ESSAYS IN GROCERY DEMAND AND FOOD POLICY

By

Katherine Anne Harris

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Economics – Doctor of Philosophy

2019

ABSTRACT

ESSAYS IN GROCERY DEMAND AND FOOD POLICY

By

Katherine Anne Harris

Chapter 1: The Effect of Online Shopping on the Nutritional Content of Grocery Purchases

This chapter utilizes novel household panel data to analyze the effect of online grocery shopping on the healthiness of grocery purchases. In order to obtain a causal estimate of the impact of online grocery shopping on the nutritional content of grocery purchases, I utilize variation in the timing that an online shopping service was introduced as a source of exogenous variation in the decision to shop online. Local average treatment effects indicate that online shopping induces a 3.8, 5.9, 5.7 and 7.4 percent increase in the average budget shares for dairy, fruit, meats and vegetables, respectively. This reallocation of funds comes at the expense of drinks, oils and snacks/sweets with estimates indicating a 5.2, 4.1 and 13.6 percent decrease in the average budget shares, respectively. I also analyze the nutrient densities of grocery purchases and find a 4.2, 5.0, 5.8 and a 5.8 percent decrease in the average amount of calories, carbohydrates, fats and sugars contained in an ounce of food purchased, respectively. These insights into consumer purchasing behavior can be utilized to inform food policy aimed at improving the nutritional quality of food purchases.

Chapter 2: The Effect of Online Shopping on Grocery Demand

This chapter analyzes the effect of shopping for groceries online on grocery demand. Utilizing variation in the timing that an online shopping service was introduced as a source of exogenous variation in the decision to shop online, I estimate a structural model of demand that allows the parameters of demand to vary with purchasing environments. I find that fifty-four percent

of the estimated demand parameters are significantly different in months in which a household engages in online shopping. Comparisons of in-store and online price elasticities indicate that households are generally less price sensitive when shopping online. Specifically, I find that own-price (cross-price) elasticities are 1.2 (1.4) times larger in-store than they are online, on average. These insights into consumer purchasing behavior can be utilized to inform optimal web design and online pricing strategies.

Chapter 3: What are SNAP Benefits Used to Purchase? Evidence from a Supermarket Retail Panel

This chapter analyzes what households utilize their Supplemental Nutrition Assistance Program (SNAP or food stamp) benefits to purchase and relates these purchasing patterns to existing research that has explored the impact of SNAP on food spending, non-food spending and health outcomes. I utilize an event study approach that compares the purchasing patterns of a household immediately prior to SNAP adoption to the purchasing patterns of the same household immediately following SNAP adoption. I find that SNAP adoption almost exclusively increases spending on SNAP eligible items with the product categories of meat, oil and prepared foods experiencing the biggest growth in food expenditure. I also find that SNAP adoption is correlated with increased spending over baby products, while spending over alcohol and tobacco products exhibits almost no change.

This dissertation is dedicated to my family: my parents, Tom and Angie, my sister, Elle and my brother, Will. Thank you for supporting me in everything. I love you all so much.

ACKNOWLEDGEMENTS

I am especially grateful for the support, guidance and mentorship of my committee chair, Mike Conlin. Thank you for all of your support, advice and encouragement throughout my graduate studies; I do not think my dissertation would look the same without you. I would also like to thank Todd Elder, Jeff Wooldridge and Robert Myers. Thank you for answering numerous questions, for your guidance and your mentorship.

Special thanks are extended to the retailer that made this research possible and the numerous employees who answered so many questions about the data, business and purchasing environments. I cannot express how grateful I am to all of you. I would also like to thank Jeff Nault for his enthusiasm and interest in my research, as well as for his mentorship and advice.

I appreciate all of the classmates who studied with me, sat through numerous presentations of my research and who provided feedback on my dissertation. I am especially grateful to Alyssa Carlson, Pallavi Pal, Sambojyoti Biswas and Dylan Brewer for their support and friendship throughout my time in graduate school. You have all helped make graduate school an enjoyable experience and I will miss you deeply. I would also like to recognize Riju Joshi, Olga Boldarieva and Maggie Brehm for offering advice on navigating graduate school, teaching and the job search process.

I would also like to thank Angelos Lagoudakis for all of the support he gave me during my final year of graduate school. Thank you for listening to numerous iterations of my job market pitch, for helping me prepare for interviews, for dealing with the crazy ups and downs of the job search process and for loving me throughout. I look forward to the life we have ahead of us; love you always.

My dissertation has benefited from generous financial support provided to me from the Department of Economics, the College of Social Science and the Graduate School at Michigan State University. Thank you for financing my graduate education and this research.

TABLE OF CONTENTS

LIST OF TABLES viii

LIST OF FIGURES xiii

CHAPTER 1 THE EFFECT OF ONLINE SHOPPING ON THE NUTRITIONAL CONTENT OF GROCERY PURCHASES 1
- 1.1 Introduction 1
- 1.2 Predictions for Online Shopping 4
- 1.3 Purchasing Environment, Data & Summary Statistics 5
- 1.4 Methodology 9
- 1.5 Results 11
  - 1.5.1 Online Shopping & Retailer Substitution Patterns 14
    - 1.5.1.1 Local Competition & Retailer Substitution Patterns 16
    - 1.5.1.2 Narrow Product Categories 18
- 1.6 Robustness Check Summary 21
- 1.7 Discussion & Conclusions 23

CHAPTER 2 THE EFFECT OF ONLINE SHOPPING ON GROCERY DEMAND . . 25
- 2.1 Introduction 25
- 2.2 Institutional Details and Data 28
  - 2.2.1 Data 29
  - 2.2.2 Summary Statistics 31
- 2.3 Modeling Grocery Demand 32
- 2.4 Demand Estimation & Results 35
  - 2.4.1 Results 37
  - 2.4.2 Elasticities 38
- 2.5 Discussion & Conclusion 41

CHAPTER 3 WHAT ARE SNAP BENEFITS USED TO PURCHASE? EVIDENCE FROM A SUPERMARKET RETAIL PANEL 42
- 3.1 Introduction 42
- 3.2 SNAP Background 44
- 3.3 SNAP Literature 45
  - 3.3.1 SNAP and Consumption 45
  - 3.3.2 SNAP and Health 47
- 3.4 Data 48
- 3.5 Summary Statistics 50
- 3.6 Empirical Analysis & Results 53
  - 3.6.1 Grocery Purchases 56
  - 3.6.2 Baby Product Purchases 57

3.6.3 Alcohol and Tobacco Purchases 58
3.7 Conclusion & Discussion 58

APPENDICES 60
APPENDIX A CHAPTER 1 APPENDIX 61
APPENDIX B CHAPTER 2 APPENDIX 111
APPENDIX C CHAPTER 3 APPENDIX 128

BIBLIOGRAPHY 159

LIST OF TABLES

Table A1: Household Demographics 63

Table A2: Monthly Purchasing Patterns 64

Table A3: Average Price and Nutrient Content Per Ounce of Food 65

Table A4: Difference in Difference / Reduced Form Estimates, τ_i - Online Households . 66

Table A5: Difference in Difference / First Stage Estimates, $\hat{\theta}_i$ - Online Households . . . 67

Table A6: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households 68

Table A7: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households 69

Table A8: Nutrition Outcomes Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households 70

Table A9: Expenditure Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households 71

Table A10: Expenditure Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households 72

Table A11: Difference in Difference / Reduced Form Estimates, $\hat{\tau}_i$, By Competition Index - Online Households 73

Table A12: Difference in Difference / Reduced Form Estimates, $\hat{\tau}_i$, By Competition Index - Online Households 74

Table A13: Average Nutrient Content Per Ounce of Food - Narrow Product Categories . 75

Table A14: Ordinary Least Squares & Fractional Probit APE Estimates - Bread Shares for Online Households 76

Table A15: Ordinary Least Squares & Fractional Probit APE Estimates - Cereal Shares for Online Households 77

Table A16: Ordinary Least Squares & Fractional Probit APE Estimates - Salty Snack Shares for Online Households 78

Table A17: Ordinary Least Squares & Fractional Probit APE Estimates - Yogurt Shares for Online Households 79

Table A18: Product Category Key 80

Table A19: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Availability Definition Based on Entire Store Footprint, Online Households Only 81

Table A20: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Availability Definition Based on Entire Store Footprint, Online Households Only 82

Table A21: Product Subcategories 83

Table A22: Comparison of Household Demographics Across Online Availability Waves . 85

Table A23: Comparison of Pre-Online Purchasing Patterns Across Online Availability Waves 86

Table A24: Ordinary Least Squares & Tobit APE Estimates - Bread Sales for Online Households 89

Table A25: Ordinary Least Squares & Tobit APE Estimates - Cereal Sales for Online Households 90

Table A26: Ordinary Least Squares & Tobit APE Estimates - Salty Snack Sales for Online Households 91

Table A27: Ordinary Least Squares & Tobit APE Estimates - Yogurt Sales for Online Households 92

Table A28: Tobit Estimates - Bread Sales for Online Households 93

Table A29: Tobit Estimates - Cereal Sales for Online Households 94

Table A30: Tobit Estimates - Salty Snack Sales for Online Households 95

Table A31: Tobit Estimates - Yogurt Sales for Online Households 96

Table A32: Event Study Estimates, $\hat{\tau}_{ik}$ - Online Households 98

Table A33: Event Study Estimates, $\hat{\tau}_{ik}$ - Online Households 99

Table A34: DID / RF Estimates, $\hat{\tau}_i$ - In-Store Households 101

Table A35: In-Store Households - Expenditure 102

Table A36: In-Store Households - Nutrient Outcomes 103

Table A37: In-Store Households - Ounce Shares 104

Table A38: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households, After January 2016 109

Table A39: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households, After January 2016 110

Table B1: Household Demographics 113

Table B2: In-store Months Compared to Online Months 114

Table B3: In-Store Elasticity Matrix 115

Table B4: Online Elasticity Matrix 116

Table B5: Product Category Key 117

Table B6: First Stage Estimates 118

Table B7: First Stage Estimates 119

Table B8: Demand Estimates - Online Households 120

Table B9: Demand Estimates - Online Households 121

Table B10: Demand Estimates - Online Households 122

Table B11: Demand Estimates - Online Households 123

Table B12: Demand Estimates - Online Households 124

Table B13: Demand Estimates - Online Households 125

Table B14: Difference in Elasticity Matrices, $\eta_{Instore} - \eta_{Online}$ 126

Table C1: Comparison of Tender Composition and Supermarket Purchases - Before and After SNAP Adoption 136

Table C2: Share of Sales Generated from Store Brand Products - Before and After SNAP Adoption 137

Table C3: Grocery Purchases - Before and After SNAP Adoption 138

Table C4: Grocery Budget Composition - Before and After SNAP Adoption 139

Table C5: Purchases over Baby Products - Before and After SNAP Adoption 140

Table C6: Purchases over Alcohol and Tobacco Products - Before and After SNAP Adoption 140

Table C7: Product Category Key 141

Table C8: Tender Composition - Event Study Estimates 142

Table C9: Tender Composition - Event Study Estimates 143

Table C10: Sales by SNAP Eligibility - Event Study Estimates 144

Table C11: Summary of Store Brand Expenditure Shares - Event Study Estimates 145

Table C12: Summary of Grocery Purchases - Event Study Estimates 146

Table C13: Summary of Grocery Purchases - Event Study Estimates 147

Table C14: Summary of Grocery Budget Shares - Event Study Estimates 148

Table C15: Summary of Grocery Budget Shares - Event Study Estimates 149

Table C16: Summary of Grocery Budget Shares - Event Study Estimates 150

Table C17: Summary of Grocery Budget Shares - Event Study Estimates 151

Table C18: Summary of Grocery Budget Shares - Event Study Estimates 152

Table C19: Summary of Grocery Budget Shares - Event Study Estimates 153

Table C20: Summary of Baby Purchases - Event Study Estimates 154

Table C21: Summary of Baby Purchases - Event Study Estimates 155

Table C22: Summary of Baby Purchases - Event Study Estimates 156

Table C23: Summary of Vice Purchases - Event Study Estimates 157

Table C24: Summary of Vice Purchases - Event Study Estimates 158

LIST OF FIGURES

Figure A1: Online Shopping Service Availability 61

Figure A2: Event Study Estimates for Online Use and Expenditure Shares 62

Figure A3: Percent of Available Products Purchased Online 107

Figure A4: Percent of In-Store Sales from Products Available Online 108

Figure B1: Online Shopping Service Availability 111

Figure B2: Own and Cross Price Elasticity Ratio, $\frac{|\eta_{Instore}|}{|\eta_{Online}|}$ 112

Figure B3: Budget Allocation & Prices 127

Figure C1: Proportion of Households Using SNAP Benefits 128

Figure C2: Tender Composition Around SNAP Adoption - Event Study Estimates . . . 129

Figure C3: Purchases by SNAP Eligibility Around SNAP Adoption - Event Study Estimates 130

Figure C4: Store Brand Share of Sales - Event Study Estimates 131

Figure C5: Grocery Purchases Around SNAP Adoption - Event Study Estimates 132

Figure C6: Grocery Budget Shares by Product Category Around SNAP Adoption - Event Study Estimates 133

Figure C7: Baby Sales Around SNAP Adoption - Event Study Estimates 134

Figure C8: Vice Sales Around SNAP Adoption - Event Study Estimates 135

CHAPTER 1

THE EFFECT OF ONLINE SHOPPING ON THE NUTRITIONAL CONTENT OF GROCERY PURCHASES

1.1 Introduction

"Plus, since I wasn't at the store I stuck to my list and didn't give into those random, impulse purchases [...]"

- Customer Review of Online Grocery Experience, April 2016

Over the past sixteen years, the rate of adult obesity in the United States has increased thirty-three percent (Hales CM, et al. 2017). Afflicting 30% of adults in 2000 and nearly 40% of adults in 2016, obesity is associated with a number of health conditions (heart disease, stroke, type 2 diabetes and some types of cancer) that can reduce both the quality and length of life (Hales CM, et al. 2017). In response to this growing public health concern, there have been a number of policies and campaigns, implemented within the last ten years, aimed at fighting obesity. For example, Michelle Obama's *Let's Move!* campaign to fight childhood obesity, the implementation of soda taxes on sugary beverages and the mandatory disclosure of calories on restaurant menu boards across the United States. In order to better inform public policies designed to combat obesity, it is important to understand the factors that influence consumer decisions over food.

This chapter explores how purchasing environments influence consumer choice over groceries. Specifically, I evaluate how shopping for groceries in an online purchasing environment affects the composition and nutritional content of grocery purchases. In order to isolate the effect of an online shopping environment, I utilize grocery scanner data generated from the purchases of 34 thousand households who shop for groceries at a traditional brick and mortar supermarket that also offers an online grocery shopping service. These data provide an attractive setting to study the effect of online grocery shopping for three reasons: first, the panel structure of the data allow for a within household comparison of purchases across the in-store and online purchasing environments; second, online and in-store purchases are fulfilled by the same retailer, alleviating concerns over differences in product selection and branding; third, the retailer of this study offers products for purchase online at the same prices as those found in the store.

This chapter complements existing behavioral research by providing a natural setting in which the validity of theories regarding self-control can be explored. Existing theoretical research suggests that consumers have difficulty exercising self-control due to time inconsistent preferences (Thaler 1981, Laibson 1997), visceral influences (Loewenstein 1996), and/or consumption cues (Laibson 2001). Theories on time inconsistent preferences predict that the decisions consumers make for themselves in the future are better than the decisions they make for themselves in the present. Thus, the time delay between ordering and receiving groceries, that exists when shopping online, could lead to more healthful purchases. Visceral influences and cue theories of consumption indicate that as the level of distraction (noise, congestion, presence of children) and the level of product placement (checkout lanes, end of aisle displays) declines in a shopping environment, a consumers' ability to exercise self-control may increase. If the online shopping experience is less distracting than the in-store shopping experience, households may be able to exercise more self-control over their purchases. The representation of products with pictures has also been theorized to improve the healthfulness of food purchases (Shiv and Fedorikhin 1999; Shiv and Fedorikhin 2002).

This chapter also contributes to existing empirical research that analyzes how an online purchasing environment, in and of itself, may influence the healthiness of consumer purchases. Huyghe et al. (2017) utilize panel data for households shopping online and in-store at the same European retailer and find that expenditure shares for unhealthy products are lower in online shopping trips relative to in-store shopping trips. However, Huyghe et al. do not address the endogeneity of the decision to shop online and their data is limited to a four month observation period over a restricted set of product categories (salty snacks, chips, chocolate, candy bars and sweets and chewing gum).[1] Milkman, Rogers, and Bazerman (2010) test whether increased delay in delivery improves the healthiness of grocery purchases utilizing online grocery orders generated from a panel of households. They find that the share of "should" items (vegetables and fruit) in an online grocery order increases the further in advance the order is placed relative to delivery. However, it is possible that the circumstances in which a consumer places an order far in advance of delivery are correlated with product choice; thus, a limitation of their work is that these findings may also not be causal.[2] In contrast, this chapter utilizes a difference-in-differences and instrumental variables framework to estimate a causal effect of online grocery shopping on the healthiness of grocery purchases.

I employ panel difference-in-differences and two-stage least squares estimation strategies that utilize variation in the time the online grocery service became available, at different store locations, as a source of exogenous variation in the decision to shop online. In order to evaluate changes in the healthiness of grocery purchases, I begin by evaluating shifts in the allocation of the households' grocery budget. I find that when ordering groceries online, households begin to allocate a larger share of their grocery budget toward product categories that generally contain healthier items (dairy, fruit, meats and vegetables) at the expense of product categories that generally contain more indulgent products (drinks, oils and snacks/sweets). Specifically, I estimate local average treatment effects that indicate a 3.8, 5.9, 5.7 and 7.4 percent increase in the average budget shares for dairy, fruit, meat and vegetables. This reallocation of funds comes at the expense of drinks, oils and snacks/sweets with estimates indicating a 5.2, 4.1 and 13.6 percent decrease in average budget shares, respectively. I then quantify the impact of shopping

[1]In order to address these limitations, Huyghe et al. run an experiment that randomizes the purchasing environment each participant experiences and find further evidence to suggest that when consumers face pictures of products they are less likely to purchase indulgent items.

[2]For example, buying groceries in advance of an event at which you plan to have a specific meal prepared.

online on the nutritional content of grocery purchases by analyzing differences in the nutrient densities of grocery purchases. I find a 4.2, 5.0, 5.8 and a 5.8 percent decrease in the average amount of calories, carbohydrates, fats and sugars contained in an ounce of food purchased in months that a household engages in online shopping.

The remainder of this chapter is structured as follows: Section 2 discusses the ways in which an online shopping environment might influence consumer choice. Section 3 describes the data. Section 4 presents the empirical model and Section 5 discusses the results. Section 6 summarizes robustness checks for the main specification and Section 7 concludes.

1.2 Predictions for Online Shopping

Online search functions and product recommendations change the way consumers "browse" when they are online relative to the in-store purchasing environment. While the in-store search path (or browsing experience) is dictated by the physical layout of the products in the store, the online search function generally does not impose a specific search path on the consumer. The online purchasing environment featured in this study, allows customers to search for products either by using the online search bar or by clicking through a hierarchy of product categories; according to the retailer, the search bar is the most popular form of search in the online purchasing environment.

The time and effort that brick and mortar retailers put into product displays and store design suggests that search paths play an important role in nudging customers towards purchases. Laibson (2001) indicates that the placement of products in checkout lanes can be interpreted as a "cue" that increases the marginal utility of consumption when an individual is exposed to it. According to this theory, in the absence of the cue, we would expect to see different consumption decisions being made. For example, the absence of a checkout lane when shopping online is likely to lead to decreased purchases of candy bars, mints and gum; additionally, if you are less likely to be hungry when shopping online (another form of cue) we may expect to see less hunger driven impulse purchases. Reduced exposure to purchasing cues while searching for groceries online could lead to less unplanned purchasing.

Beyond differences in exposure to purchasing cues, there are many other elements of the online purchasing experience that could influence consumer choice. For example, time delays between the point of purchase and actual receipt of the goods could also lead to differences in consumer choice across the two purchasing environments. A multiple selves framework in which our long-term selves value "should" products and our short-term selves value "want" products predicts that shoppers might purchase more healthful foods when shopping online simply because they are receiving the goods further in the future then they would if they were in the store (Schelling 1984, Bazerman et al. 1998, Thaler and Shefrin 1981). Additionally, the valuation of goods that are generally consumed immediately after purchase will likely decrease in the presence of time delays.

It could be difficult for consumers to verify the quality of a product when shopping online due to the inability to physically inspect it. Shiv and Fedorikhin (1999, 2002) suggest that symbolic product representation creates sensory distance, which decreases a product's vividness and makes immediate gratification less important.[3] Hence, in the online shopping environment, households may be less tempted to purchase indulgent products simply because they are represented by pictures rather than by the physical products themselves.

The literature discussed above generates predictions about how online grocery purchases should differ from in-store grocery purchases. Specifically, differences in exposure to purchasing cues, timing and the representation of products suggest that households may be less likely to make unhealthy purchases when shopping online.

1.3 Purchasing Environment, Data & Summary Statistics

The supermarket chain featured in this study offers grocery products as well as a large variety of general merchandise items. Over the course of two and a half years, the retailer

[3] Other research on this topic includes the following chapters: Hoch and Loewenstein (1991); Loewenstein (1996); Mischel and Ebbesen (1972).

began to introduce an online shopping service which allows customers, for a small convenience fee, to select their groceries online, choose an appointment window with their local store, and pick-up and pay for their groceries at a designated "drive-through."[4] The wait time to pick up groceries depends on the size of the order and the volume of orders the retailer receives at the time of the order.[5]

Over the time frame of this study, thirty-three store locations introduced the online purchasing service. The online service was first introduced in March 2015 and was slowly rolled out to additional stores following the initial introduction of the program. Figure B1 illustrates the proportion of households that had access to the online shopping service over time.[6] In March 2015, roughly 20% of households have access to the online shopping service. This proportion increases over time as more stores begin to offer the service and by March 2017, all of the households in my sample have access to the online shopping service.

[4]The convenience fee varies by the location but is between $5 to $10 per online shopping occasion. This convenience fee changed for some stores over the time period of this study.

[5]Unfortunately, I do not have access to the average wait time in my data; however, through personal experience, it seems as if same day pick-up is probable (if you place an order in the morning) and next day pick-up is very likely. There is one idiosyncrasy of the online shopping environment that is worth noting. First, shoppers are not able to use chapter coupons when they shop online, but they are allowed to use digital coupons. chapter coupon offerings are primarily composed of the coupons that print when the customer checks out at the store. According to the retailer, they rarely publish chapter coupons in their weekly ads and chapter coupons are rarely used.

[6]I constructed the date it was available to a given household based on the stores the household visited in the six months prior to any store having the service available (i.e. Septemer 2015-February 2015). After constructing the store footprint for each household in the six months prior to introduction, I then assigned each household an availability date based on the first store (within their pre-online service footprint) that offered the online purchasing service. Roughly three thousand in-store households and three thousand online households did not visit a store in the six months prior to introduction that later introduced the online purchasing service. Since I cannot assign these households an availability date according to the definition of availability outlined above, these households have been dropped from the main estimation results of this chapter. However, Tables A19 andA20 of the Appendix present estimation results that includes these households by changing the definition of online availability to be based off of the entire store footprint of the household. These results illustrate that the main findings of this chapter are not sensitive to changes in the definition of online service availability.

I have access to household level purchasing data at the day, store, universal product code (UPC) level before and after the introduction of the online purchasing service. Within these data, I have the entire purchasing history (over grocery products) for roughly 130 thousand households from September 2014 through March 2017. This sample of households was constructed based on two criteria: (1) all households that had used the online service in that time frame; and (2) a random sample of households that had not yet used the service but have visited a store that offered the online purchasing service. I limit the households in my sample based on visit and purchase requirements in order to identify households that frequently shop with the retailer.[7] The final household sample consists of 34 thousand households, 25 thousand of which have used the online service and 9 thousand of which have not used the online service (over the time frame of my data). The data also contain detailed product information; including the product name, category, nutritional content and product attribute claims made by the manufacturer (i.e. organic, gluten free, etc.). Additionally, I can distinguish, at the household-day-store-UPC level, purchases that were made online from purchases that were made in the store.

Based on United States Department of Agriculture (USDA) classifications, I have assigned products to eleven different product categories: Dairy, Drinks, Fruits, Grains, Meat, Oils, Other, Prepared, Snacks/Sweets, Sugars and Vegetables.[8] I collapse the purchasing data to the household-year-month level and defined an indicator for online service use if the service was used to buy any products in the monthly basket. I evaluate the impact of online service

[7]First, I drop households that do not visit the retailer at least once every two months (roughly 87,171 households). Next, I drop households that spend less than $20 per month on average (72 households). Additionally, there are small businesses in the data set so I drop households who spend more than $1,500 per month on average (2,290 households). I further limit the household sample to the group of households for whom I have demographic information on; this restriction drops 7% of the eligible households from my sample. Additional households were dropped based on the definition of online service availability; these restrictions are discussed in the previous footnote.

[8]These product categories were chosen and created based on a document authored by the United States Department of Agriculture (USDA) called, "What We Eat in America". The descriptions of the products assigned to each of these product categories can be found in Table A18 of the Appendix.

availability on combined (in-store and online) monthly grocery purchases because I am interested in understanding how using the online service impacts overall food purchases rather than understanding how online orders differ from in-store orders.[9]

Tables A1 and A2 compare the demographics and purchasing patterns of households who eventually adopt the online purchasing service (online households) to households who never adopt the online purchasing service (in-store only households). The comparisons between these two different types of shoppers are made over the time period in which no one had access to the online purchasing service. Table A1 illustrates that households who adopt the online purchasing service tend to be younger, are more likely to be in a higher income group, are more likely to be married and are more likely to have children. Table A2 indicates that the households that eventually adopt the online purchasing service tend to spend more with the retailer per month ($448 vs. $331) and make more trips to the store each month (7.5 vs. 6.8), prior to online service adoption, relative to the households who never adopt the online purchasing service (in-store only households). Furthermore, online adoption households allocate a larger percentage of their grocery spending towards dairy (13.2% vs. 11.9%), fruit (7.5% vs. 7.3%), grains (7.6% vs. 7.2%) and other (1.8% vs. 1.7%); while in-store only households allocate a larger proportion of their budgets towards drinks (10.1% vs. 10.9%), meats (18.5% vs. 18.9%) and snacks/sweets (15.5% vs. 16.1%).[10] In the analysis that follows, I restrict the majority of my attention to the subset of households that eventually use the online purchasing service

[9]For example, suppose households use the online service only to buy healthy foods; if I were to analyze orders, I would find that online orders are much healthier than in-store orders. However, analysis at the order level ignores the fact that the same household may be supplementing all of their healthy online purchases with unhealthy in-store purchases that could perfectly balance their grocery purchases (in-store and online) to where they were before the household began shopping online. Hence, in this hypothetical scenario, online service use has had no impact on consumer choice; it has only impacted how the consumer chooses to purchase the various items in their basket.

