Cash assistance used to account for 70% of AFDC spending (Ziliak, 2015). Under TANF, cash assistance has dropped to a national average of 26%, with ten states spending below 10% (Schott et al., 2015).

Decreased access to cash assistance corresponded with increased demand for in-kind “cash-like” assistance—most notably the Supplemental Nutrition Assistance Program (SNAP) (US Department of Health and Human Services, 0400). SNAP is the most popular cash-like assistance available to families coping with poverty. At 45.8 million participants in FY2015, is also the largest food assistance program in the US (USDA FNS, 2016b). Millions of families not only depend on SNAP to provide sustained, predictable access to food, but also as a cash-like income supplement. But SNAP benefits are not cash. They cannot pay the rent or the bills. And when economic instability forces families to make tough decisions, it is a lack of cash that prompts families to search for help from formal and informal networks of support.

SNAP benefits should act as a buffer, alleviating strained food budgets and allowing families to shift cash towards other priorities, like rent, utilities, and health care (Hoyne et al., 2015). Theory, however, assumes SNAP benefits are treated like cash; that an increase in SNAP benefits should induce similar spending behavior as an equivalent increase in cash. Or, in economic terms, that the marginal propensity to spend SNAP benefits on food should equal the marginal propensity to spend cash on food. This assumption is false; SNAP benefits are not treated like cash. For example, when the 2009 American Recovery and Reinvestment Act temporary increased SNAP benefits by an average of 13.6%, for every 1\$ dollar of SNAP benefits, 48 cents were spent on food, compared to only 5 cents when given a dollar in cash (Beatty and Tuttle, 2015).

SNAP benefits are also inadequate. They fail to cover monthly food expenditures for the majority of cash-strapped families—even when families maximize every dollar by consuming cheaper, less healthful foods (Wiig and Smith, 2009). This is not to say SNAP benefits don’t help. On the contrary, they are incredibly important. Many families depend on SNAP. It can

account for a majority of food expenditure. Some families even schedule their lives and budget priorities around the timing of their SNAP benefits (Edin et al., 2013).

The inadequacy of SNAP benefits to carry families through the end of the month, coupled with hyperbolic discounting, produces what is known as the “SNAP benefit cycle” (Smith et al., 2016). This negative cycle is characterized by high spending within the first 3 days of receiving SNAP benefits, followed by a sharp decline (Goldin et al., 2016). In the days leading up to the next scheduled monthly transfer, families often have no benefits left to spend on food (Wilde and Ranney, 2000; Shapiro, 2005). Low on cash and benefits, families often sustain themselves by tighten their belts and consuming less nutritious foods (Todd, 2015). The cycle then repeats.

The SNAP benefit cycle makes families vulnerable to unexpected negative income shocks. When cash is limited, unexpected expenses can be devastating. Health emergencies or job loss can strain cash supplies and leave families homeless or hungry (Curtis et al., 2013). For families coping with poverty, informal safety nets (e.g. family, friends) tend to be the first line of defense when cash needs are high and formal safety nets like SNAP fall short (Schenck-Fontaine et al., 2016). However, informal safety nets are not always available. Family and friends for those coping with poverty often struggle with similar levels of economic insecurity. Limited access to cash means families on the most extreme margins will turn to other forms of support, like food banks/pantries or emergency social services for assistance.

Some formal services exists that can provide families with emergency cash to pay for necessities like rent, electricity, and food. Food banks/pantries are an example of formal service that can, for some families, be considered emergency assistance. Emergency cash assistance also exists to help with rent and utilities but access can be quite restricted. Durham County Social Services, for example, provides emergency TANF assistance, which is limited to a \$400 dollars per 365 days (Durham County Department of Social Services, 2016). Emergency food cards also exists, but SNAP recipients are ineligible.¹

In this paper, I investigate how the SNAP benefit cycle affects demand for emergency assistance from formal support networks. I hypothesis that demand for emergency assistance is most likely to occur towards the end of the benefit cycle. I test my hypothesis by checking household demand for emergency assistance and demand from food banks/pantries in Durham County, North Carolina.

Data

The main data for this proposed papers comes from Durham Social Services (DSS) in North Carolina. Of the datasets provided by DSS, two pertain to this paper. The first is the SNAP (or FNS) data. The second is request for emergency assistance, known as the Community Access Database (CADB).

¹One of the conditions to receiving a food card is that households must sign up for SNAP.