[10]There are no statistically significant differences among the two household types in the budget shares for oils (4.4%), prepared (10.8%) and vegetables (9.1%).

(i.e. the online households).[11] The pre-existing differences between early online adopters and non-adopters suggest that the results of this chapter will not be representative of the effect of online shopping for the general population of shoppers; however, the results of this chapter are representative of the effect of online shopping for early adopters of the online purchasing service.

Table A3 presents the average price and nutrition content per ounce of food in each product category.[12] The most expensive product categories are other ($0.46/oz), meat ($0.23/oz) and snacks/sweets ($0.21/oz); while the least expensive product categories are drinks ($0.07/oz), vegetables ($0.09/oz), dairy ($0.10/oz) and fruit ($0.10/oz).[13] Unsurprisingly, there are considerable differences in the mean amount of calories and nutrients contained in an ounce of food across product categories. For example, snacks/sweets contains the highest amount of calories (120 kcal/oz), while meats contain the most protein (7.7 g/oz), grains the most carbs (18.5 g/oz), oils the most fat (7.7 g/oz) and sugars the most sugar (14.9 g/oz).

1.4 Methodology

The gradual roll-out of the online service lends itself nicely to a difference-in-differences framework, where the treatment group are households that have the service available to them in year-month m and the control group is the set of households for whom the service is not yet available in year-month m. In order to correctly employ this estimation strategy, I restrict the time periods of my data so that there is always a control group of households who have not yet received access to the online shopping service [14] Explicitly, I only use data prior to October

[11] The in-store households (households that do not adopt the online purchasing service over the time frame of my data) are utilized as a robustness check.

[12] The price averages represent the average price paid by all households over all time periods, while the nutrition averages are conducted over all of the products assigned to that product category.

[13] The category of other has the largest price ($0.46/oz) because it contains spices, which are extremely expensive per ounce.

[14] Borusyak & Jaravel (2016) show that event study estimates suffer from under identification and negative weighting when all units or groups are treated.

2016, the month in which the last group received access to the online shopping service.

There are two identifying assumptions in this framework: first, the time that the service was made available to households is independent of other factors that may influence grocery demand and second, the households that received access to the service later have parallel grocery purchasing patterns to households that received access to the service earlier. I believe these assumptions to be valid for three reasons: (1) there were no operational changes to the in-store shopping experience that occurred at the same time the online shopping service was introduced; (2) the first location chosen to pilot this service was close to the corporate headquarters, where it was presumably easiest to manage; and (3) the ability of a location to provide this service is highly dependent on the existing infrastructure of the store. In order to effectively implement this program a location needs to have a designated space to stage groceries for customer pickup and a convenient entrance for employees to exit and re-enter when delivering groceries to customers' cars. The Appendix compares the demographics and pre-online service shopping patterns of the households assigned to different dates of availability; this analysis reveals that there are differences between the households who received access to the online purchasing service earlier compared to those that received access later. The pre-existing differences between the households assigned to different online service availability waves motivates the household fixed effects model I employ in the analysis that follows.

I estimate the effect of online service use by utilizing availability of the service as an instrument for the decision to shop online. Specifically, my equation of interest is the following:

$$s_{ihm} = \alpha_i + \phi_i 1\{Online_{hm}\} + \gamma_{im} + \gamma_{ih} + \varepsilon_{ihm} \tag{1.1}$$

where s_{ihm} is the budget share of product category i for household h in year-month m, $1\{Online_{hm}\}$ is an indicator that equals one if the online service was ever used by household h in year-month m, γ_{im} is a year-month fixed effect to control for differences across time and γ_{ih} is a household fixed effect to control for unobserved household preferences. Specifications without household and year-month fixed effects include treatment group indicators and post-online-availability time indicators in order to maintain the panel difference-in-differences framework that is featured in the two-stage least squares estimation strategy presented shortly. For specifications without household fixed effects, demographic characteristics of the households are included as covariates.[15]

I estimate the local average treatment effect of online service availability by instrumenting online use, $1\{Online_{hm}\}$, with online availability, $1\{OnlineAvail_{hm}\}$. This produces panel difference-in-differences reduced form and first stage equations that estimate the average treatment effect of online availability on the expenditure shares for product category i and the probability of shopping online, respectively. Explicitly, the reduced form is:

$$s_{ihm} = \nu_i + \tau_i 1\{OnlineAvail_{hm}\} + \gamma_{im} + \gamma_{ih} + \omega_{ihm} \tag{1.2}$$

and the first stage is:

$$1\{Online_{hm}\} = \lambda_i + \theta_i 1\{OnlineAvail_{hm}\} + \gamma_{im} + \gamma_{ih} + \upsilon_{ihm} \tag{1.3}$$

Thus, the two-stage least squares estimate of ϕ_i, the average effect of online service use or the local average treatment effect of online availability, is the ratio of two panel difference-in-differences estimates; specifically, $\phi_{i,2SLS} = \tau_i / \theta_i$.

1.5 Results

Table A4 presents the difference-in-differences estimates, $\hat{\tau}_i$. The estimates presented in column (1) do not include year-month or household fixed effects, column (2) presents estimates from regressions that include year-month fixed effects and column (3) presents the estimates that incorporate both year-month and household fixed effects. The results of these regressions indicate modest increases in the budget shares of dairy, fruit, meat and vegetables and modest decreases in the budget shares for drinks, oils and snacks/sweets. Specifically, the results of the

[15]Since my demographic variables are provided categorically, I include the demographics by creating indicators for whether household h belongs to a given demographic category. Additionally, the demographic information I have access to does not vary over time.

full model indicate a 0.10, 0.08, 0.20 and a 0.13 percentage point increase in the budget shares for dairy, fruit, meat and vegetables (respectively) and a 0.10, 0.04 and a 0.41 percentage point decrease in the budget shares of drinks, oils and snacks/sweets (respectively). Each of these shifts represents less than a three percent change in the average pre-online service budget share, which is calculated over the six months prior to online service introduction at any store location. Table A5 presents the first-stage estimates, $\hat{\theta}_i$. These estimates indicate a strong and positive relationship between the availability of the online service and actual use of the online service.[16] The full model indicates that the introduction of the online service increases the probability of shopping online, in a given month, by 19.3 percentage points, on average.

Table A6 and A7 present the ordinary least squares and two-stage least squares estimates of the effect of online shopping. The two-stage least squares estimates (columns 4, 5 and 6) are aligned with the findings of the reduced-form estimates. Furthermore, the two-stage least squares estimates are stable across three different specifications and indicate a 0.5, 0.4, 1.1 and 0.7 percentage point increase in the budget shares for dairy, fruit, meat and vegetables, (respectively), and a 0.5, 0.2 and 2.1 percentage point decrease in the budget shares for drinks, oil and snacks/sweets, respectively. Interpreted relative to the pre-online service average budget shares, these estimates indicate a 3.8, 5.9, 5.7 and 7.4 percentage increase in the average pre-online service budget shares for dairy, fruit, meat and vegetables, respectively. These estimates also indicate a 5.2, 4.1 and 13.6 percentage decrease in the average pre-online service budget shares for drinks, oil and snacks/sweets, respectively.

These results suggest that when households shop online they allocate a larger share of their budget towards healthier product categories at the expense of product categories that are traditionally thought to contain less healthy items. In order to better understand the implications that online shopping may have for consumer health, I evaluate changes in the average nutrient content per ounce of food purchased by the households in my sample. I follow the same estimation

[16] The first stage is a linear probability model.

strategy presented above but with nutrients per ounce as the dependent variable.[17] The results of the ordinary least squares and two-stage least squares regressions are presented in Table A8, where $1\{Online_{hm}\}$ is instrumented with $1\{OnlineAvail_{hm}\}$. The results of the two-stage least squares models indicate that the average amount of calories, carbohydrates, fats and sugars per ounce of food purchased decreases in the months that households shop online. My estimates indicate an average decrease of 1.97 kcal/oz, 0.3 g/oz, 0.11 g/oz and 0.13 g/oz for the nutrient categories of calories, carbohydrates, fat and sugars, respectively. Furthermore, there are no significant changes in the average amount of protein, cholesterol and sodium content per ounce of food purchased. Interpreted relative to the pre-online service average, these results equate to a 4.2, 5.0, 5.8 and a 5.8 percent decrease in the average amount of calories, carbohydrates, fats and sugars contained in an ounce of food purchased, respectively.

In the interest of making the estimated declines in caloric content more tangible, I perform a back of the envelope calculation in order to translate these results into a familiar unit – projected weight loss.[18] Before the online shopping service was available, households purchased 2,383 ounces of food per month, on average. Holding the amount of food purchased constant, an average decline of two calories per ounce equates to 4,766 fewer calories being purchased in the months in which a household shops online. Extrapolating this result to the individual-day level, the change in the amount of calories purchased represents a decline of 53 calories per person, per day.[19] If the declines in caloric purchases perfectly translated into declines in caloric intake, these changes would induce an average adult to lose one pound every ten weeks or roughly five pounds over the course of a year.

[17]Nutrition information is available for 90% of the items purchased by these households. Hence, these regressions test changes in the nutritional value of purchases made over the products for which I have nutrition information. The majority of the gaps in the nutrition information data occur for products that are not purchased in a package (i.e. fresh produce and meats).

[18]Note that this projection makes a number of assumptions that may or may not be realistic. The purpose of the exercise is to translate the results into something that is easy to relate to.

[19]This number is generated by dividing 4,766 by thirty days and three people (the size of the average online household).

The magnitude and signs of the estimates presented above support the prediction that the online shopping environment reduces the incidence of impulsive and unhealthy purchases. Furthermore, estimated changes in the caloric content of food purchased suggest that online shopping could contribute to slow but gradual improvements in consumer health through weight loss. However, more dramatic changes in consumer health could be made by improving the nutritional value of the purchases households *intend* to make.

1.5.1 Online Shopping & Retailer Substitution Patterns

If consumers change retailer substitution patterns differentially across product categories when shopping online, then consumer "crowd-in" (or "crowd-out") could explain the changes we observe in grocery basket composition as well as the documented changes in the nutritional content of food purchased. For example, suppose that the households in this study, prior to using the online shopping service, purchased produce at other grocery stores (health food grocery stores, etc.) and/or a farmers market. Then, further suppose that after transitioning to the online shopping service, these households stopped buying their produce from other retailers and began purchasing more produce with the retailer in this study. In this hypothetical scenario, we would expect to see the budget share for fruits and vegetables increase, but these shifts are the result of changing retailer substitution patterns rather than an effect of the online shopping environment.

Similar to Pozzi (2013a), the households studied in this chapter also exhibit increases in monthly grocery expenditure when they begin using the online shopping service.[20] Following the estimation strategy outlined in equation (1), but with expenditures as the outcome variable, the two-stage least squares estimates presented in Tables A9 and A10 indicate that households spend $49 more per month (roughly a 10.9% increase over average pre-online service expen-

[20]Prior research by Pozzi (2013a) documents that online grocery services can lead consumers to divert their grocery business away from other retailers, toward the online shopping service provider. Pozzi finds evidence to suggest that households living in areas with higher levels of retailer competition increase monthly expenditures with the online retailer at a higher rate than households living in areas with relatively lower levels of outside competition.

ditures), on average, in months that they shop online.[21] Additionally, all product categories, with the exception of other and snacks/sweets, experience significant increases in total expenditure.[22]

I explore whether consumer crowd-in can explain the entirety of the documented differences between online and in-store purchases in two ways. First, I identify stores that are likely to capture the entirety of a household's grocery purchases because the store location faces less outside competition. I find that households who engage with the online shopping service in store locations where there is little outside competition do not exhibit any significant changes in overall food expenditures after the service becomes available, but these households still exhibit shifts in the allocation of their grocery budget. Second, I analyze the effect of online shopping on purchasing decisions made within narrower product spaces. Consumer decisions over product choice in a more narrowly defined product space are less likely to be influenced by changes in the mix of retailers the consumer visits.[23] Under the assumption that households buy the same variety of products, within a narrow product space, at each retailer they shop with, if consumers allocate more of their purchases toward the retailer of this study when shopping online, we would not expect consumer "crowd-in" to change the composition of products purchased. In this analysis, I find changes in the product mix of breads and salty snacks purchased, but no changes in the product mixes of yogurt and cereal. These results indicate that shopping online

[21]Note that these figures are conditional on arrival to the store in a given month. Explicitly, observations of $0 have not been imputed for year-month occasions in which a household does not buy any grocery products from the retailer of this study.

[22]Specifically, the two-stage least squares estimates indicate a $7.7, $4.0, $7.2, $3.8, $11.8, $1.7, $2.7, $0.6 and $8.0 average increase in monthly spending for the product categories of dairy, drinks, fruit, grains, meat, oil, prepared, sugars and vegetables, respectively. The final column of Tables A9 and A10 present the percent change in average spending that the two-stage least squares estimates represent. The calculated percent changes in categorical expenditures illustrate that, in general, the estimated changes in budget shares are positive if the percent change for product category expenditure increased by more than 10.9% (the average percent change in total expenditure) and are negative if the percent change for product category expenditure increased by less than 10.9%.

[23]For example, it is less likely that consumers shop for bread at multiple retailers than it is for them to shop for different types of grocery products at different types of retailers.

may not induce households to purchase healthier options across all product categories; rather, households may be less likely to engage in impulsive purchases over more indulgent products.

1.5.1.1 Local Competition & Retailer Substitution Patterns

I begin exploring the extent to which shopping online influences retailer substitution patterns by evaluating how the effect of online shopping on total grocery expenditures varies with the level of competition each store location faces. In order to classify high and low competition store locations, I utilize a competition index provided to me by the retailer. The competition index provides a measure of the competition faced by each store location relative to all other store locations owned by the retailer. Specifically, this index is based on how close the store is to competitors as well as how much of their sales are at threat to each outside competitor. I split online households in two groups: those whose online service availability was determined by a store location that faces below average competition and those whose online service availability was determined by a store location that faces above average competition.[24]

Tables A11 and A12 present difference-in-differences estimates, utilizing the estimation strategy presented in equation (2), for the low competition (columns 1-3), high competition (columns 4-6) and the total online household population (columns 7-9). Tables A11 and A12 indicates that households who adopt the online purchasing service in store locations that face lower levels of outside competition do not increase their monthly expenditure with the retailer of this study after the online purchasing service becomes available; however, these households still exhibit changes in the composition of their grocery purchases. After the online service becomes available, low competition households exhibit significant increases in the budget shares of fruit and meat. Additionally, this reallocation of funds comes at the expense of the snacks/sweets product category. The point estimates indicate a 0.10, 0.22 and -0.24 percentage point change

[24] To provide some context on what the competition index is capturing, stores that have a lower than average competition index have (on average) two fewer major competitors and twelve fewer minor competitors compared to store locations that have a higher than average competition index.

in the budget shares of fruit, meat and snacks/sweets, respectively. These findings illustrate that even when households do not exhibit changes in substitution patterns across retailers when shopping online, they still change the composition of their purchases when shopping online.

In contrast, households in competitive purchasing environments significantly increase monthly grocery expenditures after the online purchasing service becomes available. Specifically, Tables A11 and A12 indicate that households in competitive environments increase monthly grocery expenditures by $10.60 when the online purchasing service becomes available. These results suggest that the online purchasing service may be effective at poaching customer's grocery purchases from competitors. The point estimates of the effect of online availability on budget shares indicate a 0.04, 0.21 and 0.17 percentage point increase in the budget shares of grain, meat and vegetables respectively. This reallocation of funds also comes at the expense of snacks/sweets with point estimates indicating a 0.49 percentage point decrease, on average.

Comparing the results of difference-in-difference estimates for low competition households to the difference-in-difference estimates for all households provides a rough indication of how much of the documented changes in grocery basket composition could be due to differences in retailer substitution patterns after households begin shopping online. The point estimates for the product categories of fruit, grains, meat, oil and other are remarkably close for the two estimation procedures.[25] In contrast, the estimates for the product categories of dairy, drinks, snacks/sweets and vegetables are not as closely aligned.[26] The differences between these estimates suggest that, on average, roughly 63 percent of the estimated effect of online shopping on the budget shares of dairy, drinks, snacks/sweets and vegetables could be due to changes in retailer substitution patterns after households begin shopping online.[27]

[25]Note, I am comparing the estimates that utilize household and year-month fixed effects and am calculating the ratio of the low competition estimate to the all household estimate.

[26]The estimates for dairy, drinks and vegetables are also no longer significant in the regressions that incorporate the low competition households only. However, we have also thrown out half of the data in these regressions.

[27]This number is calculated by taking the ratio of the low competition estimate to the all household estimate and averaging this ratio across the dairy, drinks, snacks/sweets and veg-

1.5.1.2 Narrow Product Categories

I further explore the extent to which consumer crowd-in can explain the changes in online grocery basket composition by analyzing online product choice within narrower product spaces. The advantage of a more narrowly defined product space is that it is less likely that a consumer would buy different types of products, within these product spaces, at different retailers. For example, it is less likely that consumers shop for different types of yogurt at different types of retailers than it is for them to shop for different types of grocery products at different types of retailers. Under the assumption that households buy the same variety of yogurt at each retailer they shop with, if consumers allocate more of their yogurt purchases toward the retailer of this study when shopping online, we would not expect consumer "crowd-in" (or "crowd-out") to change the composition of yogurts purchased, only total expenditures over yogurt.

This section evaluates whether there are significant differences in the types of bread, breakfast cereal, salty snacks and yogurt purchased when households shop online. Specifically, I analyze whether households begin to allocate a larger portion of their expenditures, within these product categories, towards healthier options. I begin by assigning individual products into different subcategories within the product group. For example, I assign individual bread UPCs to five different bread categories: white, wheat, other, seed and grain. Cereal UPCs are assigned to the categories of kids, organic kids, standard, frosted standard and healthy. Within salty snacks I create the product classifications of chips, healthy chips, popcorn, pretzels and tortilla chips. Lastly, I assign yogurt products to the categories of probiotic, light greek, greek, indulgent, kids, organic, light traditional and traditional.[28]

Table A13 presents the average nutritional content (per ounce of food) for each product

etable product categories. The average of this ratio is 0.37, indicating that the low competition household estimate is 37% as large as the total household estimate. Hence, assuming the low competition household estimate is free of the confounding effect of retailer switching, 63% of the total household estimates (on average, for these product categories) could be due to changes in retailer substitution patterns after the households begin shopping online.

[28]Table A21, in the Appendix, briefly describes the subcategories of products that have been created within each product category.

subcategory within breads, cereals, salty snacks and yogurt. In the product category of bread, wheat bread is generally considered a healthier choice. Table A13 illustrates that all breads contain roughly 70 calories per ounce; however, wheat, grain and seed breads tend to contain more protein per ounce (2.8 g vs. 2.3 g).[29] Within the product category of cereals, healthy (Grape Nuts, Kashi, Fiberone) and standard cereals (Cheerios, Chex, Cornflakes) tend to have better nutritional values than kids (Apple Jacks, Fruity Pebbles), organic kids (Annies, Cascadian Farm) and frosted standard cereals (Frosted Flakes, Corn Pops). Healthy cereals contain less calories per ounce, more protein per ounce and less sugar per ounce. Standard cereals also exhibit lower levels of fat per ounce and sugars per ounce. Healthy chips (Sun Chips, Veggie chips etc.), pretzels and tortilla chips are healthier snack options relative to regular chips; healthy chips, pretzels and tortilla chips contain fewer calories per ounce, more protein and less fat than regular chips. Lastly, Table A13 illustrates that greek, light greek and light traditional yogurt have better nutritional values than other types of yogurt in terms of calorie, protein and sugar content. These yogurts have fewer calories per ounce, higher amounts of protein and contain less sugar than other yogurt varieties, on average.

In order to better understand how shopping online influences the composition of the different types of products purchased within these categories, I analyze the effect of online service availability on the budget shares for each product subcategory.[30] I analyze the budget share outcomes utilizing ordinary least squares and a fractional probit model, which accounts for the

[29] Breads in the other category tend to have a higher sugar content per ounce, likely due to cinnamon raisin breads, etc.

[30] The Appendix presents and discusses the estimated effect of online service availability on sales ($\hat{\tau}_k$) for three ordinary least squares specifications, as well as the estimated average partial effects for two tobit specifications. A preliminary analysis of the data indicates that it is not uncommon for households to purchase more than one type of bread, cereal, salty snack and/or yogurt in a given month. Hence, I chose to model the decision of product choice in a continuous framework rather than a discrete choice environment. Specifically, 50% of bread purchases, 60% of cereal purchases, 70% of salty snack purchases and 62% of yogurt purchases in a year-month purchase occasion contain more than one type of bread, cereal, salty snack or yogurt product purchased.

fractional nature of the share outcome and alleviates concerns associated with corner solutions. The underlying data in these regressions is generated from the year-month purchase occasions in which a household buys at least one item from the parent product category (i.e. households that purchase at least one bread for the bread share outcomes, one cereal for the cereal share outcomes, etc.). I estimate regressions of the following form:

$$s_{khm} = \nu_k + \tau_k 1\{OnlineAvail_{hm}\} + \gamma_{km} + \gamma_{kh} + \omega_{khm} \tag{1.4}$$

where s_{khm} is the share of product category sales (bread, cereal, etc.) allocated to product subcategory k for household h in year-month m, $1\{OnlineAvail_{hm}\}$ is an indicator that equals one if the online service is available to household h in year-month m, γ_{km} is a year-month fixed effect to control for differences across time and γ_{kh} is a household fixed effect to control for unobserved household preferences.[31]

Tables A14, A15, A16 and A17 present the estimates of τ_k from the ordinary least squares specifications, as well as estimates of the average partial effects for the fractional probit regressions. These tables indicate that after the online purchasing service becomes available, the only product categories that exhibit changes in the composition of products purchased are bread and salty snacks. The fractional probit estimates indicate that the budget share for wheat bread increases by 0.63 percentage points, while the budget share for other bread decreases by 0.37 percentage points. Additionally, the budget share for tortilla chips increases by 0.5 percentage points, while the budget share for pretzels decreases by 0.34 percentage points, on average. Lastly, the budget shares for products within the cereal and yogurt product categories remain unchanged.

[31]Specifications without household and year-month fixed effects include treatment group indicators and post-availability time indicators in order to maintain the panel difference-in-differences framework. Additionally, specifications without household fixed effects include demographic characteristics of the households. Since my demographic variables are provided categorically, I include the demographics by creating indicators for whether household h belongs to a given demographic category.

These results suggest that shopping online does not induce households to become more health conscious within all product categories. I do not find any changes in the composition of cereals or yogurts purchased, a finding which is consistent with theories that predict decreased brand exploration in the online shopping environment due to an inability to verify product quality.[32] However, there are significant differences in the composition of bread and salty/snacks purchased when households shop online. These changes could be explained by differences in product search and (or) product placement across the two purchasing environments. For example, there are increases in wheat bread sales, as well as increases in the budget share for wheat bread. Furthermore, the increases in the budget share for wheat bread come at the expense of "other" bread. This result could be explained by in-store shopping behavior in which the consumer adds other breads (cinnamon raisin bread, etc.) to their cart because they see these breads and are reminded to buy them when shopping in the store. In the absence of these visual reminders when shopping online, the consumer may forgo purchases of other bread types. Additionally, differences in the location of products when shopping online could also lead to changes in purchasing patterns. For example, when in the store, the pretzels, popcorn and chips are all displayed on the shelves of the same aisle. However, when shopping online, tortilla chips are nested within the chips category, while popcorn and pretzels are listed in their own product categories. Tortilla chips could become more popular when households shop online because, in the online purchasing environment, they are displayed relative to regular chips only.

1.6 Robustness Check Summary

This section summarizes robustness checks performed. I first asses the validity of the parallel trends assumption. I then test whether the timing of the introduction of the online shopping service was correlated with other changes that may be influencing grocery purchases. Last, I

[32]However, I do find that households spend significantly more on all types of yogurt when they shop online. This could be due to households bringing their yogurt demand from other retailers to the retailer of the study and (or) yogurt could be more attractive product when shopping online.

verify that the main results of the chapter are not driven by differences in product offerings across the two purchasing environments.

I estimate event study specifications to determine whether or not there were shifts in budget share allocations before the online service was introduced and to evaluate the effect of online shopping over time. Figure A2 presents the estimates of τ_{ik}, with 95% confidence intervals, for each budget share outcome as well as for the outcome of online service use.[33] Eleven of the twelve graphs do not indicate a consistent pre-trend violation. However, the graph for dairy illustrates that the the point estimates of τ_{ik} were increasing in the months before online service introduction, indicating that caution should be exercised when drawing conclusions about the effect of online grocery shopping on dairy purchases. Furthermore, Figure A2 illustrates striking discontinuities in the estimates of τ_{ik} at the period of online introduction (t=0) for the product categories of drinks, meat, snacks/sweets and vegetables. A more detailed discussion of the event study specification is available in the Appendix.

In order to test whether or not there are other changes influencing demand that occur simultaneously with the introduction of the online purchasing service, I estimate difference-in-difference regressions over the subset of households that never adopt the online service. I find no evidence to suggest that online service availability has any significant effect on the budget share allocations of households who never use the online purchasing service. Please refer to the Appendix for a deeper discussion of the results of these regressions.

I also verify that limited online product offerings are not responsible for my main results. There are some challenges to understanding what products were available online. Primarily, I do not know what products were available online at any given point in time; I only have access to information regarding whether or not a product was purchased online and (or) in the store. In the Appendix, I verify that online product offerings are representative of in-store product offerings by January of 2016. I then test whether limited product offerings are driving the results of the previous analysis by restricting the data to all dates after January 2016. The results of

[33]The estimates of these regressions are presented in Tables A32 and A33 of the Appendix.

these regressions, presented and discussed in the Appendix, indicate that limited online product offerings alone cannot explain the main results of the chapter.

1.7 Discussion & Conclusions

This chapter analyzes the effect of online grocery shopping on the nutritional content of grocery purchases. I find that households allocate a significantly larger share of their total grocery expenditures toward healthier product categories (dairy, fruit, meats, vegetables) at the expense of more indulgent product categories (drinks, oils, snacks/sweets) when shopping online. In addition, I find that the nutritional content of grocery purchases is improved in the months in which households engage in online shopping. The findings of this chapter illustrate that consumer choice is sensitive to variation in purchasing environments. Differences in exposure to purchasing cues, time delays between order and receipt of the goods and the representation of products with pictures are all potential mechanisms that could explain my finding of healthier online grocery purchases.

The design of this study makes it difficult to pin point the magnitude of each mechanism individually. However, despite this shortcoming, my results have immediate food policy implications, particularly for Supplemental Nutrition Assistance Program (SNAP or food stamp) participants. For example, if we would like to improve the nutritional content of grocery purchases made by SNAP participants, we may be able to do so by implementing a policy that allows SNAP participants to pre-order their groceries online.[34]

My findings also have implications that extend beyond food policy. A retailer interested in boosting online purchases might do so by incorporating purchasing cues, that exist in the in-store shopping experience, into their online grocery web design. For example, the retailer could incorporate "check-out lane" pop-ups or more sophisticated product recommendation banners

[34] Just et al., in a 2007 United States Department of Agriculture (USDA) report, theorized that allowing SNAP participants to pre-order food, either by phone or online, could lead to healthier grocery purchases.

into their web design. On the other hand, a traditional brick and mortar retailer interested in boosting in-store sales may also be able to do by increasing the level of in-store purchasing cues that exist in their shopping environment.

CHAPTER 2

THE EFFECT OF ONLINE SHOPPING ON GROCERY DEMAND

2.1 Introduction

Online grocery purchases amounted to $20.5 billion dollars in sales and represented 4.3 percent of all groceries purchased in 2016 (Nielsen & FMI). In recent years, online grocery shopping has become more and more commonplace. Many brick and mortar retailers have begun to offer online grocery services and web based retailers, such as Amazon, have also entered the online grocery market. Due to increasing accessibility and consumer adoption of online grocery services, it is projected that within the next ten years 20 percent of all grocery purchases will be conducted online (Nielsen & FMI). Despite the large predicted growth rate, there has been relatively little research that examines how online purchasing environments influence demand. This chapter evaluates whether or not there are structural changes in demand when households shop online.

One of the most predominant differences between an in-store and online purchasing environments is the way in which consumers search for products. Sales filters and price sorting options featured in the online purchasing environment reduce the cost of price comparison, which may lead consumers to have heightened price sensitivities when shopping online as well as fiercer price competition (Bakos 1997; Brynjolfsson and Smith 2000; Ellison and Ellison 2005). Additionally, decreased search cost over prices could also motivate consumers to seek out brands that they have previously never purchased (Brown and Goolsbee 2002).

On the other hand, product recommendations and customer favorite's lists can reduce shopping costs by eliminating the need for search. The online favorites list allows the customer to instantly add the items they frequently purchase to their order on each shopping occasion. However, time savings could come at the expense of price comparison because the consumer is no longer comparing the price of each product to its close substitutes. Thus, features of website design could lead to decreased price sensitivity in the online shopping environment. Whether price comparison or convenience features of the online purchasing environment influence price elasticities more remains an empirical question.

Existing empirical research suggests that even when a consumer is able to determine the lowest price for a given product, search frictions in the online marketplace limit the extent to which a consumer searches. Hann and Terwiesch (2003), utilize data from an online Name-Your-Own-Price (NYOP) retailer in order to explore whether or not consumers submit sequential bids, each a little larger than the last rejected bid, in order to find the lowest price at which the retailer is willing to sell the product. They find that consumers generally do not engage a sequential bidding behavior that results in the lowest possible price paid and estimate online frictional transaction costs to range from 3.5 euros (for a MP3 player) to 6.1 euros (for a personal digital assistant).

Papers more closely related to this study find evidence that the convenience features of the online shopping experience may outweigh the effect of price comparison features. Pozzi (2012) analyzes how online shopping lists and the convenience of being able to instantly generate your grocery basket with previous purchases influences decisions over brand choice within breakfast cereals. While brand choice is the main focus of the chapter, he also finds that households are generally less price sensitive when they shop online; specifically, he finds that in-store own-price elasticities are 50 percent larger and in-store cross-price elasticities are almost three times larger than their online counterparts.[1] Similarly, Chu et al. (2008) also study how purchasing patterns vary across in-store and online grocery shopping environments fulfilled by the same retailer. Chu et al. employ a discrete choice analysis across a number of different product categories and consistently find that households are more brand loyal, more size loyal and less

[1]Pozzi also finds that brand exploration is systematically more prevalent in-store than online and quantifies how features of the ordering website (favorites lists and difficulty of quality verification) contribute to decreased brand exploration behavior.

price sensitive when they shop for groceries online.[2] In a follow-up chapter (Chu et al., 2010), the authors find that the magnitude of the effect of online shopping on brand loyalty, size loyalty and price sensitivity varies with household and product characteristics.

Pozzi (2012) and Chu et al. (2008, 2010) provide valuable insight into how and why purchasing behavior is different online; however, they only shed light on decision making processes over narrowly defined product spaces (cereal, drinks, laundry detergent, frozen pizza, etc.). In contrast, this chapter estimates structural changes in demand over a more broadly defined product space that incorporates all grocery products; analysis at this level of aggregation effectively analyzes a different set of substitution patterns than those that have been previously studied.

This chapter also contributes to existing reduced form approaches that document differences in purchases when households shop online. Pozzi (2013) employs a panel difference-in-differences estimation strategy to evaluate how online convenience influences purchases over products that are inconvenient to transport, namely, bulk products. He finds that when households use an online grocery service, they increase their monthly share of expenditure for bulk items in laundry detergent and soda by 30 and 80 percent, respectively.[3] Harris (2019), estimates the effect of shopping online on the nutritional content of grocery purchases. Utilizing variation in the time that the online shopping service became available at different store locations, and subsequently to different households at different times, Harris (2019) employs panel difference-in-differences and instrumental variables strategies to show that households make healthier purchases in months in which they engage in online shopping. In contrast to the aforementioned chapters, this chapter estimates structural differences in demand parameters between months in which all purchases are conducted in the store compared to months in which a proportion of purchases are made online.

[2]The authors do not identify the mechanism that explains this finding but suggest that time constraints, online shopping list creation, the presence of non-price information for products (nutrition facts), lack of online competition and convenience could be contributing to this result.

[3]Pozzi attributes this finding to the decreased transportation cost of purchasing bulk products online.

In order to isolate the effect of an online shopping environment, I utilize grocery scanner data generated from the purchases of 34 thousand households who shop with a traditional brick-and-mortar retailer that has begun to offer an online purchasing service. These data provide an attractive setting to study the effect of online grocery shopping on demand for three reasons: first, the panel structure of the data allows for a within household comparison of purchases across the two environments; second, online and in-store purchases are fulfilled by the same retailer, alleviating concerns over differences in product selection and branding; third, the retailer of this study offers products for purchase online at the same prices as those found in the store (Harris, 2019).

I estimate a structural model of grocery demand that allows demand parameters to vary in months in which households shop online. I find that fifty-four percent of the demand parameters are significantly different in months in which a household engages in online shopping. I also find that households are generally less price sensitive when shopping online. Specifically the estimated own-price elasticities and cross-price elasticities are, on average, 1.2 and 1.4 times larger in-store than they are online, respectively.[4] Differences in price elasticities across the two purchasing environments suggest that firms may be able to increase online revenues by implementing more sophisticated pricing strategies in the online environment.

The remainder of this chapter is structured as follows: Section 2 discusses the online purchasing service and data. Section 3 presents the grocery demand model. Section4 discusses the estimation strategy and presents the results. Section 5 discusses and concludes.

2.2 Institutional Details and Data

The data in this study is generated from the purchases of households shopping with a supermarket chain that offers grocery products as well as a large variety of general merchandise

[4]This is for the price elasticities that are significantly different across the two purchasing environments. Unconditional on significant differences, the estimated own-price elasticities and cross-price elasticities are, on average, 0.9 and 1.2 times larger in-store compared to online, respectively.

items. Over the time-frame of my data, the retailer began to offer an online purchasing service which allows customers, for a small convenience fee, to build their grocery order online, choose a pick-up time with their local store, and then pick-up and pay for their groceries at their local store.[5] According to the retailer, online product offerings are representative of in-store grocery product offerings.[6] The one idiosyncrasy of the online shopping environment is that chapter coupons cannot be used when making an online purchase; however, chapter coupons are very rarely redeemed.

Figure B1 illustrates the proportion of households that had access to the online shopping service over time.[7] In March 2015 the first store location introduced the online purchasing service and roughly 20% of households gained access to the online shopping service. As more stores began to offer the service over time, more households have access to the service and by March 2017, all of the households in my sample have access to the online shopping service.

2.2.1 Data

This chapter utilizes household level panel data at the day, store, universal product code (UPC) level. These data contain the entire purchasing history (over grocery products) for roughly 130

---

[5]As documented in Harris (2019), the convenience fee varies by the store location but is between \$5 to \$10 per online shopping occasion. This convenience fee did change for some stores over the time period of this study.

[6]Harris (2019) explores the validity of this statement is greater detail.

[7]Following Harris (2019), I constructed the date it was available to a given household based on the stores the household visited in the six months prior to any store having the service available (i.e. Septemer 2015-February 2015). After constructing the store footprint for each household in the six months prior to introduction, I then assigned each household an availability date based on the first store (within their pre-online service footprint) that offered the online purchasing service. Roughly three thousand in-store households and three thousand online households did not visit a store in the six months prior to introduction that later introduced the online purchasing service. Since I cannot assign these households an availability date according to the definition of availability outlined above, these households have been dropped from the main estimation results of this chapter. However, Harris (2019) shows that the main estimation results of their chapter were insensitive to a definition of online availability that included these households.

thousand households from September 2014 through March 2017. The sample of households can be broken into two groups: (1) all of the households that had engaged in online shopping between September 2014 and March 2017 and (2) a sample of households who had the online shopping service available to them but had not yet adopted the service between September 2014 and March 2017. Following Harris (2019), I limit the household sample to households that shop frequently with the retailer.[8] I further restrict my household sample to the subset of households that eventually use the online purchasing service (i.e. the online households); hence, the final household sample consists of 25 thousand households.[9] Within the data, I also have indicator for whether or not the item was purchased online or in the store.

Based on United States Department of Agriculture (USDA) classifications, I have assigned products to eleven different product categories: Dairy, Drinks, Fruits, Grains, Meat, Oils, Other, Prepared, Snacks/Sweets, Sugars and Vegetables.[10] Furthermore, I collapse the purchasing data to the household-year-month level and define an indicator for online service use if the service was used to buy any products in the monthly basket. I evaluate the impact of online service use on combined (in-store and online) monthly grocery demand because I am interested in understanding how using the online service impacts overall food demand rather than understanding how online orders differ from in-store orders. Additionally, analysis at the monthly level, re-

[8] Specifically, I drop households that do not visit the retailer at least once every two months. I also drop households that spend less than $20 per month on average and households who spend more than $1,500 per month on average. I further limit the household sample to the group of households for whom I have demographic information on. Additional households were dropped based on the definition of online service availability; these restrictions are discussed in Harris (2019).

[9] Harris (2019) compares the demographics and pre-online service purchases of household that adopt the online shopping service and those who choose not to adopt the purchasing service. Pre-existing differences between these populations suggest that the results of this chapter will not be representative of the effect of online shopping for the general population of shoppers; however, my results are general to early-adopters of the online purchasing service.

[10] These product categories were chosen and created based on a document authored by the United States Department of Agriculture (USDA) called, "What We Eat in America". The descriptions of the products assigned to each of these product categories can be found in Table B5 of the appendix. This table is courtesy of Harris (2019).

duces the prevalence of purchasing zero items from a given product category.

2.2.2 Summary Statistics

Table B1 presents the demographic information of the households included in my sample. Roughly two-thirds of the households that adopt the online purchasing service are married and 60% of these households have at least one child; hence, the average household size is three. Table B1 also illustrates that, on average, household income is between \$80 thousand to \$99 thousand per year and the head of the household is between 36 to 45 years old.

Table B2 compares months in which online adoption households only shop in the store to months in which they engage in online shopping. The average household spends \$468 on groceries and makes eight trips to the store in a month in which they shop exclusively in the store. Table B2 also illustrates that households spend more money on groceries, with the retailer of study, in months in which they engage in online shopping. Specifically, they spend roughly \$70 more on average, purchase twenty-five additional grocery items and have 0.5 additional grocery shopping occasions throughout the month.[11] Households spend 40% of their total monthly grocery budget online, in the months in which they engage in online shopping.

The middle pane of Table B2 illustrates how the average household in my sample allocates their budget. Specifically, households allocate 18% of their budget towards meat, 16% towards snack/sweets, 13% towards dairy, 11% towards drinks, 10% towards prepared products, 9% towards vegetables and 8% towards fruits and grains, individually. The product categories of oils, other and sugar account for roughly 8% of the grocery budget, combined. Mean comparison tests reveal that the grocery budget is allocated differently in months in which the household engages in online shopping. Specifically, the product categories of dairy, fruits, grains and vegetables experience significant increases in budget shares; while, the product categories of drinks, other, prepared and snacks/sweets experience significant decreases in budget shares.

[11] A grocery shopping occasion is measured as a day in which grocery purchases were made.

The bottom pane of Table B2 presents the average price paid per ounce of food in each product category. The most expensive product categories are other (\$0.92/oz), meat (\$0.25/oz), sugar (\$0.24) and snacks/sweets (\$0.22/oz); while the least expensive product categories are drinks (\$0.09/oz), vegetables (\$0.11/oz), dairy (\$0.11/oz) and fruit (\$0.11/oz).[12] Mean comparison tests across in-store and online months reveal that differences in mean prices paid are small, one cent in the largest case, but statistically significant.

2.3 Modeling Grocery Demand

I estimate the LA/AIDS demand system, developed by Deaton and Muellbauer (1980), and also incorporate an extension from Atkin (2013) that models varying household tastes by allowing the vector of first price coefficients (τ_{ih}, in the expenditure system defined shortly) to vary by household.[13] The LA/AIDS demand system is derived from an expenditure function, $e(p,u;\tau_h)$: the minimum expenditure necessary to achieve utility u, given a vector of prices p and varying household tastes, τ_h. The log expenditure function over I goods is defined as follows:

$$ln(e(p,u;\tau_h)) = \alpha_0 + \sum_{i=1}^{I} \tau_{ih} ln(p_i) + 1/2 \sum_{i=1}^{I} \sum_{i\prime=1}^{I} \gamma_{ii\prime} ln(p_i) ln(p_{i\prime}) + u\beta_0 \prod_{i=1}^{I} p_i^{\beta_i} \tag{2.1}$$

where i indexes good i and $i\prime$ indexes good $i\prime$.[14] Note that by Shephard's Lemma: $\frac{\partial e(p,u;\tau_h)}{\partial p_i} = q_{ih}$. This equality implies:

$$\frac{\partial ln(e(p,u;\tau_h))}{\partial ln(p_i)} = \frac{p_i q_{ih}}{e(p,u;\tau)} = s_{ih} \tag{2.2}$$

[12] The category of other has the largest price (\$0.92/oz) because it contains spices, which are extremely expensive per ounce.

[13] Allowing the first price coefficients to vary by household is a reasonable way to model tastes for the following reason: if a household really values a particular item, price changes for that item are likely to change their total expenditure differently than it would for a household who has little value for that item.

[14] Goods i and $i\prime$ are both within I and are sometimes equivalent and sometimes different than each other.

where s_{ih} is the share of household h's budget allocated to good i. Differentiating the right hand side of equation (2.1) with respect to $ln(p_i)$ and setting it equal to s_{ih} produces the following:[15]

$$s_{ih} = \tau_{ih} + \sum_{i\prime=1}^{I} \gamma_{ii\prime} ln(p_{i\prime}) + \beta_i u \beta_0 \prod_{i=1}^{I} p_i^{\beta_i} \tag{2.3}$$

Recall that a utility maximizing consumer sets $e(p,u;\tau_h)$ equal to total expenditure, m; thus, I re-write utility as a function of total expenditure and prices by rearranging equation (2.1). I use the functional form of utility to get budget shares as a function of tastes (τ_{ih}), prices (p), and total expenditure (m_h):

$$s_{ih} = \tau_{ih} + \sum_{i\prime} \gamma_{ii\prime} ln(p_{i\prime}) + \beta_i ln(\frac{m_h}{P}) \tag{2.4}$$

Where $ln(P)$ is defined by the following equation:

$$ln(P) = \alpha_0 + \sum_i \tau_{ih} ln(p_i) + 1/2 \sum_i \sum_{i\prime} \gamma_{ii\prime} ln(p_i) ln(p_{i\prime}) \tag{2.5}$$

Following Deaton and Muellbauer (1980), I approximate $ln(P)$ with a Stone Index, $ln(P) = \sum_i \bar{s}_i log(p_i)$, making the system linear.[16] I assume weak separability between grocery products and other expenditures which allows me to replace household expenditure with total expenditure over grocery products and calculate budget shares as the share of grocery expenditure allocated to product category i.[17]

Note that household tastes, τ_{ih}, act as budget share shifters in this setting. I assume that tastes are a function of unobserved household preferences and seasonal fluctuations that influence

[15] I use the fact that $\frac{\partial ln(e(p,u;\tau_h))}{\partial ln(p_i)} = \frac{\frac{\partial ln(e(p,u;\tau_h))}{\partial p_i}}{\frac{\partial ln(p_i)}{\partial p_i}}$ in order to get equation 2.3.

[16] In the definition of $ln(P)$, $\bar{s}_i$ is the average budget share of category i over all periods of the data. This is substituted in place of s_{iht} in order to avoid the endogeneity that arises when the dependent variable also appears as an independent variable.

[17] Technically, I assume weak separability between grocery purchases from this retailer and other expenditures.

preferences over food groups.[18] Hence, I define τ_{iht} as follows:

$$\tau_{iht} \stackrel{\text{def}}{=} \alpha_i + \nu_{ih} D_h + \nu_{it} Z_t \tag{2.6}$$

where D_h is a vector of demographic variables (household size, age, income, marital status and number of children) and Z_t is a vector containing month dummies (to control for seasonality) and a linear time trend.

Adding a time subscript (year-month, t) and substituting τ_{iht} into equation (2.4) produces the following:

$$s_{iht} = \alpha_i + \sum_{i\prime=1}^{11} \gamma_{ii\prime} ln(p_{i\prime ht}) + \beta_i ln(\frac{m_{ht}}{P_{ht}}) + \nu_{ih} D_h + \nu_{it} Z_t + \varepsilon_{iht} \tag{2.7}$$

I allow for structural differences to exist between the in-store and online demand functions by permitting the underlying parameters to vary in months that a household shops online. Explicitly, I include $1\{Online_{ht}\}$, an indicator that equals one when the household purchases at least one good online in year-month t, and I interact prices and expenditure with $1\{Online_{ht}\}$.[19] Modifying equation (2.7) to allow for structural differences between in-store and online demand produces the following:

$$\begin{aligned} s_{iht} = \alpha_i + \phi_i 1\{Online_{ht}\} + \sum_{i\prime=1}^{11} [\gamma_{ii\prime} ln(p_{i\prime ht}) + \gamma_{ii\prime o} ln(p_{i\prime ht}) 1\{Online_{ht}\}] \\ + \beta_i ln(\frac{m_{ht}}{P_{ht}}) + \beta_{io} ln(\frac{m_{ht}}{P_{ht}}) 1\{Online_{ht}\} + \nu_{ih} D_h + \nu_{it} Z_t + \varepsilon_{iht} \end{aligned} \tag{2.8}$$

Theoretical properties of demand systems imply the following constraints on the parameters in equation (2.8):

Zero Homogeneity:

$$\sum_{i\prime=1}^{11} \gamma_{ii\prime} = 0, \quad \sum_{i\prime=1}^{11} \gamma_{ii\prime o} = 0 \tag{2.9}$$

[18] Atkin (2013) provides evidence that tastes are a function of what type of food an individual was fed as a child.

[19] These interactions nest two demand equations (in-store and online) within one estimating equation.

Slutsky Symmetry:

$$\gamma_{ii'} = \gamma_{i'i}, \quad \gamma_{ii'o} = \gamma_{i'io} \tag{2.10}$$

Adding Up:

$$\sum_i \alpha_i = 1, \quad \sum_i \beta_i = 0, \quad \sum_i \phi_i = 0, \quad \sum_i \beta_{io} = 0 \tag{2.11}$$

I jointly estimate a system of ten demand equations, as presented in equation (2.8), subject to the constraints presented in equations (2.9) and (2.10). The parameters of the eleventh demand equation are derived from the estimation results of the ten equation system.[20] Specifically, I calculate $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\phi}_i$ and $\hat{\beta}_{io}$ of the eleventh demand equation by imposing the adding up restrictions presented in equation (2.11); additionally, the price coefficients of the eleventh equation are defined by the symmetry restrictions presented in equation (2.10).

2.4 Demand Estimation & Results

This section outlines how I address endogeneity and efficiency concerns when estimating the demand parameters. First, prices defined at the household level are likely endogenous to the demand system due to unobserved preference shocks and/or preferences over unobserved product quality. In order to alleviate these endogeneity concerns, I instrument prices with the mean wholesale costs of products available to the household. This isolates the variation in household prices that is due to factors that shift supply. In order to ensure household level variation in the wholesale costs of products available, I utilize the fact that each household has a unique store footprint (i.e. the stores visited by the household) in a given year-month. Specifically, I define the wholesale costs, at the household level, by first calculating the mean wholesale cost at the store level. I then average store costs across the store locations that the household conducted shopping occasions at in a given year-month.[21] I also instrument $1\{Online_{ht}\}$ with

[20]The iterated FGLS estimates, presented in this chapter, are equivalent to MLE and are invariant to which equation is dropped.

[21]Specifically, I define the price instruments as follows: first, I calculate the average cost of the products purchased at the category-store-year-month level, then, I average the category-store-year-month level wholesale costs over the stores the household visited in a given year-

$1\{OnlineAvail_{ht}\}$ following the logic presented earlier in the chapter. In order to efficiently address the endogeneity of prices and online service use, I follow Murtazashvili and Wooldridge (2016) by employing a control function approach.

The second estimation concern is efficiency. Since I estimate ten demand equations for grocery products, it is likely that the errors for a given budget share equation, i, are correlated with the errors of another budget share equation, $i\prime$; in other words, cov(ε_{iht} , $\varepsilon_{i\prime ht}$) $\neq 0$. Note that efficiency gains can be achieved from generalized least squares, in this setting, because I have placed restrictions on the parameters across equations (Greene 2012).[22] In order improve efficiency, and to address the endogeneity concerns outlined above, I utilize a three-step estimation strategy. The three steps of the estimation procedure are as follows:

1. Estimate the first-stages for continuous endogenous variables (all eleven $ln(p_{i\prime ht})$) via Ordinary Least Squares (OLS) and obtain the estimated residuals, $\hat{v}_{iht}$.

$$ln(p_{i\prime ht}) = \beta_0 + \sum_{i\prime=1}^{11} \beta_{i\prime} ln(c_{i\prime ht}) + \beta_{12} 1\{OnlineAvail_{ht}\} + \beta_{ih} D_h + \beta_{it} Z_t + v_{iht} \quad (2.12)$$

2. Estimate a Probit model for the endogenous variable $1\{Online_{ht}\}$ which includes all 11 estimates of $\hat{v}_{iht}$ as controls. Then obtain the predicted generalized residual, $\hat{GR}_{ht}$.

month. Explicitly, $c_{iht} = \sum_s \frac{\bar{c}_{ist}}{S_{ht}}$, where s indexes the store locations frequented by household h in year-month t, S_{ht} is the number of stores visited by household h in year-month t and $\bar{c}_{ist}$ is the mean wholesale cost of the products sold in category i, at store s in year-month t.

[22] There are three cases in which there are no efficiency gains from generalized least squares relative to equation by equation ordinary least squares: (1) if the disturbance terms across equations are independent of each other, (2) the independent variables in each equation are identical and (3) if the regressors of one equation are a subset of the regressors in another equation (Greene 2012). My demand system satisfies the second of these conditions because each of the share equations contains the same independent variables but because I have implemented cross-equation parameter restrictions this result no longer holds.

$$1\{Online_{ht}\} = \beta_0 + \sum_{i\prime=1}^{11} \beta_{i\prime} ln(c_{i\prime ht}) + \beta_{12} 1\{OnlineAvail_{ht}\} + \beta_{ih} D_h + \beta_{it} Z_t + \beta \sum_{i=1}^{11} \hat{v}_{iht} + \rho_{ht} \tag{2.13}$$

3. Lastly, estimate Equation 2.8 including all 11 estimates of $\hat{v}_{iht}$ and the estimate of $\hat{GR}_{ht}$ as additional controls, in order to address endogeneity. This last stage utilizes iterated FGLS to estimate the system of equations incorporating cross-equation restrictions.

Standard errors are computed by bootstrapping the entire estimation procedure with a clustered bootstrap. Clusters are defined by the store that determined the household's access to the online shopping service, hereafter referred to as the store-availability level. The results of this chapter utilize standard errors that are computed from 250 bootstrap replications.[23]

2.4.1 Results

The results of the first-stage regressions are presented in Tables B6 and B7 of the appendix. Each of the proposed instruments is strong in the sense that it is highly correlated with its corresponding endogenous variable. For prices, the cost instruments indicate a strong and positive relationship between wholesale costs and prices. The coefficients on the log cost instruments range from to 0.3 to 1.0, indicating that a one percent increase in average store costs results in a 0.3 to 1 percent increase in household prices. Additionally, online availability has a significant and positive impact on the probability of utilizing the online shopping service in a given month; the average partial effect (APE) indicates a 15.8 percentage point increase in the probability of shopping online, in a given month, after the online service becomes available.[24]

[23]The bootstrap procedure takes a week to complete; I am currently limited to a one week computing limit given the restrictions of the super computer I am using to complete this estimation task.

[24]The APE estimate is significant at the one percent significance level and the estimated standard error is 0.028. Standard errors for the APE were cluster bootstrapped at the store-availability level with 250 bootstrap replications.