At the moment, I do not have permission to describe either data set in detail. I also do not have permission to link these two datasets together, despite being from the same source. I am waiting to receive approval from the Director of DSS. I expect his support but have been told not to show any data details or results.

The other data I plan to use comes from Urban Ministries of Durham. It is their database of food pantry donations distributed per day. I hypothesize that aggregate demand for food assistance is highest during the 3rd and 4th weeks of any given calendar month. The second half of every month is when the largest fraction of SNAP families would be out, or running low, on benefits. I must emphasize that I do not expect the increase to be dramatic. But I do expect to see a cyclical pattern where the peak occurs near week 4.

Durham Social Services Data

SNAP/FNS Data

Without going into too much detail, the important thing to note about these data is that they contain names of the household head and dependents, a case numbers to link with other datasets, benefit amounts, and the SNAP certification period in month. The current SNAP data is also incomplete. It is missing many years of data and doesn't contain a benefit transfer date. I'm working with DSS to fix each of these problems.

From these data, what I care about most is names, case number, and the SNAP transfer date, and the certificate periods. The case number is what should link the SNAP data to the CADB data. Just in case, I can attempt to fuzzy match by name. I can determine start times for any event study using the benefit transfer data and the certificate period. The certificate period helps determine if and when a household—that does not renew—stops receiving benefits.

The transfer date variable is incredibly important. In the state of North Carolina, transfer dates are determined by the last digit of people's social security numbers. Social security numbers are mapped to every odd day from the 3rd to the 21st of every month. Those ending in 0 are mapped to the 3rd, 1 to the 5th, and so forth, with 9 mapping to the 21st. Those without social security numbers are mapped to the 3rd, creating a slight bump in probability to an otherwise uniform distribution. This implies that transfer dates are assigned essentially at random.

This randomness is essential towards identifying if events are impacted by the SNAP benefit cycle. If, for example, the transfer date occurred during the 1st of the month for all SNAP participants, then many other calendar-month events—like rent payments, utility payments, or payment schedules—become endogenous to the SNAP benefit cycle.

CADB

These data contain all requests made for emergency financial assistance. For this paper, what matter is the applicants case number, name, date of application, and type of assistance requested.

As before, the case number and name are to help link between CADB and SNAP. The date of application and assistance type requested is the “event” of interest.

Approach

The first step is to identify overlapping years between the two databases, SNAP and CADB. Once determined, the population of interest will be sourced from the SNAP dataset. I will then search and tag any names found in the CADB that overlap.

Next, I would need to determine continuity of SNAP benefits. This should not be difficult given that the SNAP data has a certification variable. This variable lists the months for which the household is to receive SNAP benefits.

Once benefit continuity has been determined, I can then structure the data for a hazard model. The specifics of the hazard model are TBD.

Food Pantry Data

I have just received these data and have not yet taken a look at the contents. It is a Microsoft Access Database file with, I expect, 2 or 3 years of daily data. I have, however, seen a printout for these data from July 2016. The pattern, given the printout, seems to support my hypothesis above—donations are highest towards the end of the month.

One thing to keep in mind is that demand for food can easily be higher than what is actually distributed. UMD doesn’t record who comes in requesting food from the food pantry. Furthermore, donations are capped at 26 families per day. Families are then turned away once the cap is hit. This means that more families could come in asking for food during distribution hours (9 am to 11 am, Monday through Friday), but such demands go unrecorded.

I should also note that these data are maintained by a single person at UMD. The data is entered, however, by a different person—a volunteer. This volunteer comes in every Tuesday and Thursday morning to manually input the data. There is likely a bit of human error, but as long as a general trend is noticeable, then it should be better than nothing.

I’m not sure if there is sufficient data here to run a regression that wouldn’t be bested by simply plotting the data. The food pantry data is therefore excluded from my methods section.