Tables B8 through B13, of the appendix, present the estimated demand parameters. These tables illustrate that fifty-four percent of the online interacted demand parameters are significantly different from zero, at the five percent significance level.[25] The product categories of dairy, drinks, fruit and snacks/sweets illustrate the largest number of differences between parameters; each respective equation has at least eight interaction parameters that are significantly different, at the five percent significance level. Grain has seven significantly different parameters; oils, sugars and vegetables have six; other has five and prepared has four.[26] Utilizing the two sets of demand parameters these estimates generate, I compute and compare Marshallian elasticities across an in-store month and a month in which the online shopping service is utilized.

2.4.2 Elasticities

In order to compare the estimated price elasticities across the two types of shopping environments, I compute Marshallian elasticities from the estimated demand parameters as follows:

Own Price Elasticity

$$\eta_{ii} = \frac{\hat{\gamma}^*_{ii}}{\bar{s}^*_i} - \hat{\beta}^*_i - 1 \tag{2.14}$$

Cross Price Elasticity

$$\eta_{ii\prime} = \frac{\hat{\gamma}^*_{ii\prime}}{\bar{s}^*_i} - \hat{\beta}^*_i \frac{\bar{s}^*_{i\prime}}{\bar{s}^*_i} \tag{2.15}$$

In-store price elasticities are obtained by setting $\hat{\gamma}^*_{ii} = \hat{\gamma}_{ii}$, $\bar{s}^*_i = \bar{s}_i$, $\hat{\beta}^*_i = \hat{\beta}_i$ and $\hat{\gamma}^*_{ii\prime} = \hat{\gamma}_{ii\prime}$, while the online elasticities are obtained by setting $\hat{\gamma}^*_{ii} = \hat{\gamma}_{ii} + \hat{\gamma}_{iio}$, $\bar{s}^*_i = \bar{s}_i + \hat{\phi}_i$, $\hat{\beta}^*_i = \hat{\beta}_i + \hat{\beta}_{io}$ and $\hat{\gamma}^*_{ii\prime} = \hat{\gamma}_{ii\prime} + \hat{\gamma}_{ii\prime o}$.[27]

[25] Sixty-one percent of the parameters are significantly different at the ten percent significance level and forty-two percent of the parameters are significantly different at the one percent significance level.

[26] Note that meat was the equation that was dropped during estimation. However, because I used iterated FGLS in my estimation strategy, the estimated parameters are invariant to which equation is dropped.

[27] In the elasticity equations, $\bar{s}_i$ is the average budget share for category i over all time periods of the data. Note that the standard errors of the elasticities are computed as in Chalfant (1987),

The in-store and online price elasticity estimates and standard errors are reported in Tables B3 and B4, respectively.[28] The in-store own-price elasticities for dairy (-0.86), drinks (-1.81), meat (-1.49), other (-1.41) and vegetables (-0.80) are negative and statistically significant at the five percent significance level; all other own-price elasticities are insignificantly different from zero at the five percent significance level.[29] In contrast, the online own-price elasticities that are negative and statistically significant are dairy (-0.84), fruit (-0.63), meat (-1.35), other (-1.34), snacks/sweets (-4.59) and vegetables (-0.85). The online own-price elasticity estimates for drinks, grains, oils and sugars are insignificantly different from zero, while the own-price elasticity estimate for prepared (0.66) is positive and statistically significant.[30]

Figure B2 presents the ratio of the in-store price elasticity to the online price elasticity.[31] Specifically, each cell is colored black if $|\eta_{Instore}|$ is significantly different and larger in magnitude than $|\eta_{Online}|$, white if $\eta_{Instore}$ is not statistically different from η_{Online} and gray if $|\eta_{Instore}|$ is significantly different and smaller in magnitude than $|\eta_{Online}|$. Figure B2 illustrates that roughly one-third of the elasticities are significantly different for the months in which a household engages in online shopping. For the product categories of grains and meat the own-price elasticities are larger (in absolute value) in-store than they are online. Many of the cross-price elasticities that are significantly different across the two shopping environments exhibit price substitution patterns across product categories that are larger in magnitude when the

treating the $\bar{s}_i$'s as constants.

[28]The elasticity matrices are not symmetric because I am computing Marshallian elasticities, which hold income (as opposed to utility for Hicksian demand) constant. Hence, the estimated cross-price elasticities reflect a symmetric price effect and an income effect, which is not necessarily symmetric.

[29]Of the statistically insignificant elasticities, fruit, oils, snacks/sweets and sugar all have negative own-price elasticity estimates, while grains and prepared have positive own-price elasticity estimates. In general, the estimated in-store elasticities are aligned with the current food demand literature.

[30]Harding and Lovenheim (2017) find positive and significant own-price elasticities for prepared foods and cereal utilizing similar data and a similar estimation strategy.

[31]Table B14 presents the difference between the in-store and online price elasticities as well as the standard errors for that difference.

household is shopping in the store exclusively. Of the own-price elasticities that are significantly different across the two purchasing environments, the in-store own-price elasticities are, on average, 1.2 times larger (in absolute value) than the online own-price elasticities.[32] Additionally, the in-store cross price elasticities are, on average, 1.4 times larger (in absolute value) than the online cross-price elasticities.[33]

Interestingly, the only product category that exhibits stronger price substitution patterns when the household blends their purchases across the online and in-store purchasing environment is snacks/sweets. Within snacks/sweets, the own-price substitution patterns as well as the cross-price substitution patterns with dairy, oil and other become stronger when the household blends their purchases across the in-store and online shopping environments. This finding could be explained by a decline in impulse purchasing behavior when households shop online. Specifically, when making an impulse purchase it is likely that price becomes a less salient variable in the consumers purchasing decision. If this is the case, we would expect to see lower levels of price sensitivity during impulse purchase occasions.

With the exception of snacks/sweets, these findings illustrate that consumers are more price sensitive and exhibit stronger substitution patterns when they shop exclusively in the store than they do when they purchase items both online and in the store. Consumers may be less sensitive to prices when shopping online due to convenience factors built into the online shopping experience and the search differences that exist across the two environments. For example, when shopping online a household may utilize features of the website that allow them to instantly generate their basket based off of their previous online order.[34] An online shopper, who values

[32]The in-store own-price elasticities are, on average, 0.9 times as large (in absolute value) as the online own-price elasticities when incorporating all own-price elasticities.

[33]This average only includes the elasticities that are significantly different from each other at the five percent significance level. The in-store cross-price elasticities are, on average, 1.2 times larger (in absolute value) than the online cross-price elasticities when incorporating all cross-price elasticities.

[34]A household may also use the search engine to find a particular brand of an item and add that item to their cart without ever looking at the prices of competing brands. Alternatively,

convenience, may have a tendency to re-create their previous order without checking item prices and/or prices of close substitutes. Furthermore, decreased own-price sensitivity when shopping online occurs for product categories that contain goods that a household would likely add to an online favorites list. For example, products like cereal, bread and chicken sound like reasonable candidates for an instant add to cart list.

2.5 Discussion & Conclusion

In this chapter, I test for structural differences in grocery demand between months in which households shop exclusively in the store to months in which households shop in blended, online and in-store, purchasing environments. I find that parameters of demand vary across these two types of purchasing environments and that households are generally less price sensitive and exhibit weaker substitution patterns in months in which they engage in online shopping. However, I also find evidence to suggest increased price-sensitivity in the blended purchasing months over products that are likely to purchased impulsively when consumers shop exclusively in the in-store shopping environment.

These findings suggest that the effects of convenient features of the online website (frequent purchase and favorites lists) outweigh the effects of price shopping features (price-sorting and sale filtering) and indicate that consumers value the convenience of instant add to cart tools more than the savings from price-comparison when shopping online. Furthermore, my findings indicate that the marginal cost of time dedicated to search is different between the online and in-store shopping environments. Hence, a more sophisticated online pricing strategy, that incorporates the fact that the value of convenience appears to be different across the two purchasing environments, would likely lead to increased online revenues.

other features of the online website may make it easier for households to find sales; specifically, households can filter their search results to items that are currently on sale or sort their search results according to price.

CHAPTER 3

WHAT ARE SNAP BENEFITS USED TO PURCHASE? EVIDENCE FROM A SUPERMARKET RETAIL PANEL

3.1 Introduction

In 2017 the Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program (FSP), provided aid to 20.8 million households with the average household receiving $254 in benefits per month (USDA)[1]. In other words, 12.9% of the United States population was exposed to SNAP benefits in 2017 (USDA). The provision of benefits to such a large proportion of the populations is quite costly; in 2017, SNAP benefits cost roughly 63 billion dollars while administrative costs amounted to 4 billion dollars (USDA). Given the high costs associated with running an aid program of this magnitude, it is important to have an understanding of how SNAP benefits are spent and they ways in which they aid the very needy. This chapter analyzes the spending patterns of households who have recently adopted SNAP benefits in order to gain a better understanding of what these benefits are used to purchase. Furthermore, I relate these purchasing patterns to existing research that has explored the impact of SNAP on food spending, non-food spending and health outcomes.

This study is conducted using household level panel data collected from a supermarket chain in the United States. This data set contains detailed purchase histories for 100 thousand SNAP households over the course of three years. Explicitly, I know the specific products purchased (identified by universal product code, UPC), date, store location and the form of payment (cash, credit, SNAP, WIC) used by the household. Following Hastings and Shapiro (2017), I identify SNAP adoption within the retail panel by periods of six consecutive months in which SNAP benefits are used as a form of payment that are preceded by a period of six consecutive months in

[1]Individually, the SNAP program served over 42 million people and the average monthly benefit amount was $126 per person in 2017 (USDA).

which SNAP benefits are not used as a form of payment. I then perform an event study analysis that compares the purchasing patterns of a household in the six months prior to SNAP adoption to the purchasing patterns of the household in the six months following SNAP adoption.

I find that upon SNAP adoption, households decrease out-of-pocket monthly expenditures with the retailer by roughly $74 per month, while increasing total expenditures with the retailer by roughly $114 per month. Furthermore, overall spending increases are almost entirely explained by SNAP eligible items, which increase by $103 per month, on average. I also find that households begin to increase spending over meat, oil and prepared products at a higher rate than other grocery product categories and I find evidence to suggest that SNAP benefits aid households in the purchase of baby formula and diapers/wipes. Lastly, I evaluate household purchases over alcohol and tobacco products and find little evidence to suggest that SNAP benefits are used to subsidize these purchases.

The SNAP literature consistently indicates that SNAP benefits increase both food and non-food spending and that SNAP exposure in infancy and early childhood can improve health outcomes later in life. However, existing findings are less clear over whether or not the marginal propensity to consume food out of cash is equivalent to the marginal propensity to consume food out of SNAP benefits and what effect, if any, SNAP has on short-run health outcomes. Given the areas of SNAP research that we have not yet reached definite conclusions for yet, this chapter aims to shed light on the first-order behavior that contributes to these second-order outcomes of interest. More explicitly, this chapter concerns itself directly with the question of what households spend their SNAP benefits on and relates these purchasing patterns to the dichotomy of results that currently exist in the literature.

The remainder of this chapter is structured as follows: section 2 provides further background on the structure of the SNAP program, section 3 contains a literature review, section 4 describes the data, section 5 provides summary statistics, section 6 describes the empirical strategy and presents the results, and section 7 concludes.

3.2 SNAP Background

The Supplemental Nutrition Assistance Program (SNAP), formerly known as food stamps, is a federal aid program that is administered by the United States Department of Agriculture (USDA). SNAP's stated objectives are to reduce hunger, malnutrition and poverty through the provision of in-kind transfers to households who are eligible for benefits. Current federal eligibility guidelines indicate that a household is eligible to receive SNAP benefits if they have less than $2,250 in savings, their income is less than 130 percent of the poverty rate and, in general, they must be engaged in employment activity in order to receive benefits.[2]

Although SNAP is a federal program, each state is responsible for distributing benefits to its residents. Furthermore, states are given the ability to accept or decline policy options within the federal policy that can influence benefit amounts, benefit lengths and eligibility for benefits. For example, states can set their own income and/or deduction definitions to increase (or decrease) the benefit amount their residents receive. States can also manipulate benefit lengths by selecting longer or shorter recertification periods and can also apply for employment waivers which remove the restriction that participants must be working in order to receive benefits.

Since 2004, benefits have been delivered electronically to households via the Electronic Benefits Transfer (EBT) system. Each SNAP household receives a card, similar to a debit card, that is electronically loaded with benefits on the appropriate distribution date for the household. Distribution dates for each household are determined at the state level and all fifty states currently deliver benefits according to a monthly distribution cycle. The amount of benefits a SNAP household receives depends directly on their income and the size of their household. Specifically, the benefit amount is determined by a formula that indicates the maximum monthly allotment of benefits available to a household of a given size, then, from this maximum, 30% of the household's net monthly income is deducted and what remains is the household's benefit amount.

[2]There are some exceptions to the work requirement.

As previously mentioned, SNAP is an in-kind transfer program. That is, households can only use SNAP benefits to purchase food that is meant to be prepared and consumed at home and (or) for seeds that can be used to plant a garden. Practically this means that households can purchase any form of food (baby formula, vegetables, frozen pizza, candy) so long as it is not heated or intended for in-store consumption (e.g. heated deli sandwiches, heated deli soups, heated rotisserie chicken are not SNAP eligible). Additionally, SNAP benefits cannot be used for alcohol or tobacco products.

3.3 SNAP Literature

There is an extensive economic literature that has studied the effects of SNAP on a variety of economic outcomes. Economists have contributed to our understanding of how the macroeconomy influences program participation as well as how SNAP affects participant consumption, food insecurity, health and labor supply decisions. Additionally, more recent research, has examined how producer pricing decisions have been influenced by the design of the SNAP benefits cycle. In this section I provide a narrow review of the SNAP literature that specifically focuses on research that evaluates how SNAP influences participant consumption and health.[3]

3.3.1 SNAP and Consumption

Economic theory predicts that in-kind benefits, such as SNAP benefits, are economically equivalent to cash transfers if the household receiving benefits spends more on the in-kind good than they receive in benefits. For example, if a household spends more on food than their SNAP benefit allotment, then SNAP benefits can be used to replace cash that is currently being spent on food and this displaced cash can then be used to purchase any product the household desires. Thus, for SNAP households whose benefits are less than their pre-benefit food expenditures, SNAP benefits are equivalent to cash transfers and should increase both food and non-food

[3] Hoynes and Schanzenbach (2015) provide a broader review of the SNAP literature.

spending.

Existing empirical work has overwhelmingly found that SNAP benefits increase purchases over both food and non-food items. For instance, Hoynes and Schanzenbach (2009) find that the introduction of the food stamp program induces decreases in out-of-pocket spending on food and increases in total expenditures on food.[4] Additionally, Kim (2016) and Bruich (2014) also find evidence that increases (decreases) in SNAP benefit amounts increase (decrease) both food and non-food spending. Both Kim (2016)[5] and Bruich (2014)[6] employ difference-in-difference frameworks that utilize the American Recovery and Reinvestment Act (ARRA) as a source of exogenous variation in the amount of benefits a SNAP household receives.[7] Lastly, Hastings and Shapiro (2017) utilize grocery panel data in order to evaluate how SNAP adoption impacts food and non-food purchases. They also find that SNAP adoption produces expenditure increases in SNAP eligible items as well as in SNAP ineligible items.

Despite the general agreement that SNAP benefits increase food and non-food spending, there is competing evidence over whether or not the marginal propensity to consume food out of cash is equivalent to the marginal propensity to consume food out of SNAP benefits despite SNAP benefits being economically equivalent to cash for most participants. For example,

[4]Hoynes and Schanzenbach (2009) employ a difference-in-difference method that utilizes the introduction of the food stamp program (FSP) to evaluate how food stamps affect food purchasing habits. They utilize food expenditure and family income data from the Panel Study of Income Dynamics (PSID).

[5]Utilizing data from the Consumer Expenditure Survey (CEX), Kim (2016) finds that SNAP households increase expenditures on food, housing and education in response to the increase in SNAP benefits. Additionally, she finds no change in expenditures for tobacco and food away from home (FAFH) following the increase in SNAP benefits.

[6]Bruich (2014) utilizes grocery scanner data to estimate how the expiration of the American Recovery and Reinvestment Act (ARRA) impacted SNAP benefits. He finds that SNAP households lost $17 per month in SNAP benefits and estimates the marginal propensity to consume food out of SNAP benefits to be 0.30.

[7]Specifically, Kim (2016) utilizes the introduction of the American Recovery and Reinvestment Act (ARRA) and Bruich (2014) uses the expiration of ARRA. According to Kim (2016) and Bruich (2014), the ARRA increased SNAP benefits by 13.6% and was in effect from April 2009 through November 2013.

Hoynes et al. (2009) indicate that the marginal propensity to purchase food out of food stamps is not significantly different than the marginal propensity to consume food out of cash, while Hastings and Shapiro (2017) present evidence that suggests the marginal propensity to consume food out of SNAP is greater than the marginal propensity to consume food out of cash.[8] Testing whether the marginal propensities to consume food out of SNAP benefits and cash are equal remains an area of active research.

3.3.2 SNAP and Health

Another strand of the SNAP literature looks more closely at the effect SNAP exposure has on health outcomes. In recent years, a considerable amount of attention has been given to statistics that reflect higher rates of obesity among SNAP participants relative to the general population. For example, Condon et al. (2015) compare obesity rates among SNAP participants and non-participants and find that 40 percent of SNAP participants are obese while only 32 percent of income-eligible nonparticipants and 30 percent of higher income nonparticipants are obese.[9] Statistics such as these have sparked interest in research that analyzes how SNAP impacts health and nutrition outcomes and have also inspired recent policy modifications aimed at reducing the rate of obesity among SNAP participants.[10]

Researchers studying the impact of SNAP on obesity rates have often employed family fixed effects and instrumental variables in order to ascertain a causal relationship between SNAP and health outcomes. For example, Gibson (2004) employs child and family fixed effects and finds

[8]Hastings and Shapiro (2017) estimate the marginal propensity to consume food out of cash by utilizing gas prices as a source of exogenous variation in cash income. Wilde and Ranney (1996) and Schanzenbach (2002) provide another example of two works in this literature that find competing evidence for whether or not the marginal propensities to consume food are equal for cash and SNAP benefits.

[9]Condon et al. utilize data from the National Health and Nutrition Examination Survey (NHANES) to analyze differences in diet, body mass index (BMI) and food consumption patterns.

[10]For example, a recent policy change doubles SNAP benefits at farmers markets hoping to incentivize shoppers to increase purchases over fresh and local produce.

that SNAP leads to a reduction in the propensity to be overweight for boys but an increase for girls. Vartanian and Houser (2012) take a similar approach but analyze whether childhood exposure to SNAP improves BMI outcomes in adulthood; they find small differences in BMI between children in low-income neighborhoods that were exposed to SNAP and children in low-income neighborhoods that were not exposed to SNAP. Alternatively, Schmeiser (2012) uses state SNAP policies in an instrumental variables approach and finds that SNAP reduces BMI for most gender-age groups.

Similar studies examine how SNAP exposure improves birth outcomes as well as how exposure in infancy improves health outcomes in adulthood. For example, Almond, Hoynes and Schanzenbach (2011) utilize exogenous variation in the rollout of the food stamp program (FSP) to evaluate its effect on infant outcomes; they find that increases in mean birth weight are small, but gains were quite large at the bottom of the birth weight distribution. Additionally, East (2015) finds improvements in health at birth for babies born to mothers with SNAP access during pregnancy, as well as improvements in childhood health outcomes (reported between the ages of six to sixteen) for children with access to SNAP between the time they were born to age five. Lastly, Hoynes, Schanzenbach and Almond (2016) extend their previous study to evaluate how exposure to food stamps in infancy and early childhood influences adult health outcomes. They find that access to food stamps in early childhood leads to a large and statistically significant reduction in "metabolic syndrome" (obesity, high blood pressure, heath disease, diabetes) as well as an increase in the reporting to be in good health.

3.4 Data

This chapter utilizes supermarket retail panel data to explore SNAP household purchasing patterns. This data set contains detailed purchase histories for 100 thousand households over the course of three years. Explicitly, this data set contains information regarding the products purchased by these households (identified by universal product code, UPCs), the dates on which these products were purchased and which stores these products were purchased in. Additionally, for each shopping occasion, I also know how the household paid for their purchase (cash, credit, SNAP benefits and/or WIC benefits) and I know the total amount of tender that came from each payment type. Furthermore, the product data available to me indicates whether or not the UPC is SNAP eligible, what brand the product is, as well as where the product is located in the retailer's product taxonomy. Finally, I also have demographic information for these households but the availability of that information is limited. For roughly fifty percent of my household sample I know the household size, the number of children present and the age of the head of the household. In contrast, for all households I know the state of residence and have access to a shopper frequency measure (created by the retailer).

Identifying SNAP adoption in single retailer data is complicated by the fact that households do not tend to shop exclusively with one retailer. Thus, observing the first time a household uses SNAP benefits in single retailer data could be due to one of two things: (1) the household recently adopted SNAP or (2) the household has been receiving SNAP benefits for some time but just recently began using their SNAP benefits with this specific retailer. Hastings and Shapiro (2017), face a similar challenge with retailer panel data obtained from a supermarket in Rhode Island. In order to address this issue, Hastings and Shapiro (2017) analyze Electronic Benefit Transfer (EBT) transactions, provided by the state of Rhode Island, in order to identify EBT purchasing patterns (within a single retailer) that are indicative of SNAP adoption.

Within the Rhode Island EBT transaction data, Hastings and Shapiro, can see a history of EBT transactions (similar to your debit card history) of where and when SNAP dollars were spent by a specific household. Since Hastings and Shapiro know the specific date that the household began receiving SNAP benefits, they can identify a length of consecutive no SNAP tender months (within a specific store) followed by a length of consecutive SNAP tender months (within a specific store) that is strongly associated with SNAP adoption. Using this approach, Hastings and Shapiro utilize only the EBT transactions that occur at a specific supermarket chain in Rhode Island and find that six consecutive months in which SNAP benefits are not used, followed by six consecutive months in which SNAP benefits are used is an EBT purchasing pattern where at least 86 percent of the households who exhibit this behavior have newly enrolled in SNAP around the first month that they began using SNAP tender. Furthermore, when these EBT transactions are limited to households who do the majority of their SNAP spending at this particular supermarket, Hastings and Shapiro find that 96 percent of the households who exhibit six consecutive months of no SNAP spending followed by six consecutive months of SNAP spending recently adopted SNAP within the first month they transitioned from no SNAP spending to SNAP spending.

Operating under the assumption that SNAP households in different states are not significantly different in their supermarket EBT transaction shopping patterns, I follow Hastings and Shapiro's identification of SNAP adoption within single retailer data. Specifically, I define SNAP adoption spells as the six (or more) consecutive months in which SNAP tender was used that were preceded by at least six consecutive months in which no SNAP tender was used. This criteria for SNAP adoption restricts the number of households with adoption spells to a subset of households who exhibit a considerable amount of loyalty to the retailer as each of these households must shop with the retailer at least once a month for twelve months consecutively. The SNAP adoption criteria limits my sample of households for whom I observe a period of SNAP adoption to roughly 2,000 households. I further restrict the household sample to only those for whom I have demographic information for and am left with a household sample of roughly 1,800 households.

3.5 Summary Statistics

Figure C1 illustrates the definition of SNAP adoption employed by this study; specifically, the households do not redeem SNAP benefits for a period of six months, followed by a spell of six months in which they redeem SNAP benefits every month. Notice that the proportion of households redeeming SNAP benefits falls to roughly 85% in month seven. Most of the households in this study receive SNAP benefits from states who require SNAP recertification after six months.[11] Hence, the decline in the proportion of households redeeming SNAP benefits and in the average amount of SNAP benefits being redeemed that occurs at month seven is likely driven by households who did not re-certify or no longer qualified for SNAP benefits upon recertification.

Table C1 compares the mean composition of tender utilized in the six months prior to the six months following SNAP adoption. Table C1 indicates a decline of roughly $53 in average cash tender, from $512 per month in the pre-adoption period to $459 per month in the post adoption period, upon SNAP adoption.[12] Additionally, the average amount of SNAP tender redeemed with the retailer during the adoption period increases from $0 to $174, while TANF and WIC tender also increase in the SNAP adoption period by $0.40 and $3.20, respectively.

The bottom panel of Table C1 presents mean expenditures over SNAP eligible and SNAP ineligible products. In the six months prior to SNAP adoption, SNAP eligible expenditures are $289, per month, on average and increase to $395 per month in the six months following SNAP adoption. In contrast, SNAP ineligible expenditures are $153 (per month) prior to adoption and $169 (per month) following adoption. Since the average household was spending more on SNAP eligible products ($289) than they redeemed in SNAP benefits with the retailer ($174), it is expected that we would see increases in SNAP ineligible spending. However, it is surprising that the increases in SNAP ineligible spending are fairly small ($17 per month) given that SNAP benefits are equivalent to cash for the average household in this sample.

Table C2 presents the average share of SNAP eligible sales and the share SNAP ineligible sales generated from store brand products. After SNAP adoption, the share of sales coming from store branded products for all SNAP eligible purchases exhibits a slight but statistically significant decline (33% to 32%), while the share of store brand sales for SNAP ineligible purchases remains stable across the months surrounding SNAP adoption.

---

[11] Other states in this study require re-certification after twelve months and one state tailors their recertification requirements to the household based on head of household age and economic status.

[12] Cash tender includes forms of payment made by credit cards, debit cards and gift cards.

Table C3 evaluates the share of total sales dedicated to grocery products, average expenditure over grocery products as well as spending over SNAP eligible and SNAP ineligible grocery products. The share of total expenditures dedicated to grocery products increases by roughly 6 percentage points and total grocery sales increase by roughly $98, on average, upon SNAP adoption. Additionally, the increases in grocery expenditure seem to be entirely explained by SNAP eligible grocery sales which exhibit a $96 increase, on average, upon SNAP adoption.

In order to evaluate changes in grocery basket composition, I have assigned products to eleven different product categories: Dairy, Drinks, Fruits, Grains, Meat, Oils, Other, Prepared, Snacks and Sweets, Sugars and Vegetables. These product categories were chosen and created based on a document authored by the United States Department of Agriculture (USDA) called, "What We Eat in America".[13] The bottom panel of Table C3 indicates that all of the grocery product categories experience significant increases in sales after SNAP adoption; hence, in order to understand which product categories experience larger sales increases than others, I evaluate changes in grocery expenditure shares at the product category level.

Table C4 presents the average share of grocery expenditures for each product category prior and post SNAP adoption. The average household, in the pre-SNAP adoption period, allocates 10 percent of their budget to dairy products, 12 percent to non-dairy beverages, 6 percent to fruits, 7 percent to grains, 18 percent toward meat and protein products, 4 percent to oils, 10 percent to prepared products, 15 percent to snacks/sweets, 8 percent to vegetables and 1 percent to oils and sugars, respectively. After adopting SNAP, the allocation of the grocery budget across product categories does change slightly. Specifically, there are statistically significant declines in the proportion of the budget allocated to dairy, fruit and grains; while, the product categories of meat, oil, other and prepared experience statistically significant increases.

Table C5 illustrates the share of total sales attributed to baby products, average household expenditures over baby products, as well as average expenditure on formula, diapers/wipes,

[13] The descriptions of the products assigned to each of these product categories can be found in Table C7.

baby food and other baby products (clothes, car seats, diaper bags etc.). This table illustrates that households begin purchasing baby products at a higher rate after SNAP adoption; this trend in the data is consistent with prior research that has found that the timing of SNAP adoption is correlated with the introduction of a newborn to the household (Hastings and Shaprio, 2017).[14] In the six months after SNAP adoption, households spend roughly \$6 more on all baby products than they did prior to SNAP adoption (\$13 vs. \$19). The majority of the increased spending is due to increased purchases of baby formula (\$5 vs. \$8).

Since SNAP benefits are economically equivalent to cash for some households, there has been concern that households would use their benefits to supplement purchases over products that tax-payers would prefer not to be "subsidized" by SNAP benefits (i.e. alcohol and tobacco). Table C6 presents average expenditures over vice products (where vice is defined to include alcohol and tobacco products) in the months prior and post SNAP adoption. There is a small upward trend in average vice sales overall (\$15 per month post adoption vs. \$14 per month prior to adoption), but this change in expenditure does not indicate an economically meaningful increase in vice purchases.

3.6 Empirical Analysis & Results

I test whether or not these average differences in purchasing patterns persist, while controlling for other factors that could be occurring, by employing an event study design. Specifically, I run regressions of the following form:

$$y_{ht} = \alpha + \sum_k \beta_k 1\{TimeSNAPAdoption_{ht} = k\} + \gamma_h + \gamma_t + \varepsilon_{ht} \tag{3.1}$$

where y_{ht} is the outcome of household h at time t, $1\{TimeSNAPAdoption = k\}$ is an indicator that turns to one when the household is k months from SNAP adoption, γ_h is a household fixed effect that controls for unobserved differences between households and γ_t is a year-month fixed

[14]Hasting and Shapiro also show that the timing of SNAP adoption is also correlated with a negative shock to household monthly earnings and unemployment benefits.

effect that controls for differences in purchasing patterns over time. In these regressions, I allow the reference time-period for $1\{TimeSNAPAdoption = k\}$ to be the period immediately prior to SNAP adoption (i.e. $k = 0$). Furthermore, k is discrete from $k = -5$ to $k = 10$ (6 months before SNAP adoption to 10 months following SNAP adoption, where time zero is the month prior to adoption); k also include two additional time periods: $k < -5$ (more than six months prior to adoption) and $k > 10$ (more than ten months after adoption). Standard errors are clustered at the household level.

Tables C8 through C24 present three different versions of the event study estimates for each outcome. Specifically, estimates presented in column (1), for a given outcome, include household demographics, seasonal fixed effects and year fixed effects; estimates presented in column (2) include household demographics and year-month fixed effects, while estimates presented in column (3) include both year-month fixed effects and household fixed effects. In general, the estimates across the three different specifications are quite similar; as such, I will direct the majority of my attention to the estimates produced from the full specification.

Figure C2 graphically depicts the event study estimates, of the full model, for changes in tender composition surrounding SNAP adoption. Consistent with the summary statistics presented earlier, there are distinct declines in the average amount of cash tender and distinct increases in the average amount of SNAP tender utilized upon SNAP adoption. Specifically, cash tender declines by about \$45 in the first month of SNAP adoption and by about \$80 in month two through six following SNAP adoption; in contrast, SNAP tender increases by about \$170 in the first month of SNAP adoption and by about \$195 in months two through six following SNAP adoption.[15] These estimates are aligned with the findings of Hoynes and Schanzenbach (2009) who found that out-of-pocket food expenditure declined after SNAP adoption.[16] Interestingly, there is no statistically significant evidence for changes in WIC and TANF tender redemption

[15] The specific point estimates for these regressions are presented in Table C8.

[16] Although, FigureC2 represents cash expenditures over all food and non-food items available at the retailer.

upon SNAP adoption. However, it does seem that adoption of WIC benefits likely occurs in the period immediately prior to SNAP adoption as the point estimates for time periods $k = -4$ to $k = -1$ are negative and significantly different from $k = 0$.[17]

Figure C3 depicts the event study estimates for changes in SNAP eligible and SNAP ineligible purchases.[18] The event study estimates illustrate an average increase of $103 in SNAP eligible spending and an $11 increase in SNAP ineligible spending upon SNAP adoption. The documented changes in average SNAP eligible spending and average SNAP ineligible spending could simply indicate that SNAP households have a very strong preference for food (specifically, for SNAP eligible food). On the other hand, these averages could also reflect that SNAP benefits are not treated like cash by the household even though SNAP benefits are economically equivalent to cash for the average household in this sample. However, further analysis that directly compares the marginal propensity to consume food out of cash to the marginal propensity to consume food out of SNAP benefits would be needed to support this claim.

Figure C4 also validates the summary statistics presented earlier. Specifically, the point estimates indicate an average decline of 1.2 percentage points in the proportion of SNAP eligible spending that is allocated to store brand products. In contrast, there are no evident changes in the purchasing patterns of store branded products over items that are not SNAP eligible.[19] The shift from store branded SNAP eligible products toward private label SNAP eligible products could be interpreted a couple of different ways. Hastings and Shapiro (2017) document a similar brand switching pattern and interpret these results to indicate a decline in "shopping effort" due to the fact that households view SNAP benefits as being earmarked for food and may now view a dollar saved on food as less valuable than a dollar saved on non-food purchases. Alternatively, the switch towards private label products after SNAP adoption could also be explained by the fact that store branded products are often viewed as inferior goods and when the household's budget

[17]The specific point estimates for these regressions are presented in Table C9.

[18]These figures present the event study estimates of the full model. The specific point estimates for these regressions can be found in Table C10.

[19]The point estimates for these graphs can be found in Table C11.

set expands, they choose private label brands over store brands. In other words, brand switching may not be a decline in shopping effort but rather a reflection of household preferences.[20]

3.6.1 Grocery Purchases

The event study estimates for grocery shopping patterns surrounding SNAP adoption are presented in Figure C5. These estimates illustrate sharp increases in the share of total expenditures allocated toward grocery products and in grocery sales, particularly for SNAP eligible grocery sales. Specifically, the share of total expenditure allocated toward grocery products increases by six percentage points, on average, in the six months following SNAP adoption.[21] Overall grocery sales increase by \$103, on average, in the six months following SNAP adoption. Furthermore, \$101 of this increase is explained by SNAP eligible grocery purchases, while \$2 of this increase is attributable to SNAP ineligible grocery purchases.[22]

Figure C6 presents the event study estimates for the regressions that evaluate changes in the grocery budget allocation across the eleven different grocery product categories discussed earlier. Figure C6 illustrates distinct changes in the grocery budget share allocation for grains, meat and prepared products upon SNAP adoption. Specifically, the budget share allocation for grains declines by 0.5 percentage points, on average, in the six months following SNAP adoption. In contrast, the budget shares for meat and prepared products both increase by 0.8 percentage points, on average, in the six months following SNAP adoption. Figure C6 also illustrates that the average budget share for oils increases in the first month after SNAP adoption

[20] It should also be noted that Hastings and Shapiro (2017) analyze coupon use and find that the rate of coupon use falls after SNAP adoption for SNAP eligible items. I agree that a decline in coupon use is more reflective of a decline in "shopping effort" than a decline in store brand products being purchased. However, it could also be that households prefer the products that are less likely to have coupons; although, this seems unlikely.

[21] Interestingly, pre-event estimates for the grocery share of total expenditures indicate very small increases prior to SNAP adoption. This trend is likely to due to budget constraints that the household faces prior to SNAP adoption; specifically, a household facing tough financial times is likely to curb non-food spending at a higher rate than food spending.

[22] The point estimates for these regressions are available in Table C12 and C13.

and then quickly tapers back toward the pre-SNAP adoption average. These estimates could be due to a stocking up behavior that occurs once SNAP benefits become available.[23]

The increases in the budget share for meat are perhaps not surprising considering that meat tends to be one of the most expensive grocery products available for purchase; thus, when a household is on a tight budget and their budget expands they may begin buying meat at a higher rate then they previously were. Additionally, the post-SNAP adoption increases in the budget shares for prepared foods indicate that SNAP household's likely have a preference for foods that are convenient and quickly prepared for consumption; this could possibly be explained by the correlation of SNAP adoption and the addition of a child to the family.

3.6.2 Baby Product Purchases

Figure C7 presents the estimates for regressions evaluating changes in purchases over baby products; this figure illustrates that overall baby sales increase by about \$2, on average, after SNAP adoption. This represents a 15% change in the pre-SNAP adoption mean baby product expenditure. Within the subcategories of baby products, it appears that formula and diapers/wipes are the biggest contributors to the change in overall baby purchases.[24]

Figure C7 does not illustrate whether or not these increases in expenditures over baby products are above the norm for a household who has recently added a newborn to their family. Therefore, it is hard to quantify the ways in which SNAP adoption may have helped these households purchase products for their children. However, previous research has documented that the health outcomes of older children and adults are improved if their household was exposed to SNAP when the individual was an infant (Almond et al., 2011; East, 2015; Hoynes et al., 2016). These trends in expenditure over baby products, in conjunction with existing research on the health outcomes of newborns exposed to SNAP, suggest that SNAP benefits help

[23]The point estimates for these regressions can be found in Tables C14 through C19.

[24]The point estimates for these regressions can be found in Tables C20 through C22.

households make additional investments in their newborns that they might not otherwise be able to afford.[25]

3.6.3 Alcohol and Tobacco Purchases

Figure C8 depicts the estimates for regressions evaluating changes in purchases over vice products (alcohol and tobacco purchases). Similar to the summary statistics provided earlier, Figure C8 provides little evidence to suggest that SNAP households have increased purchases over vice products in an economically meaningful way. Following SNAP adoption, there are slight upward trends in vice purchases, with point estimates indicating an average increase of $1 per month. However, only of two of the first six post-adoption estimates are statistically significant.[26]

3.7 Conclusion & Discussion

This chapter utilizes supermarket retailer data to analyze within household changes in purchasing patterns upon SNAP adoption. I find that households decrease out of pocket expenditures while increasing overall expenditure with the retailer of study. Furthermore, the majority of increased spending occurs over products that are SNAP eligible. Households also increase spending over the product categories of meats, oils and prepared products at a higher rate than other grocery product categories and there is some evidence to suggest that SNAP benefits may aid households in making additional purchases of baby products. I find little evidence to suggest that SNAP benefits are utilized to subsidize alcohol and tobacco purchases.

This chapter contributes to a large literature on SNAP benefits that has analyzed how SNAP benefits influence consumption patterns as well as health outcomes. Specifically, this chapter analyzes the first-order purchasing behavior by looking specifically at *what* households use

[25] On the other hand, it could also be the case households who adopt SNAP benefits do so because they would like to invest more in the health and wellbeing of their children.

[26] The point estimates for these regressions can be found in Tables C23 and C24.

SNAP benefits to buy from a large supermarket retail chain. I then relate these findings to the variety of second order outcomes that have been analyzed in prior research.

Future research plans to further explore purchasing patterns surrounding the SNAP benefit cycle and to compare the bundle of goods SNAP households actually purchase to the bundle of goods that is used to calculate SNAP benefit amounts. I would also like to further explore how variation in products eligible for purchase with SNAP benefits might be utilized in order to compare the marginal propensity to consume food out of cash to the marginal propensity to consume food out of SNAP benefits. This variation could also be useful in simulating how SNAP household purchasing patterns might change if the definition of products eligible for purchase with SNAP benefits were to be changed.

APPENDICES

APPENDIX A

CHAPTER 1 APPENDIX

Figure A1: Online Shopping Service Availability

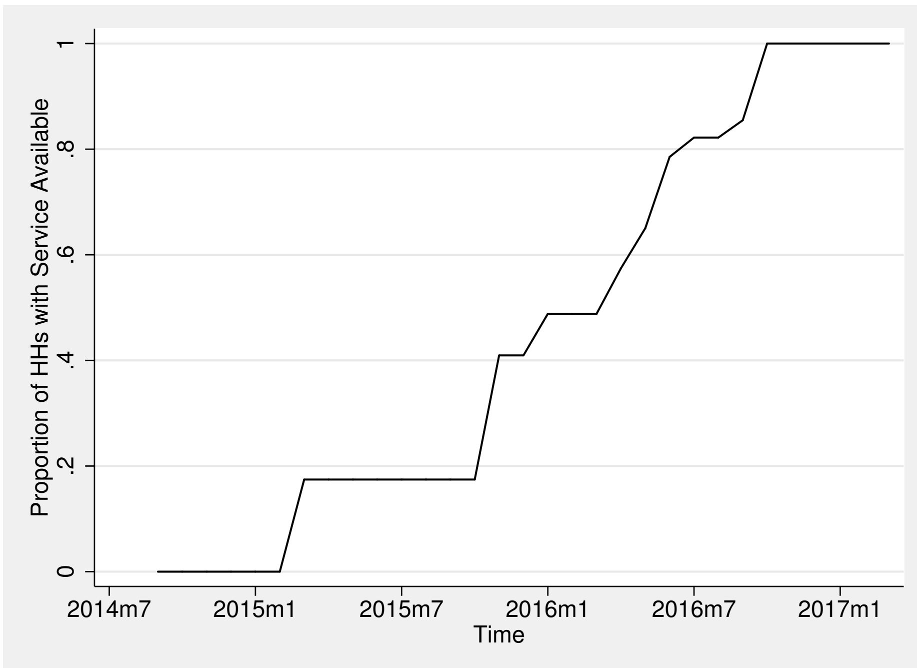

Figure A1 illustrates the proportion of households who have access to the online purchasing service over time.

Figure A2: Event Study Estimates for Online Use and Expenditure Shares

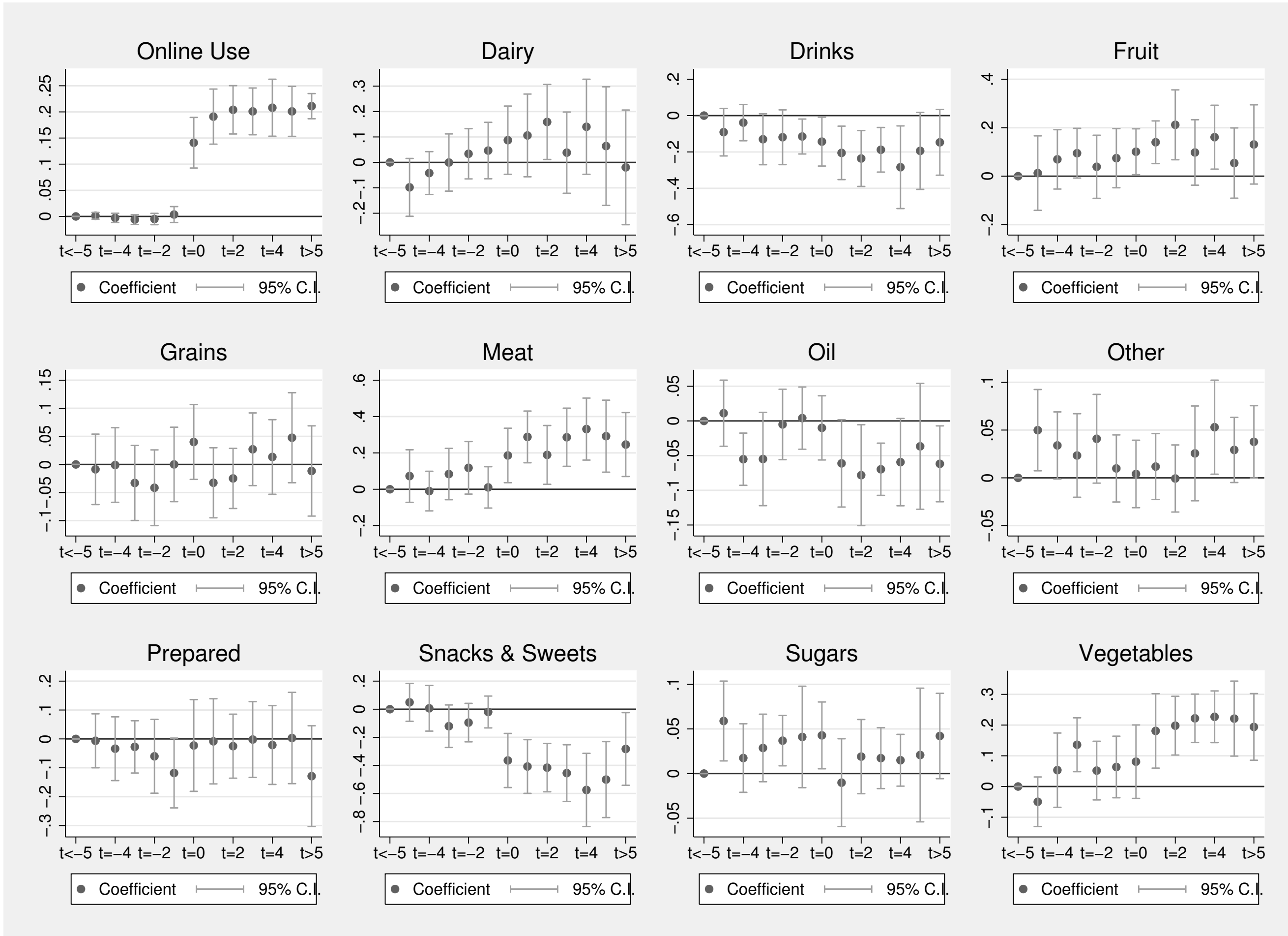

Figure A2 presents the event study estimates of the effect of online availability for online households.

Table A1: Household Demographics

Household Demographics	All Households	In-Store Only Households	Online Adoption Households
1{Married}	0.68	0.67	0.69

Household Size	All	In-Store	Online
1{1 Person}	0.10	0.12	0.10
1{2 People}	0.22	0.22	0.22
1{3 People}	0.24	0.22	0.25
1{4 People}	0.17	0.17	0.17
1{5+ People}	0.26	0.26	0.27

Household Income	All	In-Store	Online
1{0-29K}	0.11	0.14	0.10
1{30-50K}	0.16	0.17	0.16
1{51-79K}	0.30	0.28	0.31
1{80-99K}	0.15	0.15	0.15
1{100-149K}	0.12	0.12	0.12
1{150K}	0.16	0.14	0.16

Number of Children	All	In-Store	Online
1{0 Children}	0.43	0.49	0.41
1{1 Child}	0.33	0.31	0.33
1{2 Children}	0.14	0.13	0.15
1{3 Children}	0.07	0.06	0.08
1{4+ Children}	0.03	0.02	0.04

Household Head Age	All	In-Store	Online
1{18-25}	0.02	0.02	0.02
1{26-35}	0.22	0.14	0.25
1{36-45}	0.28	0.20	0.32
1{46-55}	0.20	0.24	0.19
1{56-55}	0.16	0.21	0.14
1{66+}	0.11	0.18	0.08

Household Count	34,797	9,777	25,020

Table A2: Monthly Purchasing Patterns

Time Period	Before & After Online Introduction	Before Online Introduction	
Household Population	All HHs	In-Store Only HHs	Online Adoption HHs
Monthly Shopping Habits	**All**	**In-Store**	**Online**
Grocery Expenditure ($)	437	331	448
Items Purchased	176	135	178
Visits to Store	7.7	6.8	7.5
Share of Sales Online	0.02	0.0	0.0
Share of Expenditure	**All**	**In-Store**	**Online**
Dairy	12.5	11.9	13.2
Drink	10.8	10.9	10.1
Fruit	8.3	7.3	7.5
Grains	7.5	7.2	7.6
Meats	18.5	18.9	18.5
Oils	4.4	4.4	4.4
Other	1.6	1.7	1.8
Prepared	10.1	10.9	10.8
Snacks/Sweets	15.8	16.1	15.5
Sugars	1.5	1.6	1.6
Vegetables	9.1	9.2	9.1
Observations	855,022	56,972	147,246

Table A3: Average Price and Nutrient Content Per Ounce of Food

Product Category	Price ($)	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)	Cholesterol (g)
Dairy	0.10	71	3.9	4.2	4.3	2.2	0.2	0.01
Drinks	0.07	22	0.2	4.5	0.2	3.9	0.0	0.00
Fruit	0.10	23	0.3	5.5	0.2	4.1	0.0	0.00
Grains	0.13	97	2.7	18.5	1.5	3.4	0.2	0.00
Meat	0.23	81	7.7	2.1	4.7	0.8	0.2	0.03
Oil	0.15	88	0.3	4.2	7.7	3.9	0.3	0.00
Other	0.46	73	1.4	11.5	2.5	5.4	1.9	0.00
Prepared	0.16	68	2.4	9.8	2.1	1.3	0.3	0.00
Snacks/Sweets	0.21	120	1.8	17.8	4.9	9.5	0.1	0.01
Sugars	0.11	98	1.4	18.1	3.6	14.9	0.0	0.00
Vegetables	0.09	22	0.7	4.1	0.4	1.5	0.3	0.00

Table A4: Difference in Difference / Reduced Form Estimates, τ_i - Online Households

Budget Shares	(1)	(2)	(3)	Avg. Budget Share (Pre-Online Service)
Dairy	0.104**	0.105**	0.0969**	13.21
	(0.0386)	(0.0387)	(0.0401)	(6.90)
Drinks	-0.103**	-0.104**	-0.100**	10.08
	(0.0380)	(0.0382)	(0.0384)	(8.31)
Fruit	0.0844**	0.0846**	0.0845**	7.48
	(0.0362)	(0.0362)	(0.0369)	(6.18)
Grain	0.0242	0.0249	0.0211	7.6
	(0.0152)	(0.0152)	(0.0148)	(4.66)
Meat	0.204***	0.205***	0.204***	18.46
	(0.0580)	(0.0581)	(0.0586)	(9.69)
Oil	-0.0350**	-0.0354**	-0.0352**	4.36
	(0.0143)	(0.0143)	(0.0150)	(3.56)
Other	-0.0121	-0.0123	-0.00970	1.81
	(0.00771)	(0.00767)	(0.00802)	(2.72)
Prepared	0.0241	0.0262	0.0305	10.78
	(0.0420)	(0.0425)	(0.0427)	(7.45)
Snacks/Sweets	-0.408***	-0.413***	-0.406***	15.52
	(0.0665)	(0.0681)	(0.0677)	(9.84)
Sugar	-0.0141	-0.0144	-0.0151	1.61
	(0.00957)	(0.00960)	(0.00976)	(2.32)
Vegetables	0.132***	0.134***	0.129***	9.09
	(0.0310)	(0.0308)	(0.0324)	(6.20)
Time Availability f.e.	X			
Treatment Cohort f.e.	X	X		
Household Demographics	X	X		
Year-Month f.e.		X	X	
Household f.e.			X	
Observations	616,357	616,357	616,357	147,246

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the budget shares.
These estimates were produced by running OLS equation by equation.
Equation by equation OLS is equivalent to SUR in this scenario.

Table A5: Difference in Difference / First Stage Estimates, $\hat{\theta}_i$ - Online Households

1{Online}	(1)	(2)	(3)
1{OnlineAvail}	0.193***	0.193***	0.193***
	(0.0216)	(0.0216)	(0.0221)
Time Availability f.e.	X		
Treatment Cohort f.e.	X	X	
Household Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Observations	616,357	616,357	616,357
R-squared	0.166	0.166	0.306
F-Statistic	79.80	79.56	76.32

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households

Budget Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Share (Pre-Service)	Percent Change
Dairy	0.784***	0.786***	0.496***	0.539***	0.543***	0.503**	13.21	3.79
	(0.0381)	(0.0381)	(0.0544)	(0.202)	(0.202)	(0.208)	(6.90)	
Drinks	-0.709***	-0.713***	-0.561***	-0.535**	-0.538**	-0.520**	10.08	-5.16
	(0.0559)	(0.0536)	(0.0422)	(0.223)	(0.225)	(0.224)	(8.31)	
Fruit	0.317***	0.336***	0.114***	0.437**	0.438**	0.439**	7.48	5.88
	(0.0564)	(0.0608)	(0.0284)	(0.209)	(0.210)	(0.211)	(6.18)	
Grain	0.239***	0.242***	0.162***	0.125	0.129*	0.110	7.6	1.45
	(0.0232)	(0.0233)	(0.0227)	(0.0775)	(0.0772)	(0.0758)	(4.66)	
Meat	0.331***	0.330***	0.539***	1.056***	1.060***	1.060***	18.46	5.74
	(0.0883)	(0.0929)	(0.0714)	(0.311)	(0.310)	(0.314)	(9.69)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	616,357	616,357	616,357	616,357	616,357	616,357	147,246	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate from a separate regression; note that OLS (2SLS) is equivalent to SUR (3SLS) in this scenario.
The percent change is calculated utilizing the estimates provided in Column 6 and average pre-online service budget shares.

Table A7: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households

Budget Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Share (Pre-Service)	Percent Change
Other	0.00392	0.000906	0.00842	-0.0626	-0.0637	-0.0503	1.81	-2.78
	(0.0152)	(0.0146)	(0.0113)	(0.0400)	(0.0400)	(0.0416)	(2.72)	
Prepared	-0.00622	-0.00580	0.0948	0.125	0.136	0.158	10.78	1.47
	(0.101)	(0.104)	(0.0714)	(0.209)	(0.211)	(0.210)	(7.45)	
Snacks/Sweets	-1.593***	-1.623***	-1.507***	-2.113***	-2.140***	-2.106***	15.52	-13.60
	(0.124)	(0.129)	(0.128)	(0.315)	(0.316)	(0.315)	(9.84)	
Sugar	0.0384***	0.0380***	0.0149*	-0.0732	-0.0745	-0.0783	1.61	-4.86
	(0.0105)	(0.0109)	(0.00844)	(0.0499)	(0.0501)	(0.0506)	(2.32)	
Vegetables	0.643***	0.656***	0.652***	0.684***	0.694***	0.668***	9.09	7.37
	(0.0701)	(0.0695)	(0.0454)	(0.166)	(0.165)	(0.173)	(6.20)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	616,357	616,357	616,357	616,357	616,357	616,357	147,246	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate from a separate regression; note that OLS (2SLS) is equivalent to SUR (3SLS) in this scenario. The percent change is calculated utilizing the estimates provided in Column 6 and average pre-online service budget shares.