Concept in a Plot

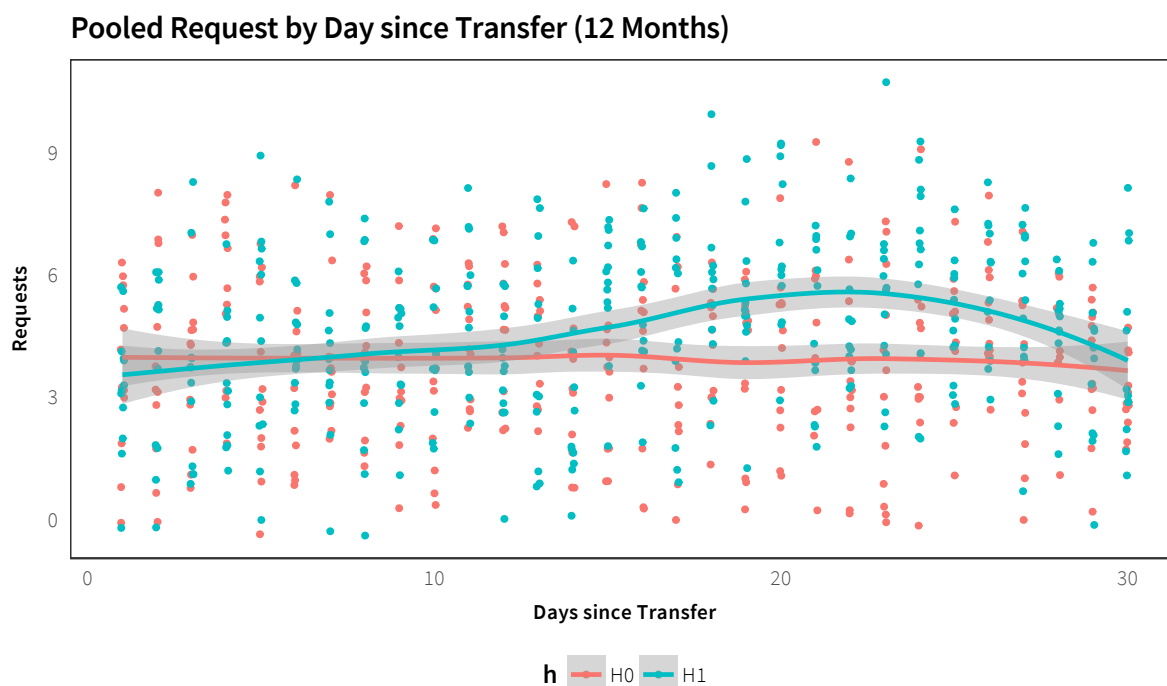


Figure 3.1: Pooled Monthly Request for Emergency Services by Day since Transfer using Fake Data

Here, $\tau=0$ lines up with the SNAP transfer date for each household. The green line in Figure 3.1 represents what I would ideally expect to find when exploring the administrative data. That is, were I to count 12 months of request for emergency services by day-since-transfer, I would expect the counts to be higher in the 3rd and 4th week since transfer. The red line represents the null hypothesis that the SNAP benefit cycle has no impact on demands for cash.

I suspect, however, that requests for emergency cash assistance will be infrequent. I also suspect seasonality will have an important impact on requests. For example, emergency assistance for utilities will likely increase during winter months. All that is to say, my actual analysis of the data will be different. Please see the Methods section for details.

Methods

I propose using a *proportional frailty model* for recurrent events (see Chapter 7; Aalen et al. (2008)).² Is this the best model? I do not know. But more basic models I've research assume that events of interest occur only once (Singer and Willett, 2003). I believe it probable that my event of interest—an application for emergency benefits—will occur more than once for some household heads.

I have a lot to learn about survival analysis. I would love to write up a model for this draft, but I would be pretending to understand something I've spent too little time thinking about.

I look forward to learning about how these methods. Until then, this section will remain regrettably sparse.

²“Frailty” is a fancy event history analysis word for unobserved heterogeneity aka endogeneity.

Next Steps

Data

- Meet with Rebecca at DSS to get transfer dates and missing SNAP data
- Get permission from Michael Becketts to link SNAP and CADB data for my paper
- Explore food pantry data and make exploratory plots

Methods

- Teach myself survival analysis (I found two well reviewed books to study)

Chapter 4

Healthy Food Experiments (BECR Project)

I'm working with a BECR Center team that is piloting a few random experiments. The aim is to nudge people towards purchasing healthier snacks. They are working in partnership with Family Fare Convenience Stores¹ to run the experiments and collect the data.

In exchange for a co-authorship, I am helping will all things data.

I'm listing this to point out that **I have a back up paper.**

¹<http://familyfareconveniencestores.com>

Bibliography

- Aalen, O., Borgan, O., and Gjessing, H. (2008). *Survival and Event History Analysis: A Process Point of View*. Springer Science & Business Media.
- Amemiya, T. (1984). Tobit models: A survey. *Journal of Econometrics*, 24(1):3–61.
- An, R. (2015). Nationwide expansion of a financial incentive program on fruit and vegetable purchases among Supplemental Nutrition Assistance Program participants: A cost-effectiveness analysis. *Social Science & Medicine*, 147:80–88.
- Andreyeva, T., Long, M. W., and Brownell, K. D. (2010). The Impact of Food Prices on Consumption: A Systematic Review of Research on the Price Elasticity of Demand for Food. *American Journal of Public Health*, 100(2):216–222.
- Andreyeva, T., Tripp, A. S., and Schwartz, M. B. (2015). Dietary Quality of Americans by Supplemental Nutrition Assistance Program Participation Status: A Systematic Review. *American Journal of Preventive Medicine*, 49(4):594–604.
- Angrist, J. D. and Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton university press.
- Aristei, D., Perali, F., and Pieroni, L. (2008). Cohort, age and time effects in alcohol consumption by Italian households: A double-hurdle approach. *Empirical Economics; Heidelberg*, 35(1):29–61.
- Baicker, K., Taubman, S. L., Allen, H. L., Bernstein, M., Gruber, J. H., Newhouse, J. P., Schneider, E. C., Wright, B. J., Zaslavsky, A. M., and Finkelstein, A. N. (2013). The Oregon Experiment — Effects of Medicaid on Clinical Outcomes. *New England Journal of Medicine*, 368(18):1713–1722.
- Bartfeld, J., Gundersen, C., Smeeding, T., and Ziliak, J. (2015). *SNAP Matters: How Food Stamps Affect Health and Well-Being*. Stanford University Press.
- Bartlett, S., Klerman, J., and Olsho, L. (2014). Evaluation of the Healthy Incentives Pilot (HIP): Final Report. Technical report, Prepared by Abt Associates for the U.S. Department of Agriculture, Food and Nutrition Service.

- Beatty, T. K. M. and Tuttle, C. J. (2015). Expenditure Response to Increases in In-Kind Transfers: Evidence from the Supplemental Nutrition Assistance Program. *American Journal of Agricultural Economics*, 97(2):390–404.
- Belot, M., James, J., and Nolen, P. J. (2014). Incentives and children's dietary choices: A field experiment in primary schools.
- Bénabou, R. and Tirole, J. (2006). Incentives and prosocial behavior. *The American economic review*, 96(5):1652–1678.
- Bertrand, M., Mullainathan, S., and Shafir, E. (2006). Behavioral economics and marketing in aid of decision making among the poor. *Journal of Public Policy & Marketing*, 25(1):8–23.
- Bhargava, S. and Manoli, D. (2012). Why are benefits left on the table? Assessing the role of information, complexity, and stigma on take-up with an IRS field experiment. *NA-Advances in Consumer Research Volume 40*.
- Bhat, C. R. (2005). A multiple discrete–continuous extreme value model: Formulation and application to discretionary time-use decisions. *Transportation Research Part B: Methodological*, 39(8):679–707.
- Bhat, C. R. (2008). The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions. *Transportation Research Part B: Methodological*, 42(3):274–303.
- Bhat, C. R. and Sen, S. (2006). Household vehicle type holdings and usage: An application of the multiple discrete-continuous extreme value (MDCEV) model. *Transportation Research Part B: Methodological*, 40(1):35–53.
- Bitler, M. P. and Currie, J. (2005). Does WIC work? The effects of WIC on pregnancy and birth outcomes. *Journal of Policy Analysis and Management*, 24(1):73–91.
- Blumenthal, S. J., Hoffnagle, E. E., Leung, C. W., Lofink, H., Jensen, H. H., Foerster, S. B., Cheung, L. W., Nestle, M., and Willett, W. C. (2014). Strategies to improve the dietary quality of Supplemental Nutrition Assistance Program (SNAP) beneficiaries: An assessment of stakeholder opinions. *Public Health Nutrition*, 17(12):2824–2833.
- Carlevaro, F., Genève, U. . D., Croissant, Y., and Réunion, U. . D. L. (2016). Multiple Hurdle Tobit Models in R: The mhurdle Package.
- Cawley, J. (2015). An economy of scales: A selective review of obesity's economic causes, consequences, and solutions. *Journal of Health Economics*, 43:244–268.
- Cawley, J. and Meyerhoefer, C. (2012). The medical care costs of obesity: An instrumental variables approach. *Journal of Health Economics*, 31(1):219–230.