Table A8: Nutrition Outcomes Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households

Nutrients per Ounce	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. (Pre-Service)	Percent Change
Calories (kcal)	-1.548***	-1.600***	-1.374***	-2.087***	-2.122***	-1.974***	47.44	-4.16
	(0.138)	(0.133)	(0.133)	(0.350)	(0.351)	(0.345)	(13.81)	
Carbs (g)	-0.220***	-0.225***	-0.205***	-0.307***	-0.311***	-0.296***	5.99	-4.94
	(0.0246)	(0.0244)	(0.0213)	(0.0496)	(0.0504)	(0.0498)	(1.96)	
Cholest. (g)	0.000135**	0.000135**	2.06e-05	-0.000484	-0.000482	-0.000464	0.005	-9.28
	(5.88e-05)	(5.76e-05)	(5.58e-05)	(0.000374)	(0.000373)	(0.000387)	(0.01)	
Protein (g)	0.00170	0.000553	0.00307	0.0226	0.0223	0.0237*	1.74	1.36
	(0.00376)	(0.00409)	(0.00308)	(0.0144)	(0.0143)	(0.0144)	(0.60)	
Sodium (g)	-0.00370	-0.00345	-0.00229	-0.0167	-0.0169	-0.0173	0.17	-10.18
	(0.00459)	(0.00471)	(0.00349)	(0.0172)	(0.0170)	(0.0177)	(0.67)	
Total Fat (g)	-0.0812***	-0.0843***	-0.0695***	-0.117***	-0.119***	-0.110***	1.90	-5.79
	(0.00637)	(0.00608)	(0.00697)	(0.0195)	(0.0195)	(0.0189)	(0.82)	
Total Sugar (g)	-0.114***	-0.116***	-0.114***	-0.134***	-0.136***	-0.130***	2.26	-5.75
	(0.0158)	(0.0165)	(0.0130)	(0.0384)	(0.0391)	(0.0391)	(1.06)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	596,112	596,112	596,112	596,112	596,112	596,112	142,301	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate from a separate regression; note that OLS (2SLS) is equivalent to SUR (3SLS) in this scenario.
The percent change is calculated utilizing the estimates provided in Column 6 and average pre-online service nutrition outcomes.

Table A9: Expenditure Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households

	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Average (Pre-Online Service)	Percent Change
Total Expenditure	56.17***	55.94***	48.64***	51.93***	52.11***	48.87***	447.52	10.92
	(1.950)	(2.050)	(2.580)	(17.84)	(17.70)	(17.63)	(328.11)	
Dairy	10.03***	10.01***	7.631***	8.059***	8.095***	7.662***	58.58	13.08
	(0.317)	(0.317)	(0.319)	(2.605)	(2.593)	(2.586)	(47.25)	
Drinks	4.079***	4.036***	4.089***	4.346***	4.352***	3.957**	43.61	9.07
	(0.413)	(0.440)	(0.504)	(1.606)	(1.606)	(1.612)	(41.12)	
Fruit	6.807***	6.881***	4.957***	7.469**	7.495**	7.238**	33.04	21.91
	(0.533)	(0.547)	(0.257)	(3.319)	(3.300)	(3.298)	(32.35)	
Grain	4.994***	4.990***	4.109***	4.048***	4.080***	3.836***	33.86	11.33
	(0.130)	(0.127)	(0.144)	(1.313)	(1.299)	(1.288)	(28.49)	
Meat	10.07***	10.02***	9.808***	12.40***	12.44***	11.82***	86.73	13.63
	(0.588)	(0.636)	(0.646)	(4.423)	(4.386)	(4.387)	(77.43)	
Oil	2.103***	2.098***	1.946***	1.800***	1.798***	1.683***	19.67	8.56
	(0.103)	(0.101)	(0.0813)	(0.621)	(0.609)	(0.599)	(18.40)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	616,357	616,357	616,357	616,357	616,357	616,357	147,246	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate from a separate regression; note that OLS (2SLS) is equivalent to SUR (3SLS) in this scenario.
The percent change is calculated utilizing the estimates provided in Column 6 and average pre-online service expenditures.

Table A10: Expenditure Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households

	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Average (Pre-Online Service)	Percent Change
Total Expenditure	56.17***	55.94***	48.64***	51.93***	52.11***	48.87***	447.52	10.92
	(1.950)	(2.050)	(2.580)	(17.84)	(17.70)	(17.63)	(328.11)	
Other	0.926***	0.908***	0.780***	0.668	0.664	0.645	8.15	7.91
	(0.121)	(0.117)	(0.0677)	(0.414)	(0.423)	(0.443)	(10.72)	
Prepared	4.847***	4.829***	4.692***	2.947**	3.016**	2.733*	48.77	5.60
	(0.587)	(0.621)	(0.521)	(1.497)	(1.522)	(1.550)	(45.27)	
Snacks/Sweets	3.799***	3.626***	3.250***	1.386	1.287	0.764	67.4	1.13
	(0.381)	(0.386)	(0.379)	(2.535)	(2.517)	(2.536)	(58.88)	
Sugar	1.082***	1.076***	0.818***	0.633***	0.629***	0.577**	7.21	8.00
	(0.0721)	(0.0729)	(0.0454)	(0.225)	(0.226)	(0.234)	(8.93)	
Vegetables	7.428***	7.465***	6.562***	8.180***	8.246***	7.963***	40.52	19.65
	(0.429)	(0.428)	(0.336)	(1.886)	(1.870)	(1.877)	(36.55)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	616,357	616,357	616,357	616,357	616,357	616,357	147,246	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate from a separate regression; note that OLS (2SLS) is equivalent to SUR (3SLS) in this scenario. The percent change is calculated utilizing the estimates provided in Column 6 and average pre-online service expenditures.

Table A11: Difference in Difference / Reduced Form Estimates, $\hat{\tau}_i$, By Competition Index - Online Households

	Low Competition Stores			High Competition Stores			All Stores		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Expenditure	4.120	4.015	3.321	11.31***	11.51***	10.59***			
	(2.733)	(2.704)	(2.599)	(3.346)	(3.403)	(3.385)			
Budget Shares									
Dairy	0.0185	0.0190	0.0116	0.0970*	0.0982*	0.0856	0.104**	0.105**	0.0969**
	(0.0757)	(0.0759)	(0.0789)	(0.0525)	(0.0529)	(0.0538)	(0.0386)	(0.0387)	(0.0401)
Drinks	-0.0324	-0.0339	-0.0326	-0.0826	-0.0823	-0.0805	-0.103**	-0.104**	-0.100**
	(0.0604)	(0.0601)	(0.0591)	(0.0513)	(0.0513)	(0.0542)	(0.0380)	(0.0382)	(0.0384)
Fruit	0.0925**	0.0933**	0.101**	0.0613	0.0610	0.0620	0.0844**	0.0846**	0.0845**
	(0.0361)	(0.0360)	(0.0360)	(0.0554)	(0.0556)	(0.0568)	(0.0362)	(0.0362)	(0.0369)
Grain	0.0185	0.0187	0.0179	0.0489*	0.0504*	0.0434*	0.0242	0.0249	0.0211
	(0.0232)	(0.0232)	(0.0244)	(0.0253)	(0.0253)	(0.0253)	(0.0152)	(0.0152)	(0.0148)
Meat	0.224**	0.222**	0.216**	0.205**	0.208**	0.205**	0.204***	0.205***	0.204***
	(0.0802)	(0.0796)	(0.0801)	(0.0882)	(0.0888)	(0.0887)	(0.0580)	(0.0581)	(0.0586)
Oil	-0.0283	-0.0288	-0.0296	-0.0318	-0.0320	-0.0306	-0.0350**	-0.0354**	-0.0352**
	(0.0276)	(0.0278)	(0.0283)	(0.0221)	(0.0222)	(0.0231)	(0.0143)	(0.0143)	(0.0150)
Time Avail. f.e.	X			X			X		
Trtmnt Cohrt f.e.	X	X		X	X		X	X	
HH Demographics	X	X		X	X		X	X	
Year-Month f.e.		X	X		X	X		X	X
Household f.e.			X			X			X
Observations	298,722	298,722	298,722	359,571	359,571	359,571	616,357	616,357	616,357

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability.
These estimates were produced equation by equation.

Table A12: Difference in Difference / Reduced Form Estimates, $\hat{\tau}_i$, By Competition Index - Online Households

	Low Competition Stores			High Competition Stores			All Stores		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Expenditure	4.120	4.015	3.321	11.31***	11.51***	10.59***			
	(2.733)	(2.704)	(2.599)	(3.346)	(3.403)	(3.385)			
Budget Shares									
Other	-0.0115	-0.0119	-0.00969	-0.0132	-0.0129	-0.00983	-0.0121	-0.0123	-0.00970
	(0.0118)	(0.0119)	(0.0126)	(0.0141)	(0.0140)	(0.0145)	(0.00771)	(0.00767)	(0.00802)
Prepared	-0.0857	-0.0844	-0.0824	0.0485	0.0520	0.0572	0.0241	0.0262	0.0305
	(0.0497)	(0.0494)	(0.0498)	(0.0631)	(0.0641)	(0.0647)	(0.0420)	(0.0425)	(0.0427)
Snacks/Sweets	-0.246***	-0.246***	-0.240***	-0.495***	-0.506***	-0.488***	-0.408***	-0.413***	-0.406***
	(0.0707)	(0.0700)	(0.0696)	(0.0964)	(0.0994)	(0.0978)	(0.0665)	(0.0681)	(0.0677)
Sugar	-0.00741	-0.00755	-0.00718	-0.0145	-0.0147	-0.0175	-0.0141	-0.0144	-0.0151
	(0.00895)	(0.00889)	(0.00946)	(0.0146)	(0.0146)	(0.0149)	(0.00957)	(0.00960)	(0.00976)
Vegetables	0.0599	0.0613	0.0567	0.175***	0.177***	0.172***	0.132***	0.134***	0.129***
	(0.0539)	(0.0538)	(0.0554)	(0.0513)	(0.0505)	(0.0544)	(0.0310)	(0.0308)	(0.0324)
Time Avail. f.e.	X			X			X		
Trtmnt Cohrt f.e.	X	X		X	X		X	X	
HH Demographics	X	X		X	X		X	X	
Year-Month f.e.		X	X		X	X		X	X
Household f.e.			X			X			X
Observations	298,722	298,722	298,722	359,571	359,571	359,571	616,357	616,357	616,357

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability.
These estimates were produced equation by equation.

Table A13: Average Nutrient Content Per Ounce of Food - Narrow Product Categories

Bread Type	Healthier Choices	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)
Whole Grain	X	68	2.8	12.7	1.2	1.8	0.1
Other		74	2.4	14.0	1.0	2.3	0.1
Seed / Nut	X	67	2.8	12.2	1.2	1.5	0.1
Wheat	X	67	2.9	12.8	0.8	1.8	0.1
White		69	2.3	13.6	1.0	1.7	0.1

Cereal Type	Healthier Choices	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)
Kids		112	1.4	23.8	1.4	10.1	0.1
Organic Kids		108	2.1	22.9	1.5	6.9	0.1
Standard	X	106	2.4	23.2	0.8	2.7	0.2
Frosted Standard		108	2.3	22.9	1.3	7.3	0.1
Healthy Cereal	X	101	3.5	20.4	1.9	4.7	0.1

Snack Type	Healthier Choices	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)
Chips		150	1.8	15.9	8.9	1.0	0.2
Healthy Chips	X	132	2.0	18.1	5.7	1.7	0.2
Popcorn		148	2.4	15.9	8.7	3.1	0.2
Pretzels	X	124	2.3	20.6	3.7	2.0	0.3
Tortilla Chips	X	139	2.0	18.0	6.8	0.3	0.1

Yogurt Type	Healthier Choices	Calories (kcal)	Protein (g)	Carbs (g)	Total Fat (g)	Total Sugar (g)	Sodium (g)
Greek	X	27	2.3	3.4	0.4	2.7	0.0
Light Greek	X	20	2.3	2.5	0.1	1.7	0.0
Indulgent		36	1.3	4.6	1.4	3.7	0.0
Kids		32	1.4	5.3	0.6	4.3	0.0
Organic		27	1.5	3.2	0.9	2.7	0.0
Probiotic		22	1.6	3.6	0.2	3.0	0.0
Traditional		26	1.1	4.4	0.5	3.6	0.0
Light Traditional	X	14	0.9	2.6	0.0	1.7	0.0

Table A14: Ordinary Least Squares & Fractional Probit APE Estimates - Bread Shares for Online Households

Shares	OLS (1)	OLS (2)	OLS (3)	F. Probit - APE (4)	F. Probit - APE (5)	Average (Pre-Online Service)	Percent Change
White	-0.167	-0.165	-0.182	-0.173	-0.167	23.56	-0.71
	(0.209)	(0.210)	(0.210)	(0.212)	(0.214)	(35.86)	
Wheat	0.615**	0.611**	0.652**	0.631**	0.627**	35.63	1.76
	(0.250)	(0.250)	(0.229)	(0.255)	(0.256)	(40.39)	
Seed	0.0487	0.0427	0.0894	0.0362	0.0292	5.47	0.53
	(0.122)	(0.121)	(0.116)	(0.114)	(0.113)	(18.35)	
Other	-0.360*	-0.360*	-0.413**	-0.367*	-0.367*	20.88	-1.76
	(0.192)	(0.204)	(0.187)	(0.190)	(0.202)	(32.79)	
Grain	-0.136	-0.128	-0.146	-0.167	-0.159	14.46	-1.10
	(0.179)	(0.177)	(0.163)	(0.194)	(0.192)	(28.63)	
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	478,724	478,724	478,724	478,724	478,724	112,039	

Robust standard errors in parentheses
Standard errors clustered at the specified level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the budget share.
These estimates were produced equation by equation.
The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A15: Ordinary Least Squares & Fractional Probit APE Estimates - Cereal Shares for Online Households

Shares	OLS (1)	OLS (2)	OLS (3)	F. Probit - APE (4)	F. Probit - APE (5)	Average (Pre-Online Service)	Percent Change
Kids	-0.065	-0.0905	-0.144	-0.079	-0.103	37.28	-0.28
	(0.191)	(0.187)	(0.173)	(0.195)	(0.191)	(36.95)	
Org. Kids	-0.065	0.0533	0.0271	0.0362	0.0394	1.05	3.75
	(0.191)	(0.0432)	(0.0404)	(0.0392)	(0.0382)	(8.13)	
Standard	-0.065	-0.123	-0.0207	-0.141	-0.152	15.50	-0.98
	(0.191)	(0.219)	(0.194)	(0.214)	(0.209)	(27.58)	
Frosted Std.	-0.065	0.256	0.211	0.235	0.255	42.60	0.60
	(0.191)	(0.191)	(0.196)	(0.196)	(0.191)	(36.74)	
Super Healthy	-0.065	-0.0952	-0.0736	-0.119*	-0.107	3.58	-2.99
	(0.191)	(0.0735)	(0.0697)	(0.0632)	(0.0653)	(14.64)	
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	435,202	435,202	435,202	435,202	435,202	100,846	

Robust standard errors in parentheses
Standard errors clustered at the specified level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the budget share.
These estimates were produced equation by equation.
The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A16: Ordinary Least Squares & Fractional Probit APE Estimates - Salty Snack Shares for Online Households

Shares	OLS (1)	OLS (2)	OLS (3)	F. Probit - APE (4)	F. Probit - APE (5)	Average (Pre-Online Service)	Percent Change
Tortilla Chips	0.508*	0.499*	0.568**	0.511**	0.504**	21.70	2.32
	(0.269)	(0.268)	(0.237)	(0.236)	(0.235)	(28.54)	
Pretzels	-0.388**	-0.374***	-0.353***	-0.352***	-0.338***	14.52	-2.33
	(0.106)	(0.103)	(0.110)	(0.102)	(0.0996)	(24.62)	
Popcorn	-0.0758	-0.0741	-0.0743	-0.0496	-0.0467	5.51	-0.85
	(0.0902)	(0.0908)	(0.0907)	(0.0857)	(0.0860)	(16.00)	
Veggie Chips	-0.0335	-0.00863	0.000258	-0.0262	-0.00462	7.70	-0.06
	(0.172)	(0.171)	(0.164)	(0.159)	(0.157)	(19.32)	
Chips	-0.0108	-0.0431	-0.141	-0.00854	-0.0417	50.57	-0.08
	(0.181)	(0.172)	(0.158)	(0.183)	(0.173)	(35.25)	
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	512,645	512,645	512,645	512,645	512,645	118,761	

Robust standard errors in parentheses
Standard errors clustered at the specified level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the budget share.
These estimates were produced equation by equation.
The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A17: Ordinary Least Squares & Fractional Probit APE Estimates - Yogurt Shares for Online Households

Shares	OLS (1)	OLS (2)	OLS (3)	F. Probit - APE (4)	F. Probit - APE (5)	Average (Pre-Online Service)	Percent Change
Traditional Light	-0.099	-0.0798	-0.0121	-0.08	-0.0605	12.41	-0.49
	(0.139)	(0.136)	(0.138)	(0.143)	(0.138)	(25.99)	
Traditional	0.0283	0.0428	0.221	0.00269	0.0162	14.99	0.11
	(0.134)	(0.137)	(0.136)	(0.126)	(0.129)	(28.06)	
Probiotics	0.0725	0.076	0.0718	0.0749	0.0785	3.41	2.30
	(0.0552)	(0.0561)	(0.0639)	(0.0551)	(0.0559)	(14.84)	
Organic	0.123	0.124	0.138	0.0951	0.0972	5.20	1.87
	(0.0845)	(0.0840)	(0.0976)	(0.0925)	(0.0914)	(18.06)	
Kids	-0.0171	-0.0292	-0.0496	-0.0198	-0.0322	17.42	-0.18
	(0.241)	(0.241)	(0.224)	(0.241)	(0.241)	(29.86)	
Indulgent	-0.0313	-0.0326	-0.0728	-0.0266	-0.0278	4.09	-0.68
	(0.0890)	(0.0886)	(0.0833)	(0.0836)	(0.0832)	(15.29)	
Greek Light	0.0506	0.0587	0.0382	0.0612	0.0679	12.34	0.55
	(0.194)	(0.195)	(0.206)	(0.185)	(0.187)	(26.39)	
Greek	-0.127	-0.16	-0.334	-0.139	-0.172	30.14	-0.57
	(0.203)	(0.197)	(0.224)	(0.205)	(0.200)	(37.12)	
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	454,041	454,041	454,041	454,041	454,041	102,503	

Robust standard errors in parentheses
Standard errors clustered at the specified level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the budget share.
These estimates were produced equation by equation.
The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A18: Product Category Key

Product Category	Description
Dairy	Milk & Milk Substitutes, Cheese, Yogurt, Cream Cheese
Drinks	Non-Alcoholic Beverages, Water, Soda, Juice
Fruit	Fresh, Dried and Frozen Fruits
Grains	Rice, Pasta, Bread, Cereal, Oatmeal
Meat	Beef, Poultry, Seafood, Eggs, Beans, Legumes
Oils	Butter, Mayonnaise, Salad Dressings, Vegetable Oils
Other	Flour, Gravy, Seasonings, Baking Items
Prepared	Rice Mixed Dishes, Pizza, Macaroni, Soups
Snacks and Sweets	Chips, Crackers, Granola Bars, Cakes, Candy, Ice Cream
Sugar	Sugar, Honey, Jams, Syrups
Vegetables	Fresh & Frozen Vegetables

Table A19: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Availability Definition Based on Entire Store Footprint, Online Households Only

Budget Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Oz. Share (Pre-Service)	Percent Change
Dairy	0.767***	0.769***	0.496***	0.811***	0.817***	0.782***	13.25	5.90
	(0.0504)	(0.0506)	(0.0755)	(0.215)	(0.217)	(0.218)	(6.96)	
Drinks	-0.758***	-0.762***	-0.594***	-0.915***	-0.922***	-0.909***	10.09	-9.01
	(0.0645)	(0.0610)	(0.0353)	(0.293)	(0.298)	(0.297)	(8.43)	
Fruit	0.335***	0.354***	0.125***	0.623***	0.626***	0.644***	7.45	8.64
	(0.0548)	(0.0566)	(0.0215)	(0.239)	(0.240)	(0.241)	(6.21)	
Grain	0.272***	0.274***	0.179***	0.222**	0.226**	0.211**	7.62	2.77
	(0.0212)	(0.0213)	(0.0223)	(0.0944)	(0.0934)	(0.101)	(4.73)	
Meat	0.288***	0.287***	0.531***	1.036***	1.038***	1.049***	18.43	5.69
	(0.0692)	(0.0728)	(0.0673)	(0.301)	(0.302)	(0.305)	(9.75)	
Oil	-0.0473*	-0.0462*	-0.00967	-0.192*	-0.195*	-0.200**	4.36	-4.59
	(0.0265)	(0.0270)	(0.0193)	(0.100)	(0.100)	(0.100)	(3.59)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	690,152	690,152	690,152	690,152	690,152	690,152	164,750	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A20: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Availability Definition Based on Entire Store Footprint, Online Households Only

Budget Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Oz. Share (Pre-Service)	Percent Change
Other	0.00428	0.00116	0.00646	-0.0937*	-0.0952*	-0.0840	1.8	-4.67
	(0.0149)	(0.0140)	(0.0100)	(0.0529)	(0.0529)	(0.0545)	(2.74)	
Prepared	0.0314	0.0315	0.118*	0.186	0.199	0.221	10.8	2.05
	(0.103)	(0.108)	(0.0692)	(0.238)	(0.240)	(0.239)	(7.51)	
Snacks/Sweets	-1.584***	-1.613***	-1.527***	-2.430***	-2.462***	-2.429***	15.53	-15.64
	(0.0891)	(0.0958)	(0.139)	(0.275)	(0.274)	(0.278)	(9.97)	
Sugar	0.0407***	0.0403***	0.0124	-0.0975*	-0.0988**	-0.103**	1.62	-6.36
	(0.00613)	(0.00643)	(0.00745)	(0.0500)	(0.0501)	(0.0503)	(2.36)	
Vegetables	0.653***	0.665***	0.663***	0.853***	0.867***	0.819***	9.05	9.05
	(0.0474)	(0.0473)	(0.0241)	(0.189)	(0.189)	(0.194)	(6.23)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	690,152	690,152	690,152	690,152	690,152	690,152	164,750	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A21: Product Subcategories

Bread	Brands/Description
White	White breads, Wonder, etc.
Wheat	Whole wheat breads
Grain	Whole grain breads, Oat breads
Seed	Seeded/nut breads
Other	Cinnamon bread, raisin bread, sourdough

Cereal	Brands/Description
Kids	Fruity Pebbles, Apple Jacks, Cocoa Puffs
Organic Kids	Annies, Cascadian Farm
Standard	Cheerios, Chex, Cornflakes, Rice Crispies
Frosted Standard	Frosted Flakes, Cornpops, Frosted Mini Wheats
Super Healthy	Kashi, Fiberone, Grapenuts

Salty Snacks	Brands/Description
Tortilla Chips	Mission, On the Border, Tostitos
Pretzels	Rold Gold, Snyder
Popcorn	Cape Cod, Skinny Pop, Smart Food
Healthy Chips	Sun Chips, Sensible Portions, Quaker
Chips	Doritos, Cheetos, Lays, Pringles

Yogurt	Brands/Description
Greek	Chobani, Dannon, Yoplait
Greek Light	Chobani, Dannon, Yoplait
Indulgent	YoCrunch, Noosa, Yoplait
Kids	Yoplait, Stoneyfield, Dannon
Organic	Stoneyfield, Wallaby, Silk
Probiotic	Dannon
Traditional	Yoplait, Dannon
Traditional Light	Yoplait, Dannon

A.0.1 Comparison of Households Across Online Availability Waves

Tables A22 and A23 compare the demographics and pre-online purchasing patterns of the online service adopters who received access to the service at earlier dates to those who received access to the service at later dates. In order to neatly compare the households that received access to the online shopping service first to those who received access later, I assign households to three waves based on the month and year that they received access. Households that received access to the online shopping service before or during January 2016 are assigned to wave one (53% of the online household sample), households that received access to the online service after January 2016 but before July 2016 are assigned to wave two (29% of the online household sample) and households who received access after or during July 2016 are assigned to wave three (18% of the online household sample). Table A22 illustrates that households in later availability dates tend to be smaller and older. Households in the last availability wave also have a higher proportion of households in lower income categories, are less likely to be married and are less likely to have children. Table A23 indicates that households in the first wave tend to spend roughly $40 more per month, purchase roughly 15 more items and make one more trip to the store per month than households in the second or last wave. Wave 1 households also tend to allocate more of their grocery budget towards dairy, other and vegetables and less of their budget toward drinks, meat, prepared and snacks/sweets relative to households in other waves.