- CBPP (2016). Chart Book: TANF at 20. <http://www.cbpp.org/research/family-income-support/chart-book-tanf-at-20>.
- Chatterjee, A., Kubendran, S., King, J., and DeVol, R. (2014). Checkup Time: Chronic Disease and Wellness in America. Technical report, Milken Institute.
- Cragg, J. G. (1971). Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica: Journal of the Econometric Society*, pages 829–844.
- Currie, J. (2006). The Take-Up of Social Benefits. *Public Policy and the Income Distribution*, page 80.
- Curtis, M. A., Corman, H., Noonan, K., and Reichman, N. E. (2013). Life Shocks and Homelessness. *Demography*, 50(6):2227–2253.
- Dahl, G. B. and Lochner, L. (2012). The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit. *The American Economic Review*, 102(5):1927–1956.
- Damon, A. L., King, R. P., and Leibtag, E. (2013). First of the Month Effect: Does It Apply across Food Retail Channels? *Food Policy*, 41:18–27.
- Deaton, A. and Irish, M. (1984). Statistical models for zero expenditures in household budgets. *Journal of Public Economics*, 23(1-2):59–80.
- Dinour, L. M., Bergen, D., and Yeh, M.-C. (2007). The Food Insecurity–Obesity Paradox: A Review of the Literature and the Role Food Stamps May Play. *Journal of the American Dietetic Association*, 107(11):1952–1961.
- Dodge, K. A., Goodman, W. B., Murphy, R. A., O'Donnell, K., Sato, J., and Guptill, S. (2013). Implementation and Randomized Controlled Trial Evaluation of Universal Postnatal Nurse Home Visiting. *American Journal of Public Health*, 104(S1):S136–S143.
- Dow, W. H. and Norton, E. C. (2003). Choosing Between and Interpreting the Heckit and Two-Part Models for Corner Solutions. *Health Services & Outcomes Research Methodology; Dordrecht*, 4(1):5–18.
- Dubé, J.-P. (2004). Multiple discreteness and product differentiation: Demand for carbonated soft drinks. *Marketing Science*, 23(1):66–81.
- Dubin, J. A. and McFadden, D. L. (1984). An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. *Econometrica*, 52(2):345–362.
- Durham County Department of Social Services (2016). Directory of Services. <http://dconc.gov/home/showdocument?id=7815>.

- Dynarski, S. M. and Scott-Clayton, J. E. (2006). The Cost of Complexity in Federal Student Aid: Lessons from Optimal Tax Theory and Behavioral Economics. *National Tax Journal*, 59(2):319.
- Edin, K., Melody Boyd, James Mabli, Jim Ohls, Julie Worthington, Sara Greene, Nicholas Redel, and Swetha Sridharan (2013). SNAP Food Security In-Depth Interview Study. Technical report, USDA FNS, Office of Research and Analysis.
- Evans, J., Heron, J., Francomb, H., Oke, S., and Golding, J. (2001). Cohort study of depressed mood during pregnancy and after childbirth. *BMJ*, 323(7307):257–260.
- Family Fare (2016). Double Up Food Bucks. <https://www.shopfamilyfare.com/DUFB>.
- Frazão, E. (1999). High costs of poor eating patterns in the United States. 732:32–1.
- García, J. and Labeaga, J. M. (1996). Alternative Approaches to Modelling Zero Expenditure: An Application to Spanish Demand for Tobacco*. *Oxford Bulletin of Economics and Statistics*, 58(3):489–506.
- Gneezy, U., Meier, S., and Rey-Biel, P. (2011). When and Why Incentives (Don't) Work to Modify Behavior. *The Journal of Economic Perspectives*, 25(4):191–209.
- Goldin, J., Homonoff, T., and Meckel, K. (2016). Is there an Nth of the Month Effect? The Timing of SNAP Issuance, Food Expenditures, and Grocery Prices.
- Grogger, J. (2003). The effects of time limits, the EITC, and other policy changes on welfare use, work, and income among female-headed families. *Review of Economics and statistics*, 85(2):394–408.
- Gundersen, C. (2015). SNAP and Obesity. *SNAP Matters: How Food Stamps Affect Health and Well Being*, pages 161–185.
- Harding, M. and Lovenheim, M. (2014). The Effect of Prices on Nutrition: Comparing the Impact of Product- and Nutrient-Specific Taxes.
- Hartmann, M. (2011). Corporate social responsibility in the food sector. *European Review of Agricultural Economics*, 38(3):297–324.
- Hay, J. W., Leu, R., and Rohrer, P. (1987). Ordinary Least Squares and Sample-Selection Models of Health-Care Demand Monte Carlo Comparison. *Journal of Business & Economic Statistics*, 5(4):499–506.
- Hendel, I. (1999). Estimating Multiple-Discrete Choice Models: An Application to Computerization Returns. *Review of Economic Studies*, 66(2):423–446.
- Hoynes, H. W., McGranahan, L., and Schanzenbach, D. W. (2015). SNAP and Food Consumption. *SNAP Matters: How Food Stamps Affect Health and Well-Being*, page 107.

- Humphreys, B. R. (2013). Dealing with zeros in economic data. *Department of Economics, University of Alberta, Alberta*.
- Iacus, S. M., King, G., and Porro, G. (2011). Causal inference without balance checking: Coarsened exact matching. *Political analysis*, page mpr013.
- Imbens, G. W. and Rubin, D. B. (2015). *Causal Inference in Statistics, Social, and Biomedical Sciences*. Cambridge University Press.
- Jansson, A., Sivberg, B., Larsson, B. W., and Udén, G. (2002). First-time mothers' satisfaction with early encounters with the nurse in child healthcare: Home visit or visit to the clinic? *Acta Pædiatrica*, 91(5):571–577.
- John, L. K., Loewenstein, G., Troxel, A. B., Norton, L., Fassbender, J. E., and Volpp, K. G. (2011). Financial Incentives for Extended Weight Loss: A Randomized, Controlled Trial. *Journal of General Internal Medicine*, 26(6):621–626.
- Jones, A. M. (1989). A double-hurdle model of cigarette consumption. *Journal of applied econometrics*, 4(1):23–39.
- Jones, A. M. (1992). A Note on Computation of the Double-Hurdle Model with Dependence with an Application to Tobacco Expenditure. *Bulletin of Economic Research*, 44(1):67–74.
- Kahneman, D., Knetsch, J. L., and Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *The journal of economic perspectives*, 5(1):193–206.
- Keiser, L. R., Mueser, P. R., and Choi, S.-W. (2004). Race, Bureaucratic Discretion, and the Implementation of Welfare Reform. *American Journal of Political Science*, 48(2):314–327.
- Kim, J., Allenby, G. M., and Rossi, P. E. (2002). Modeling consumer demand for variety. *Marketing Science*, 21(3):229–250.
- Klerman, J. A., Bartlett, S., Wilde, P., and Olsho, L. (2014). The Short-Run Impact of the Healthy Incentives Pilot Program on Fruit and Vegetable Intake. *American Journal of Agricultural Economics*, 96(5):1372–1382.
- Kneipp, S. M., Lutz, B. J., and Means, D. (2009). Reasons for Enrollment, the Informed Consent Process, and Trust Among Low-Income Women Participating in a Community-Based Participatory Research Study. *Public Health Nursing*, 26(4):362–369.
- Landy, C. K., Jack, S. M., Wahoush, O., Sheehan, D., and MacMillan, H. L. (2012). Mothers' experiences in the Nurse-Family Partnership program: A qualitative case study. *BMC Nursing*, 11(1):15.
- Lee, D. S. and Lemieux, T. (2010). Regression Discontinuity Designs in Economics. *Journal of Economic Literature*, 48(2):281–355.