Table A22: Comparison of Household Demographics Across Online Availability Waves

Household	Online Adoption Households		
Demographics	Wave 1	Wave 2	Wave 3
1{Married}	0.70	0.68	0.67
Household Size	Wave 1	Wave 2	Wave 3
1{1 Person}	0.09	0.10	0.10
1{2 People}	0.21	0.21	0.23
1{3 People}	0.25	0.25	0.24
1{4 People}	0.17	0.18	0.17
1{5+ People}	0.27	0.26	0.25
Household Income	Wave 1	Wave 2	Wave 3
1{0-29K}	0.09	0.10	0.10
1{30-50K}	0.16	0.15	0.17
1{51-79K}	0.31	0.31	0.32
1{80-99K}	0.16	0.15	0.14
1{100-149K}	0.12	0.13	0.13
1{150K}	0.17	0.17	0.13
Number of Children	Wave 1	Wave 2	Wave 3
1{0 Children}	0.40	0.41	0.43
1{1 Child}	0.33	0.33	0.33
1{2 Children}	0.15	0.15	0.14
1{3 Children}	0.08	0.08	0.07
1{4+ Children}	0.04	0.04	0.03
Household Head Age	Wave 1	Wave 2	Wave 3
1{18-25}	0.03	0.02	0.02
1{26-35}	0.27	0.24	0.24
1{36-45}	0.31	0.32	0.32
1{46-55}	0.19	0.20	0.18
1{56-55}	0.14	0.14	0.15
1{66+}	0.07	0.08	0.09
Household Count	13,208	7,267	4,545

Table A23: Comparison of Pre-Online Purchasing Patterns Across Online Availability Waves

Monthly Purchasing Habits	Online Adoption Households Wave 1	Wave 2	Wave 3
Grocery Expenditure ($)	467	420	434
Items Purchased	187	166	172
Visits to Store	8.0	6.9	7.1
Proportion of Sales Online	0.0	0.0	0.0

Share of Expenditure	Wave 1	Wave 2	Wave 3
Dairy	13.4	13.1	12.9
Drink	9.9	10.2	10.4
Fruit	7.6	7.5	7.1
Grains	7.6	7.6	7.6
Meats	18.3	18.5	18.9
Oils	4.4	4.3	4.4
Other	1.8	1.8	1.8
Prepared	10.7	10.8	10.9
Snacks/Sweets	15.4	15.6	15.7
Sugars	1.6	1.6	1.6
Vegetables	9.3	9.0	8.6
Observations	77,925	42,608	26,713

A.0.2 Narrow Product Category Analysis

There are two ways in which online shopping could affect the demand for different types of products. First, shopping online could change the probability that a household purchases products within these product categories; secondly, shopping online could also affect the amount that a household purchases within these product categories. In order to accurately model the purchasing patterns of households in this context, I begin by estimating the change in sales volumes for each product subcategory utilizing ordinary least squares and tobit regression models.[1] Specifically, I estimate regressions of the following form:

$$Sales_{ihm} = \nu_i + \tau_i 1\{OnlineAvail_{hm}\} + \gamma_{im} + \gamma_{ih} + \omega_{ihm} \tag{A.1}$$

where $Sales_{ihm}$ is the sales of product sub-category i for household h in month m, $1\{OnlineAvail_{hm}\}$ is an indicator that equals one if the online service is available to household h in year-month m, γ_{im} is a year-month fixed effect to control for differences across time and γ_{ih} is a household fixed effect to control for unobserved household preferences.[2]

Tables A24, A25, A26 and A27 present the estimated effect of online service availability on sales ($\hat{\tau}_i$) for three ordinary least squares specifications, as well as the estimated average partial effects for two tobit specifications.[3] The results of these regressions illustrate that online service availability has a positive and significant effect on the sales of wheat (\$0.09) and seed breads (\$0.01), frosted cereals (\$0.08), tortilla chips (\$0.06), traditional light (\$0.03), traditional (\$0.06), organic (\$0.02) and greek yogurts (\$0.12). Furthermore, there is no evidence for statistically significant changes in the sales volumes for

[1] The underlying data for these specifications consists of all households who shop with the retailer in a given year-month regardless of whether or not they buy something from the parent category (bread, cereal, salty snacks, yogurt).

[2] Specifications without household and year-month fixed effects include treatment group indicators and post-availability time indicators in order to maintain the panel difference-in-differences framework. Additionally, specifications without household fixed effects include demographic characteristics of the households. Since my demographic variables are provided categorically, I include the demographics by creating indicators for whether household h belongs to a given demographic category.

[3] I present the average partial effect for the unconditional expectation of the effect of online service availability on sales. The estimated $\hat{\tau}_i$'s from the Tobit regressions can be found in Tables A28, A29, A30 and A31 of the appendix.

white, other and grain breads; kids, standard and healthy cereals; pretzels, popcorn, healthy chips and chips; or kids and indulgent yogurts. In general, the estimated average partial effects from the tobit regressions closely mirror the ordinary least squares estimates of τ_i.[4] In summary, these results illustrate the following changes in sales volumes by category: there is an increase in the sales of wheat and seed breads but no changes in the sales volumes for other bread types; the only cereal category that exhibits sales increases is that of frosted standard cereal; there is an increase in the sales volumes of tortilla chips but no changes to the sales volumes of other salty snacks; lastly, there are significant increases across most yogurt categories with only two categories (kids and indulgent) exhibiting no significant changes in sales. These results indicate that households increase the purchases of healthier breads and salty snacks. In contrast, online availability increases expenditures on frosted cereals and most kinds of yogurt.

[4]However, there are few exceptions to this; specifically, the ordinary least squares estimates for organic kids cereal indicate positive and significant changes in sales when the online service becomes available ($0.01), while the average partial effects from the tobit regressions produce estimates that are roughly half the size in magnitude ($0.006) and are insignificantly different from zero. Additionally, the regressions for probiotic and greek light yogurt reflect a similar pattern; the ordinary least squares estimates are larger ($0.02 vs. $0.01 for probiotics and $0.08 vs. $0.05 for greek light) and significant at the 95% significance level, while the APEs for the full Tobit specification is only significant at the 10% significance level. Given the nature of the data generating process, ordinary least squares will be biased due to the corner solution of $0. Hence, I do not find these differences particularly concerning.

Table A24: Ordinary Least Squares & Tobit APE Estimates - Bread Sales for Online Households

Sales	OLS (1)	OLS (2)	OLS (3)	Tobit- APE (4)	Tobit- APE (5)	Average (Pre-Online Service)	Percent Change
White	0.0151	0.0154	0.0112	0.0178	0.0180	1.26	1.43
	(0.0159)	(0.0160)	(0.0162)	(0.0164)	(0.0165)	(2.67)	
Wheat	0.100***	0.100***	0.0972***	0.0894***	0.0895***	1.92	4.66
	(0.0175)	(0.0175)	(0.0178)	(0.0162)	(0.0162)	(3.31)	
Seed	0.0195**	0.0194**	0.0183*	0.0127**	0.0124**	0.37	3.35
	(0.00895)	(0.00886)	(0.00907)	(0.00538)	(0.00533)	(1.49)	
Other	0.00552	0.00553	0.00327	0.000964	0.000707	1.41	0.05
	(0.0135)	(0.0135)	(0.0135)	(0.0141)	(0.0141)	(3.08)	
Grain	0.0138	0.0141	0.0116	0.0111	0.0112	0.96	1.17
	(0.0109)	(0.0108)	(0.0112)	(0.00850)	(0.00855)	(2.48)	
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	616,899	616,899	616,899	616,900	616,899	147,372	

Robust standard errors in parentheses
Standard errors clustered at the specified level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the sales volume.
These estimates were produced equation by equation.
The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A25: Ordinary Least Squares & Tobit APE Estimates - Cereal Sales for Online Households

Sales	OLS (1)	OLS (2)	OLS (3)	Tobit- APE (4)	Tobit- APE (5)	Average (Pre-Online Service)	Percent Change
Kids	0.0372	0.0375	0.0300	0.0338	0.0339	3.49	0.97
	(0.0350)	(0.0349)	(0.0355)	(0.0290)	(0.0290)	(6.10)	
Org. Kids	0.0132***	0.0133***	0.0129**	0.00575	0.00559	0.10	5.59
	(0.00469)	(0.00472)	(0.00473)	(0.00351)	(0.00347)	(0.97)	
Standard	0.0314	0.0313	0.0296	0.0147	0.0139	1.36	1.02
	(0.0226)	(0.0228)	(0.0232)	(0.0168)	(0.0170)	(3.27)	
Frosted Std.	0.110***	0.111***	0.106***	0.0822***	0.0831***	4.02	2.07
	(0.0306)	(0.0305)	(0.0307)	(0.0281)	(0.0282)	(6.51)	
Super Healthy	0.00292	0.00314	0.00299	-0.00580	-0.00580	0.34	-1.71
	(0.0115)	(0.0115)	(0.0119)	(0.00715)	(0.00711)	(1.80)	
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	616,899	616,899	616,899	616,899	616,899	147,372	

Robust standard errors in parentheses
Standard errors clustered at the specified level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the sales volume.
These estimates were produced equation by equation.
The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A26: Ordinary Least Squares & Tobit APE Estimates - Salty Snack Sales for Online Households

Sales	OLS (1)	OLS (2)	OLS (3)	Tobit- APE (4)	Tobit- APE (5)	Average (Pre-Online Service)	Percent Change
Tortilla Chips	0.0683**	0.0676**	0.0666**	0.0627**	0.0616**	2.42	2.55
	(0.0250)	(0.0255)	(0.0265)	(0.0254)	(0.0262)	(3.89)	
Pretzels	-0.0123	-0.0125	-0.0140	-0.0232	-0.0239	1.55	-1.54
	(0.0169)	(0.0169)	(0.0172)	(0.0170)	(0.0169)	(3.05)	
Popcorn	0.00396	0.00393	0.00257	-0.00844	-0.00822	0.71	-1.16
	(0.0158)	(0.0158)	(0.0159)	(0.0130)	(0.0131)	(2.43)	
Veggie Chips	0.0253	0.0259	0.0260	0.00154	0.00181	0.92	0.20
	(0.0324)	(0.0321)	(0.0328)	(0.0209)	(0.0207)	(2.70)	
Chips	0.0569	0.0551	0.0432	0.0543	0.0520	6.54	0.80
	(0.0637)	(0.0631)	(0.0653)	(0.0627)	(0.0623)	(8.64)	
Time Availability f.e.	X						
Treatment Cohort f.e.	X	X					
Household Demographics	X	X					
Year-Month f.e.		X	X				
Household f.e.			X				
Observations	616,899	616,899	616,899	616,899	616,899	147,372	

Robust standard errors in parentheses
Standard errors clustered at the specified level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the sales volume.
These estimates were produced equation by equation.
The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A27: Ordinary Least Squares & Tobit APE Estimates - Yogurt Sales for Online Households

Sales	OLS (1)	OLS (2)	OLS (3)	Tobit- APE (4)	Tobit- APE (5)	Average (Pre-Online Service)	Percent Change
Traditional Light	0.0197	0.0205	0.0187	0.0252**	0.0253**	1.11	2.28
	(0.0125)	(0.0126)	(0.0128)	(0.0127)	(0.0127)	(3.11)	
Traditional	0.0746***	0.0755***	0.0742***	0.0602***	0.0606***	1.32	4.59
	(0.0164)	(0.0165)	(0.0165)	(0.0122)	(0.0123)	(3.35)	
Probiotics	0.0210**	0.0212**	0.0204**	0.0117*	0.0117*	0.40	2.93
	(0.00915)	(0.00917)	(0.00930)	(0.00668)	(0.00667)	(2.25)	
Organic	0.0505***	0.0506***	0.0496***	0.0200**	0.0195**	0.58	3.36
	(0.0158)	(0.0159)	(0.0168)	(0.00973)	(0.00979)	(2.84)	
Kids	0.0401	0.0408	0.0367	0.0371	0.0373	1.87	1.99
	(0.0341)	(0.0341)	(0.0346)	(0.0319)	(0.0319)	(4.62)	
Indulgent	0.0125	0.0127	0.0116	0.00928	0.00948	0.46	2.06
	(0.0210)	(0.0209)	(0.0212)	(0.0105)	(0.0105)	(2.38)	
Greek Light	0.0788***	0.0800***	0.0757***	0.0534**	0.0530*	1.49	3.56
	(0.0262)	(0.0263)	(0.0270)	(0.0269)	(0.0273)	(4.68)	
Greek	0.202***	0.203***	0.199***	0.116***	0.116***	3.65	3.18
	(0.0599)	(0.0593)	(0.0604)	(0.0353)	(0.0354)	(7.64)	
Time Availability f.e.	X			X			
Treatment Cohort f.e.	X	X		X	X		
Household Demographics	X	X		X	X		
Year-Month f.e.		X	X		X		
Household f.e.			X				
Observations	616,899	616,899	616,899	616,899	616,899	147,372	

Robust standard errors in parentheses
Standard errors clustered at the specified level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the sales volume.
These estimates were produced equation by equation.
The percent change is derived utilizing the APE estimates in column (5) and the pre-online service average.

Table A28: Tobit Estimates - Bread Sales for Online Households

Sales	(1)	(2)
White	0.0609	0.0615
	(0.0560)	(0.0564)
Wheat	0.216***	0.216***
	(0.0390)	(0.0390)
Seed	0.145**	0.142**
	(0.0611)	(0.0607)
Other	0.00346	0.00254
	(0.0505)	(0.0506)
Grain	0.0551	0.0557
	(0.0421)	(0.0424)
Time Availability f.e.	X	
Treatment Cohort f.e.	X	X
Household Demographics	X	X
Year-Month f.e.		X
Household f.e.		
Observations	616,899	616,899

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A29: Tobit Estimates - Cereal Sales for Online Households

Sales	(1)	(2)
Kids	0.0781	0.0781
	(0.0670)	(0.0668)
Org. Kids	0.372	0.365
	(0.227)	(0.226)
Standard	0.0617	0.0585
	(0.0704)	(0.0714)
Frosted Std.	0.169***	0.171***
	(0.0578)	(0.0580)
Super Healthy	-0.111	-0.111
	(0.137)	(0.137)
Time Availability f.e.	X	
Treatment Cohort f.e.	X	X
Household Demographics	X	X
Year-Month f.e.		X
Household f.e.		
Observations	616,899	616,899

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A30: Tobit Estimates - Salty Snack Sales for Online Households

Sales	(1)	(2)
Tortilla Chips	0.138**	0.136**
	(0.0559)	(0.0575)
Pretzels	-0.0681	-0.0700
	(0.0497)	(0.0496)
Popcorn	-0.0536	-0.0523
	(0.0826)	(0.0832)
Veggie Chips	0.00796	0.00939
	(0.108)	(0.107)
Chips	0.0821	0.0785
	(0.0948)	(0.0940)
Time Availability f.e.	X	
Treatment Cohort f.e.	X	X
Household Demographics	X	X
Year-Month f.e.		X
Household f.e.		
Observations	616,899	616,899

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A31: Tobit Estimates - Yogurt Sales for Online Households

Sales	(1)	(2)
Traditional Light	0.139**	0.140**
	(0.0697)	(0.0697)
Traditional	0.254***	0.256***
	(0.0517)	(0.0522)
Probiotics	0.235*	0.236*
	(0.134)	(0.134)
Organic	0.243**	0.237**
	(0.118)	(0.119)
Kids	0.150	0.151
	(0.129)	(0.129)
Indulgent	0.121	0.124
	(0.137)	(0.137)
Greek Light	0.283**	0.282*
	(0.143)	(0.146)
Greek	0.314***	0.312***
	(0.0952)	(0.0955)
Time Availability f.e.	X	
Treatment Cohort f.e.	X	X
Household Demographics	X	X
Year-Month f.e.		X
Household f.e.		
Observations	616,899	616,899

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

A.0.3 Event Study

I estimate event study specifications to determine whether or not there were shifts in budget share allocations before the online service was introduced and to evaluate the effect of online shopping over time. Specifically, I estimate regressions of the following form:

$$s_{ihm} = \nu_i + \sum_k \tau_{ik} 1\{TimeAvail_{hm} = k\} + \gamma_{im} + \gamma_{ih} + \omega_{ihm} \tag{A.2}$$

where s_{ihm} is the budget share of good, i, for household, h, in year-month, m, $1\{TimeAvail_{hm} = k\}$ is an indicator that equals one when the household is k time-periods from online service introduction, γ_{im} and γ_{ih} are year-month and household fixed effects, respectively. I allow the reference time-period for $1\{TimeAvail_{hm} = k\}$ to be all time-periods that were more than five months prior to the online service introduction. Furthermore, k is discrete from $k = -5$ to $k = 5$ (5 months before online service introduction to 5 months following introduction, where time zero is the month of introduction) with one additional indicator for 6 months or more following introduction.

Figure **??** presents the estimates of τ_{ik}, with 95% confidence intervals, for each budget share outcome as well as for the outcome of online service use.[5] Eleven of the twelve graphs do not indicate a consistent pre-trend violation. However, the graph for dairy illustrates that the the point estimates of τ_{ik} were increasing in the months before online service introduction, indicating that caution should be exercised when drawing conclusions about the effect of online grocery shopping on dairy purchases.

The estimates for drinks, meat, snacks/sweets and vegetables illustrate post-treatment effects that remain fairly stable in the post-treatment time periods. However, the negative effects for drinks seems to fade six or more months after treatment. In contrast, the treatment effects on the budget shares for dairy, fruit and oil are fairly noisy, with each graph illustrating only one or two post-introduction coefficients that are significant. In summary, the graphs in Figure **??** illustrate striking discontinuities in the estimates of τ_{ik} at the period of online introduction (t=0) for the product categories of drinks, meat, snacks/sweets and vegetables.

[5]The estimates of these regressions are presented in Tables A32 and A33 of the appendix.

Table A32: Event Study Estimates, $\hat{\tau}_{ik}$ - Online Households

	1{Online}	Dairy	Drink	Fruit	Grain	Meat
t=-5	0.00125	-0.0982	-0.0911	0.0128	-0.00870	0.0726
	(0.00329)	(0.0580)	(0.0667)	(0.0784)	(0.0320)	(0.0738)
t=-4	-0.00273	-0.0420	-0.0385	0.0695	-0.00102	-0.00999
	(0.00446)	(0.0430)	(0.0509)	(0.0625)	(0.0339)	(0.0556)
t=-3	-0.00609	-0.000427	-0.130*	0.0949*	-0.0330	0.0838
	(0.00479)	(0.0574)	(0.0715)	(0.0523)	(0.0341)	(0.0720)
t=-2	-0.00495	0.0339	-0.119	0.0389	-0.0415	0.118
	(0.00553)	(0.0504)	(0.0768)	(0.0664)	(0.0344)	(0.0737)
t=-1	0.00364	0.0465	-0.115**	0.0744	4.54e-06	0.0104
	(0.00776)	(0.0566)	(0.0490)	(0.0623)	(0.0338)	(0.0580)
t=0	0.141***	0.0873	-0.143**	0.101**	0.0400	0.186**
	(0.0247)	(0.0685)	(0.0686)	(0.0483)	(0.0340)	(0.0764)
t=1	0.191***	0.106	-0.205***	0.140***	-0.0326	0.288***
	(0.0269)	(0.0830)	(0.0750)	(0.0449)	(0.0318)	(0.0725)
t=2	0.204***	0.159**	-0.236***	0.212***	-0.0249	0.189**
	(0.0236)	(0.0753)	(0.0784)	(0.0735)	(0.0273)	(0.0825)
t=3	0.201***	0.0383	-0.188***	0.0979	0.0270	0.286***
	(0.0228)	(0.0815)	(0.0626)	(0.0689)	(0.0330)	(0.0816)
t=4	0.208***	0.140	-0.284**	0.161**	0.0133	0.331***
	(0.0278)	(0.0954)	(0.116)	(0.0672)	(0.0339)	(0.0870)
t=5	0.201***	0.0641	-0.194*	0.0542	0.0476	0.292***
	(0.0244)	(0.119)	(0.108)	(0.0739)	(0.0409)	(0.101)
t>5	0.211***	-0.0196	-0.147	0.131	-0.0116	0.246***
	(0.0123)	(0.115)	(0.0923)	(0.0834)	(0.0410)	(0.0897)
Year-Month f.e.	X	X	X	X	X	X
Household f.e.	X	X	X	X	X	X
Observations	616,357	616,357	616,357	616,357	616,357	616,357
R-Squared	0.306	0.364	0.332	0.399	0.312	0.368

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A33: Event Study Estimates, $\hat{\tau}_{ik}$ - Online Households

	Oil	Other	Prepared	Snack/Sweet	Sugar	Vegetables
t=-5	0.0111	0.0499**	-0.00653	0.0489	0.0589**	-0.0497
	(0.0243)	(0.0217)	(0.0476)	(0.0689)	(0.0228)	(0.0412)
t=-4	-0.0552***	0.0339*	-0.0339	0.00647	0.0174	0.0532
	(0.0192)	(0.0179)	(0.0563)	(0.0829)	(0.0196)	(0.0617)
t=-3	-0.0549	0.0234	-0.0276	-0.121	0.0287	0.136***
	(0.0343)	(0.0223)	(0.0462)	(0.0772)	(0.0193)	(0.0447)
t=-2	-0.00510	0.0409*	-0.0602	-0.0952	0.0369**	0.0518
	(0.0259)	(0.0237)	(0.0652)	(0.0699)	(0.0144)	(0.0487)
t=-1	0.00404	0.00982	-0.118*	-0.0197	0.0410	0.0636
	(0.0229)	(0.0179)	(0.0616)	(0.0579)	(0.0290)	(0.0511)
t=0	-0.0100	0.00407	-0.0227	-0.365***	0.0428**	0.0808
	(0.0236)	(0.0180)	(0.0810)	(0.0983)	(0.0191)	(0.0610)
t=1	-0.0612*	0.0118	-0.00837	-0.408***	-0.0102	0.181***
	(0.0321)	(0.0176)	(0.0752)	(0.0976)	(0.0251)	(0.0618)
t=2	-0.0782**	-0.000670	-0.0252	-0.416***	0.0190	0.198***
	(0.0371)	(0.0179)	(0.0565)	(0.0878)	(0.0212)	(0.0488)
t=3	-0.0697***	0.0256	-0.00214	-0.455***	0.0173	0.222***
	(0.0192)	(0.0253)	(0.0669)	(0.103)	(0.0174)	(0.0402)
t=4	-0.0594*	0.0530**	-0.0212	-0.575***	0.0149	0.227***
	(0.0321)	(0.0251)	(0.0696)	(0.133)	(0.0148)	(0.0429)
t=5	-0.0366	0.0292	0.00314	-0.501***	0.0208	0.221***
	(0.0463)	(0.0174)	(0.0806)	(0.138)	(0.0382)	(0.0623)
t>5	-0.0618**	0.0377*	-0.129	-0.283**	0.0421*	0.194***
	(0.0279)	(0.0193)	(0.0890)	(0.132)	(0.0244)	(0.0554)
Year-Month f.e.	X	X	X	X	X	X
Household f.e.	X	X	X	X	X	X
Observations	616,357	616,357	616,357	616,357	616,357	616,357
R-Squared	0.183	0.172	0.353	0.319	0.166	0.414

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

A.0.4 Placebo Test

In order to test whether or not there are other changes influencing demand that occur simultaneously with the introduction of the online purchasing service, I estimate difference-in-difference regressions over the subset of households that never adopt the online service. I expect these estimates to indicate that online service availability has no effect on the budget shares of households that never use the online service. Table A34 presents the difference-in-difference regressions for in-store only households. These results are as one would expect; there is no strong evidence to suggest that online service availability has any significant effect on the budget share allocations of households who never use the online purchasing service. Although the difference-in-difference estimates for the prepared category are significant at the 10% significance level, regressions evaluating the effect of online service availability on in-store households' expenditures (Appendix Table A35), nutrition outcomes (Appendix Table A36) and ounce shares (Appendix Table A37) reveal no statistically significant changes over any of these outcomes. The results of these regressions suggest that there were no changes to other factors that influence demand at the time of online service introduction.

Table A34: DID / RF Estimates, $\hat{\tau}_i$ - In-Store Households

Budget Shares	(1)	(2)	(3)	Avg. Budget Share (Pre-Online Service)
Dairy	0.0876	0.0888	0.0855	11.95
	(0.0676)	(0.0676)	(0.0699)	(8.01)
Drinks	-0.0451	-0.0454	-0.0299	10.9
	(0.0858)	(0.0858)	(0.0845)	(10.26)
Fruit	-0.0106	-0.0114	-0.0293	7.26
	(0.0462)	(0.0463)	(0.0453)	(7.55)
Grain	-0.0291	-0.0276	-0.0203	7.2
	(0.0432)	(0.0428)	(0.0445)	(5.61)
Meat	-0.00571	-0.00406	0.0142	18.88
	(0.0890)	(0.0887)	(0.0902)	(12.09)
Oil	0.0259	0.0258	0.0228	4.36
	(0.0267)	(0.0267)	(0.0268)	(4.49)
Other	0.0105	0.0101	0.00930	1.73
	(0.0286)	(0.0287)	(0.0287)	(3.04)
Prepared	-0.116*	-0.112*	-0.111*	10.87
	(0.0644)	(0.0648)	(0.0639)	(9.19)
Snacks/Sweets	0.0295	0.0221	0.0128	16.11
	(0.0681)	(0.0666)	(0.0688)	(11.86)
Sugar	0.00935	0.00896	0.00731	1.56
	(0.0237)	(0.0238)	(0.0238)	(2.87)
Veg	0.0413	0.0432	0.0364	9.19
	(0.0547)	(0.0544)	(0.0532)	(7.77)
Time Availability f.e.	X			
Treatment Cohort f.e.	X	X		
Household Demographics	X	X		
Year-Month f.e.		X	X	
Household f.e.			X	
Observations	238,665	238,665	238,665	56,973

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online availability on the budget share.
These estimates were produced equation by equation.

Table A35: In-Store Households - Expenditure

Difference in Difference / Reduced Form Estimates, (τ_i)

Expenditure	(1)	(2)	(3)
1{OnlineAvail}	1.099	1.153	0.537
	(2.035)	(2.030)	(1.977)
Time Availability f.e.	X		
Treatment Cohort f.e.	X	X	
Household Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Observations	238,665	238,665	238,665
R-squared	0.501	0.506	0.809

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A36: In-Store Households - Nutrient Outcomes

Difference in Difference / Reduced Form Estimates, (τ_i)

Nutrients per Ounce	(1)	(2)	(3)
Calories	0.00383	-0.00427	0.00624
	(0.118)	(0.118)	(0.121)
Carbohydrates	-0.0108	-0.0117	-0.0108
	(0.0161)	(0.0161)	(0.0172)
Cholesterol	-0.000187	-0.000187	-0.000203
	(0.000134)	(0.000135)	(0.000138)
Protein	0.00554	0.00550	0.00572
	(0.00476)	(0.00474)	(0.00487)
Sodium	0.00236	0.00238	0.00247
	(0.00605)	(0.00602)	(0.00596)
Total Fat	0.00188	0.00136	0.00200
	(0.00775)	(0.00772)	(0.00787)
Total Sugar	-0.00252	-0.00326	-0.00320
	(0.00822)	(0.00828)	(0.00883)
Time Availability f.e.	X		
Treatment Cohort f.e.	X	X	
Household Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Observations	226,532	226,532	226,532

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table A37: In-Store Households - Ounce Shares

Difference in Difference / Reduced Form Estimates, (τ_i)

Ounce Shares	(1)	(2)	(3)
Dairy	0.0406	0.0424	0.0323
	(0.114)	(0.113)	(0.115)
Drinks	0.0894	0.0869	0.0962
	(0.186)	(0.185)	(0.181)
Fruit	-0.0482	-0.0475	-0.0665
	(0.0713)	(0.0711)	(0.0679)
Grain	-0.0128	-0.0121	-0.00194
	(0.0431)	(0.0428)	(0.0441)
Meat	-0.0333	-0.0323	-0.0207
	(0.0556)	(0.0554)	(0.0571)
Oil	0.0218	0.0213	0.0216
	(0.0233)	(0.0233)	(0.0245)
Other	0.0117	0.0113	0.00995
	(0.0210)	(0.0210)	(0.0212)
Prepared	-0.0448	-0.0413	-0.0366
	(0.0463)	(0.0463)	(0.0466)
Snacks/Sweets	0.0119	0.00792	0.00261
	(0.0594)	(0.0597)	(0.0573)
Sugar	0.00341	0.00248	0.00225
	(0.0288)	(0.0289)	(0.0292)
Veg	-0.0397	-0.0392	-0.0392
	(0.0722)	(0.0720)	(0.0714)
Time Availability f.e.	X		
Treatment Cohort f.e.	X	X	
Household Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Observations	238,563	238,563	238,563

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

A.0.5 Online Product Offerings

When the online purchasing environment was launched the retailer only had select products available for online purchasing. At the time of launch, roughly 22 thousand unique items were available for purchase online. In contrast, by January 2016, roughly 78 thousand unique items were available for purchase online.[6] However, the retailer has indicated that most of the growth in product offerings came from general merchandise products rather than grocery products.