- Leung, C. W., Hoffnagle, E. E., Lindsay, A. C., Lofink, H. E., Hoffman, V. A., Turrell, S., Willett, W. C., and Blumenthal, S. J. (2013). A Qualitative Study of Diverse Experts' Views about Barriers and Strategies to Improve the Diets and Health of Supplemental Nutrition Assistance Program (SNAP) Beneficiaries. *Journal of the Academy of Nutrition and Dietetics*, 113(1):70–76.
- Leung, S. F. and Yu, S. (1996). On the choice between sample selection and two-part models. *Journal of Econometrics*, 72(1–2):197–229.
- List, J. A. and Samek, A. S. (2015). The behaviorist as nutritionist: Leveraging behavioral economics to improve child food choice and consumption. *Journal of Health Economics*, 39:135–146.
- List, J. A., Samek, A. S., and Zhu, T. (2015). Incentives to Eat Healthy: Evidence from a Grocery Store Field Experiment. SSRN Scholarly Paper ID 2664818, Social Science Research Network, Rochester, NY.
- Loewenstein, G., Price, J., and Volpp, K. (2016). Habit formation in children: Evidence from incentives for healthy eating. *Journal of Health Economics*, 45:47–54.
- Lynn Bonner (2016). NC begins drug tests for welfare applicants. <http://www.newsobserver.com/news/politics-government/state-politics/article59389341.html>.
- Madden, D. (2008). Sample selection versus two-part models revisited: The case of female smoking and drinking. *Journal of Health Economics*, 27(2):300–307.
- Manning, W. G., Duan, N., and Rogers, W. H. (1987). Monte Carlo evidence on the choice between sample selection and two-part models. *Journal of Econometrics*, 35(1):59–82.
- Margaret Schnuck (2016). Doubling Produce Purchasing Power: Implementing Nutrition Incentive Programs in Grocery Stores. Technical report, Fair Food Network.
- Mente, A., de Koning, L., Shannon, H. S., and Anand, S. S. (2009). A Systematic Review of the Evidence Supporting a Causal Link Between Dietary Factors and Coronary Heart Disease. *Archives of Internal Medicine*, 169(7):659–669.
- Miller, D. and Morrissey, T. (2017). Using Natural Experiments to Identify the Effects of SNAP on Child and Adult Health. *University of Kentucky Center for Poverty Research Discussion Paper Series*.
- Moffitt, R. (1983). An Economic Model of Welfare Stigma. *The American Economic Review*, 73(5):1023–1035.
- Monnat, S. M. (2010). The Color of welfare sanctioning: Exploring the individual and contextual roles of race on TANF case closures and benefit reductions. *The Sociological Quarterly*, 51(4):678–707.

- National Center for Health Statistics (2015). *Health, United States, 2014: With Special Feature on Adults Aged 55–64*. Health, United States. National Center for Health Statistics (US), Hyattsville (MD).
- Network, F. F. (2014). *Double Up Food Bucks: A Five-Year Success Story*. Fair Food Network.
- Newman, C., Henchion, M., and Matthews, A. (2003). A Double-Hurdle Model of Irish Household Expenditure on Prepared Meals. *Applied Economics*, 35(9):1053–1061.
- Nguyen, B. T. and Powell, L. M. (2015). Supplemental nutrition assistance program participation and sugar-sweetened beverage consumption, overall and by source. *Preventive Medicine*, 81:82–86.
- Nutrition Evidence Library (2014). A Series of Systematic Reviews on the Relationship Between Dietary Patterns and Health Outcomes. Technical report, U.S. Department of Agriculture, Center for Nutrition Policy and Promotion, Alexandria, VA.
- O'Donnell, K. and Wright, P. (2015). Family Connects: Implementation and Policy Manual. Technical report, Center for Child and Family Health.
- Olsho, L. E., Klerman, J. A., Wilde, P. E., and Bartlett, S. (2016). Financial incentives increase fruit and vegetable intake among Supplemental Nutrition Assistance Program participants: A randomized controlled trial of the USDA Healthy Incentives Pilot. *The American Journal of Clinical Nutrition*, 104(2):423–435.
- Organization, W. H. and others (2013). WHO recommendations on postnatal care of the mother and newborn. In *WHO Recommendations on Postnatal Care of the Mother and Newborn*, pages 72–72.
- Pudney, S. (1989). Modelling Individual Choice: The Econometrics of Corners, Kinks and Holes.
- Ribar, D. (2014). How to improve participation in social assistance programs. *IZA World of Labor*.
- Schenck-Fontaine, A., Gassman-Pines, A., and Hill, Z. (2016). Use of informal safety nets during the SNAP benefit cycle: How African-American families cope with within-month economic instability. *Working Paper*.
- Schott, L., Pavetti, L., and Finch, I. (2015). How states have spent federal and state funds under the TANF block grant. *Center for Budget and Policy Priorities*.
- Shapiro, J. M. (2005). Is there a daily discount rate? Evidence from the food stamp nutrition cycle. *Journal of public Economics*, 89(2):303–325.
- Singer, J. D. and Willett, J. B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. Oxford university press.

- Smith, D. A. and Brame, R. (2003). Tobit models in social science research some limitations and a more general alternative. *Sociological Methods & Research*, 31(3):364–388.
- Smith, T. A., Berning, J. P., Yang, X., Colson, G., and Dorfman, J. H. (2016). The Effects of Benefit Timing and Income Fungibility on Food Purchasing Decisions among Supplemental Nutrition Assistance Program Households. *American Journal of Agricultural Economics*, 98(2):564–580.
- Sommers, B. D., Baicker, K., and Epstein, A. M. (2012). Mortality and Access to Care among Adults after State Medicaid Expansions. *New England Journal of Medicine*, 367(11):1025–1034.
- Sommers, B. D. and Oellerich, D. (2013). The poverty-reducing effect of Medicaid. *Journal of Health Economics*, 32(5):816–832.
- Sonik, R. A. (2016). Massachusetts Inpatient Medicaid Cost Response to Increased Supplemental Nutrition Assistance Program Benefits. *American Journal of Public Health*, 106(3):443–448.
- Stewart, J. (2013). Tobit or Not Tobit? *Journal of Economic and Social Measurement*, 38(3):263–290.
- Stuber, J. and Kronebusch, K. (2004). Stigma and Other Determinants of Participation in TANF and Medicaid. *Journal of Policy Analysis and Management*, 23(3):509–530.
- Su, S. J. and Yen, S. T. (1996). Microeconomic models of infrequently purchased goods: An application to household pork consumption. *Empirical Economics*, 21(4):513–533.
- Thaler, R. (1985). Mental Accounting and Consumer Choice. *Marketing Science*, 4(3):199–214.
- Todd, J. E. (2015). Revisiting the Supplemental Nutrition Assistance Program cycle of food intake: Investigating heterogeneity, diet quality, and a large boost in benefit amounts. *Applied Economic Perspectives & Policy*, 37(3):437–458.
- Todd, J. E. and Ploeg, M. V. (2014). Caloric Beverage Intake Among Adult Supplemental Nutrition Assistance Program Participants. *American Journal of Public Health*, 104(9):e80–5.
- Train, K. E. (2009). *Discrete Choice Methods with Simulation*. Cambridge university press.
- US Department of Health and Human Services (2015-03-10T04:32:24-04:00). Welfare Indicators and Risk Factors: Thirteenth Report to Congress. <https://aspe.hhs.gov/report/welfare-indicators-and-risk-factors-thirteenth-report-congress>.
- USDA (2015). Scientific Report of the 2015 Dietary Guidelines Advisory Committee. Technical report, USDA.
- USDA FNS (2016a). SNAP Retailer Data. <http://www.fns.usda.gov/snap-retailer-data>.

- USDA FNS (2016b). Supplemental Nutrition Assistance Program (SNAP). <http://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap>.
- USDA NIFA (2015). USDA Awards \$31 Million in Grants to Help SNAP Participants Afford Healthy Foods. <https://nifa.usda.gov/resource/usda-awards-31-million-grants-help-snap-participants-afford-healthy-foods>.
- Wales, T. J. and Woodland, A. D. (1983). Estimation of consumer demand systems with binding non-negativity constraints. *Journal of Econometrics*, 21(3):263–285.
- Wiig, K. and Smith, C. (2009). The art of grocery shopping on a food stamp budget: Factors influencing the food choices of low-income women as they try to make ends meet. *Public Health Nutrition*.
- Wilde, P. E. and Ranney, C. K. (2000). The Monthly Food Stamp Cycle: Shopping Frequency and Food Intake Decisions in an Endogenous Switching Regression Framework. *American Journal of Agricultural Economics*, 82(1):200–213.
- Wolfson, J. A. and Bleich, S. N. (2015). Fruit and vegetable consumption and food values: National patterns in the United States by Supplemental Nutrition Assistance Program eligibility and cooking frequency. *Preventive Medicine*, 76:1–7.
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*.
- Yen, S. T. (1993). Working Wives and Food away from Home: The Box-Cox Double Hurdle Model. *American Journal of Agricultural Economics*, 75(4):884–895.
- Yen, S. T. and Su, S. J. (1995). Modeling US butter consumption with zero observations. *Agricultural and resource economics review (USA)*.
- Ziliak, J. P. (2015). Temporary Assistance for Needy Families. *NBER*.