There are some challenges to understanding what products were available online. Primarily, I do not know what products were available online at any given point in time; I only have access to information regarding whether or not a product was purchased online and (or) in the store. Given that the online service was slowly introduced and that only a subset of households are able to shop online at any given point in time, there may be more products available online than are purchased online.

Figure A3 presents the percent of products that were purchased in-store and also purchased online. In March 2015, 27% of the products in the dairy category that were purchased in-store were also purchased online (the maximum of any product category); in contrast, only 9% of products in the other category that were purchased in-store were also purchased online (the minimum of any product category). However, by January 2016, these proportions significantly increased to the point where at least 53% of the products (in any given category) purchased in-store have also been purchased online. Figure A4 presents the percent of in-store sales that come from products that were also purchased online in each month. The column for January 2016 indicates that the minimum percentage of in-store sales represented by products that were also purchased online is 86%. Thus, 53% of the products represent 86% of the sales in a product category, snacks/sweets, that has been shown to be less popular online.[7] Given that the most popular in-store items are also being purchased online and that only half of my household sample has access to the online purchasing service by January 2016, I assume that online product offerings are representative of in-store product offerings from January 2016 on.

[6] The retailer has provided me a list of roughly 108 thousand unique products within grocery that have been available for sale in their store at any point in time. Actual product offerings in the store are almost surely lower than this at any given point in time. As of March 2017 there were 89 thousand unique products available for purchase online.

[7] Additionally, only 56% of the households in my sample have access to the online shopping service by January 2016.

Under this assumption, I test whether limited product offerings are driving the results of the previous analysis by restricting the data to all dates after January 2016 and estimating equation (1). If limited product offerings are responsible for the main results of my chapter, the time-restricted regressions should indicate that shopping online has no effect on any of the budget share outcomes. Tables A38 and A39 present the ordinary least squares and two-stage least squares estimates from the time restricted regressions. The results indicate that the effect of online shopping for dairy and fruit budget shares remains positive and significant and the effect for snacks and sweets remains negative and significant. In contrast, the estimated effects for drinks, meat, oils and vegetables retain the same signs as earlier regressions, but are no longer statistically significant.[8] The magnitudes of the estimates over all time periods and the time restricted estimates are remarkably similar for the product categories of dairy, fruit and snacks/sweets with larger discrepancies occurring in the product categories of drinks, meat, oils and vegetables.

Identification is driven by the households whose status of online availability changes over time. Thus, estimates of the effect of online shopping that are derived from the restricted set of time periods are identified only by the Wave 2 and Wave 3 households defined in Section 3. There is no way to parse out the differences in these results that are due to heterogeneous treatment effects and those that are due to increased availability of online product offerings.[9] However, because differences in online and offline budget shares continue to persist in time periods in which the online product offerings are representative of in-store offerings, this robustness check indicates that the results estimated over all time periods cannot be explained by limited online product offerings alone.

[8]The estimates obtained from running regressions over later time periods of the data indicate the following percent changes in average budget shares: dairy (5.2%), fruit (5.5%), meat (3.5%), vegetables (4.4%), drinks (-1.3%), oil (-1.2%), snacks/sweets (-13.5%). For comparison, the estimates over all time periods indicated the following percent changes in average budget shares: dairy (3.8%), fruit (5.9%), meat (5.7%), vegetables (7.4%), drinks (-5.2%), oil (-4.1%), snacks/sweets (-13.6%).

[9]Figure **??**, of the Appendix, illustrates that wave two and wave three households allocated more of their budget towards drinks and less of their budgets towards vegetables compared to wave one households. On the other hand, the drinks product category exhibited a lot of growth in product offerings between March 2015 and January 2016 but it is unclear if this growth came from additional products being offered online or more people purchasing these UPCs online.

Figure A3: Percent of Available Products Purchased Online

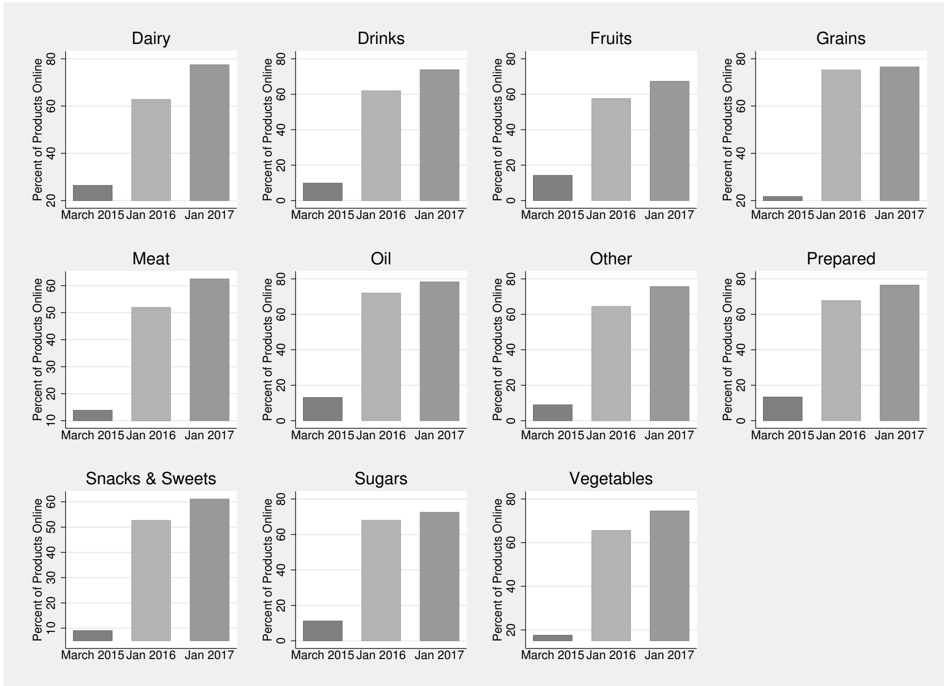

Figure A3 presents the percentage of upcs purchased both in-store and online in March 2015, January 2016 and January 2017.

Figure A4: Percent of In-Store Sales from Products Available Online

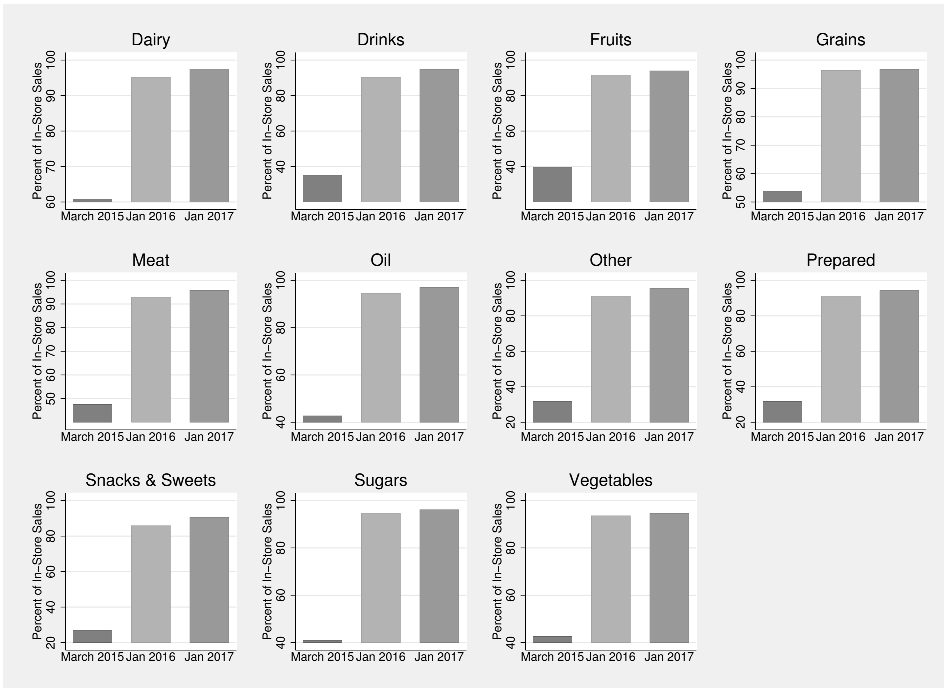

Figure A4 presents the percentage of in-store sales that are generated from upcs that have also been purchased online. This figure illustrates that by January 2016, the most popularly purchased in-store products are also available online.

Table A38: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households, After January 2016

Budget Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Share (Pre-Service)	Percent Change
Dairy	0.768***	0.773***	0.539***	0.726***	0.732***	0.678***	13.21	5.15
	(0.0553)	(0.0546)	(0.0577)	(0.152)	(0.154)	(0.149)	(6.90)	
Drinks	-0.729***	-0.729***	-0.564***	-0.137	-0.135	-0.126	10.08	-1.25
	(0.0596)	(0.0592)	(0.0575)	(0.242)	(0.242)	(0.245)	(8.31)	
Fruit	0.297***	0.294***	0.118***	0.424**	0.423**	0.412**	7.48	5.48
	(0.0607)	(0.0608)	(0.0370)	(0.183)	(0.183)	(0.190)	(6.18)	
Grain	0.214***	0.216***	0.148***	0.0686	0.0779	0.0286	7.6	0.38
	(0.0276)	(0.0277)	(0.0310)	(0.147)	(0.147)	(0.139)	(4.66)	
Meat	0.402***	0.404***	0.583***	0.656	0.676	0.640	18.46	3.47
	(0.0805)	(0.0821)	(0.0676)	(0.444)	(0.445)	(0.455)	(9.69)	
Oil	-0.0545**	-0.0554**	-0.0228	-0.0430	-0.0441	-0.0536	4.36	-1.23
	(0.0223)	(0.0222)	(0.0272)	(0.100)	(0.100)	(0.107)	(3.56)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	222,261	222,261	222,261	222,261	222,261	222,261	147,246	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online service use on the budget share.
These estimates were produced equation by equation.
The percent change is derived utilizing the 2SLS estimates in column (6) and the pre-online service average.

Table A39: Ordinary Least Squares & Two-Stage Least Squares Estimates, $\hat{\phi}_i$ - Online Households, After January 2016

Budget Shares	OLS (1)	OLS (2)	OLS (3)	2SLS (4)	2SLS (5)	2SLS (6)	Avg. Share (Pre-Service)	Percent Change
Other	-0.00758	-0.00691	0.000401	-0.0877	-0.0860	-0.0932	1.81	-5.15
	(0.0196)	(0.0196)	(0.0143)	(0.0819)	(0.0814)	(0.0847)	(2.72)	
Prepared	0.103	0.110	0.138**	0.314	0.333	0.347	10.78	3.22
	(0.0736)	(0.0749)	(0.0561)	(0.288)	(0.286)	(0.269)	(7.45)	
Snacks/Sweets	-1.679***	-1.691***	-1.623***	-2.210***	-2.281***	-2.099***	15.52	-13.53
	(0.0953)	(0.100)	(0.106)	(0.399)	(0.398)	(0.381)	(9.84)	
Sugar	0.0341***	0.0343***	0.0102	-0.138***	-0.140***	-0.136***	1.61	-8.70
	(0.00971)	(0.00978)	(0.00969)	(0.0460)	(0.0459)	(0.0451)	(2.32)	
Vegetables	0.652***	0.652***	0.674***	0.428*	0.445*	0.403	9.09	4.43
	(0.0749)	(0.0751)	(0.0502)	(0.260)	(0.258)	(0.263)	(6.20)	
Time Availability f.e.	X			X				
Treatment Cohort f.e.	X	X		X	X			
HH Demographics	X	X		X	X			
Year-Month f.e.		X	X		X	X		
Household f.e.			X			X		
Observations	222,261	222,261	222,261	222,261	222,261	222,261	147,246	

Robust standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Each cell represents an estimate of the effect of online service use on the budget share.
These estimates were produced equation by equation.
The percent change is derived utilizing the 2SLS estimates in column (6) and the pre-online service average.

APPENDIX B

CHAPTER 2 APPENDIX

Figure B1: Online Shopping Service Availability

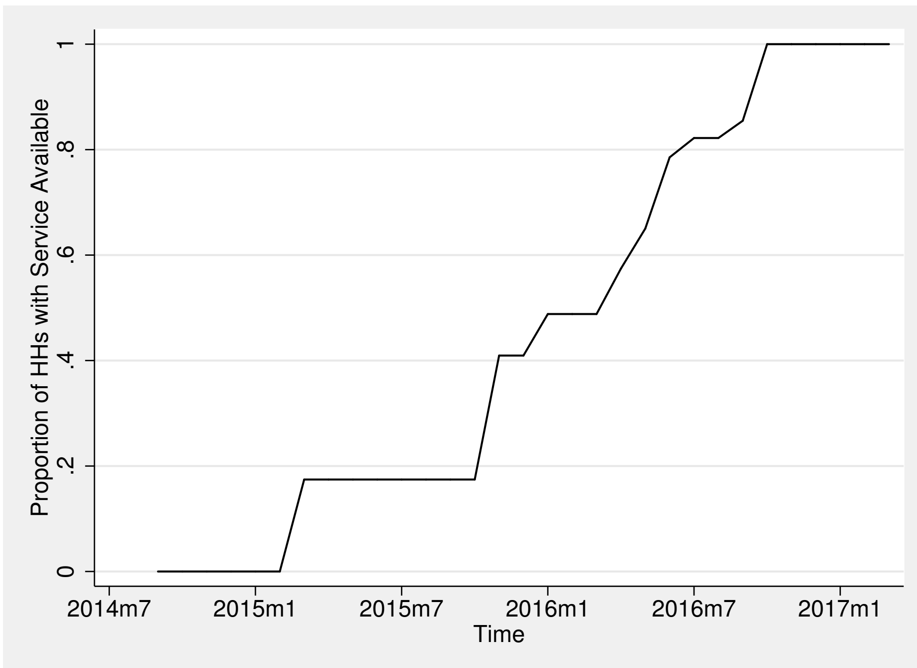

Figure B1 illustrates the proportion of households who have access to the online purchasing service over time. This Figure is courtesy of Harris (2019).

Figure B2: Own and Cross Price Elasticity Ratio, $\frac{|\eta_{Instore}|}{|\eta_{Online}|}$

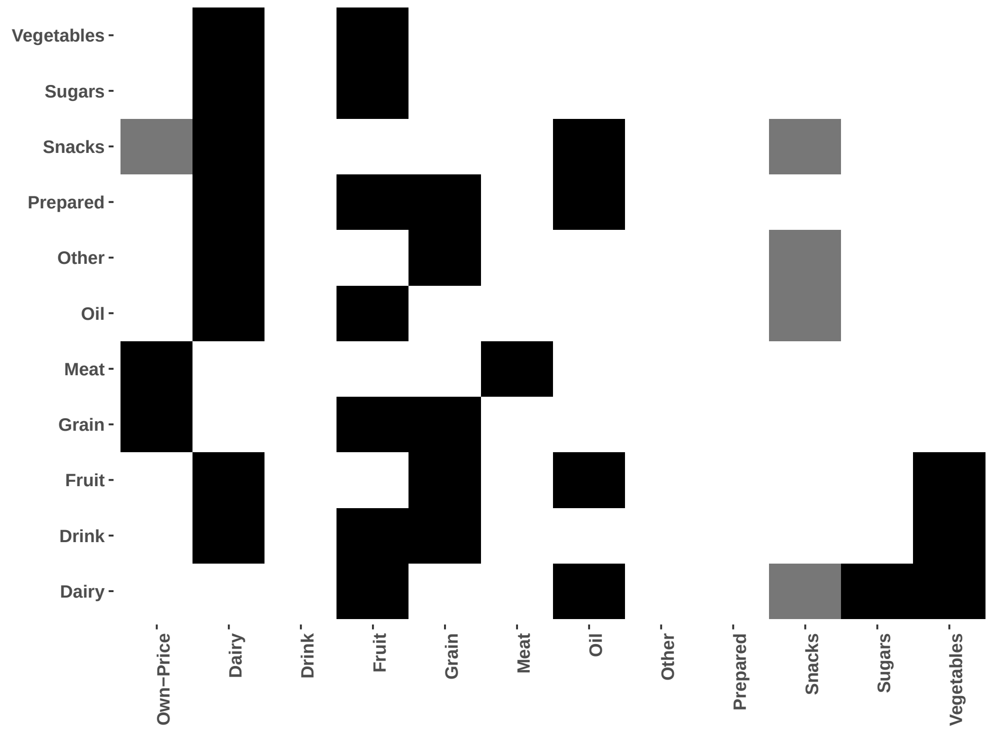

Figure B2 the ratio of the in-store and online own and cross price elasticities. Black indicates that the in-store elasticity is significantly different and greater, in absolute value, than the online elasticity. White means that the two elasticities are not significantly different from each other, at the 95% confidence level, and gray indicates that the in-store elasticity is significantly different and smaller, in absolute value, than the online elasticity.

Table B1: Household Demographics

Household Demographics	Online Adoption Households
1{Married}	0.69

Household Size	Online
1{1 Person}	0.10
1{2 People}	0.22
1{3 People}	0.25
1{4 People}	0.17
1{5+ People}	0.27

Household Income	Online
1{0-29K}	0.10
1{30-50K}	0.16
1{51-79K}	0.31
1{80-99K}	0.15
1{100-149K}	0.12
1{150K}	0.16

Number of Children	Online
1{0 Children}	0.41
1{1 Child}	0.33
1{2 Children}	0.15
1{3 Children}	0.08
1{4+ Children}	0.04

Household Head Age	Online
1{18-25}	0.02
1{26-35}	0.25
1{36-45}	0.32
1{46-55}	0.19
1{56-55}	0.14
1{66+}	0.08

Household Count	25,020

Table B2: In-store Months Compared to Online Months

Purchasing Habits	In-store Month	Online Month	Difference	Difference t-stat
Grocery Expenditure ($)	468	537	-69	-44.28
Items Purchased	187	211	-25	-39.01
Shopping Occasions	7.9	8.4	-0.5	-19.50
Proportion of Sales Online	0.00	0.41	-0.41	-1069.35

Share of Expenditure	In-store Month	Online Month	Difference	Difference t-stat
Dairy	0.13	0.13	-0.01	-21.95
Drink	0.11	0.10	0.01	17.06
Fruit	0.08	0.09	-0.01	-33.06
Grain	0.08	0.08	0.00	-13.51
Meat	0.18	0.18	0.00	0.60
Oil	0.04	0.04	0.00	1.37
Other	0.02	0.02	0.00	6.27
Prepared	0.10	0.10	0.00	11.06
Snacks/Sweets	0.16	0.14	0.02	37.49
Sugar	0.02	0.02	0.00	-0.59
Vegetables	0.09	0.10	-0.01	-30.27

Price per Ounce	In-store Month	Online Month	Difference	Difference t-stat
Dairy	0.11	0.10	0.01	28.09
Drink	0.09	0.09	0.01	5.17
Fruit	0.11	0.11	0.00	-0.33
Grain	0.15	0.14	0.00	6.23
Meat	0.25	0.24	0.01	16.58
Oil	0.18	0.18	0.00	0.13
Other	0.92	0.93	-0.01	-0.71
Prepared	0.18	0.18	0.00	-2.60
Snacks/Sweets	0.22	0.22	0.00	3.60
Sugar	0.24	0.24	0.00	2.18
Vegetables	0.11	0.10	0.00	6.72
Observations	564,244	51,916		

Table B3: In-Store Elasticity Matrix

	Dairy	Drink	Fruit	Grain	Meat	Oil	Other	Prepared	Snacks	Sugars	Vegetables
Dairy	-0.86	0.31	0.61	-0.19	0.09	0.31	0.53	-0.53	-0.79	0.66	0.47
	(0.14)	(0.07)	(0.18)	(0.13)	(0.10)	(0.12)	(0.26)	(0.20)	(0.13)	(0.23)	(0.12)
Drink	0.23	-1.81	0.69	0.16	-0.17	-0.06	0.63	-0.10	-0.13	0.27	0.40
	(0.06)	(0.10)	(0.13)	(0.06)	(0.07)	(0.08)	(0.15)	(0.11)	(0.08)	(0.18)	(0.09)
Fruit	0.39	0.56	-0.59	-0.52	0.15	0.73	-0.04	-0.98	-0.28	1.55	-0.48
	(0.12)	(0.10)	(0.35)	(0.17)	(0.20)	(0.32)	(0.52)	(0.28)	(0.21)	(0.46)	(0.16)
Grain	-0.11	0.12	-0.48	0.21	0.09	0.41	-0.47	-0.58	0.03	-0.60	-0.16
	(0.08)	(0.05)	(0.15)	(0.29)	(0.09)	(0.27)	(0.22)	(0.14)	(0.07)	(0.53)	(0.09)
Meat	0.14	-0.25	0.33	0.24	-1.49	-0.33	1.45	0.09	0.39	-0.13	-0.25
	(0.15)	(0.12)	(0.44)	(0.23)	(0.28)	(0.28)	(0.62)	(0.27)	(0.31)	(0.40)	(0.27)
Oil	0.10	-0.02	0.39	0.24	-0.08	-0.28	0.02	-0.30	-0.20	-0.64	-0.07
	(0.04)	(0.03)	(0.17)	(0.16)	(0.07)	(0.30)	(0.21)	(0.14)	(0.07)	(0.37)	(0.07)
Other	0.06	0.09	-0.01	-0.10	0.12	0.01	-1.41	0.07	-0.13	-0.33	-0.08
	(0.03)	(0.02)	(0.10)	(0.04)	(0.05)	(0.07)	(0.19)	(0.09)	(0.05)	(0.17)	(0.05)
Prepared	-0.41	-0.07	-1.20	-0.76	0.04	-0.69	0.49	0.78	0.30	-0.87	0.20
	(0.16)	(0.10)	(0.34)	(0.18)	(0.15)	(0.33)	(0.59)	(0.43)	(0.18)	(0.46)	(0.14)
Snacks	-0.99	-0.19	-0.55	0.06	0.30	-0.74	-1.33	0.44	-0.18	-0.39	-0.25
	(0.15)	(0.12)	(0.40)	(0.15)	(0.26)	(0.24)	(0.45)	(0.28)	(0.32)	(0.45)	(0.24)
Sugar	0.08	0.04	0.29	-0.12	-0.01	-0.22	-0.32	-0.14	-0.04	-0.18	-0.04
	(0.03)	(0.03)	(0.09)	(0.11)	(0.03)	(0.13)	(0.17)	(0.07)	(0.04)	(0.24)	(0.03)
Vegetables	0.34	0.36	-0.53	-0.18	-0.13	-0.14	-0.44	0.18	0.14	-0.25	-0.80
	(0.08)	(0.07)	(0.18)	(0.11)	(0.14)	(0.14)	(0.28)	(0.13)	(0.11)	(0.20)	(0.11)

Cluster-bootstrapped standard errors reported in parentheses
Standard errors clustered at the store-availability level

Table B4: Online Elasticity Matrix

	Dairy	Drink	Fruit	Grain	Meat	Oil	Other	Prepared	Snacks	Sugars	Vegetables
Dairy	-0.84	-4.14	0.38	-0.14	0.07	0.24	0.54	-0.50	3.36	0.54	0.26
	(0.08)	(4.51)	(0.12)	(0.08)	(0.09)	(0.09)	(0.27)	(0.17)	(0.79)	(0.21)	(0.06)
Drink	0.14	10.03	0.45	0.10	-0.15	-0.06	0.62	-0.09	0.58	0.24	0.21
	(0.04)	(11.85)	(0.10)	(0.04)	(0.06)	(0.06)	(0.17)	(0.10)	(0.34)	(0.14)	(0.04)
Fruit	0.23	-7.97	-0.63	-0.35	0.11	0.56	-0.07	-0.88	1.27	1.33	-0.25
	(0.07)	(8.41)	(0.23)	(0.11)	(0.17)	(0.26)	(0.54)	(0.22)	(0.89)	(0.40)	(0.09)
Grain	-0.08	-1.66	-0.33	-0.08	0.07	0.31	-0.50	-0.52	-0.02	-0.56	-0.09
	(0.05)	(1.96)	(0.10)	(0.19)	(0.08)	(0.21)	(0.23)	(0.13)	(0.28)	(0.43)	(0.05)
Meat	0.09	4.43	0.20	0.15	-1.35	-0.24	1.51	0.07	-1.48	-0.14	-0.15
	(0.09)	(5.24)	(0.29)	(0.15)	(0.24)	(0.22)	(0.62)	(0.24)	(1.38)	(0.34)	(0.14)
Oil	0.06	0.47	0.25	0.15	-0.07	-0.37	0.01	-0.27	0.85	-0.55	-0.03
	(0.03)	(0.72)	(0.12)	(0.11)	(0.06)	(0.24)	(0.21)	(0.11)	(0.38)	(0.31)	(0.04)
Other	0.04	-1.33	-0.01	-0.07	0.10	0.00	-1.34	0.07	0.54	-0.27	-0.04
	(0.02)	(1.52)	(0.06)	(0.03)	(0.04)	(0.06)	(0.21)	(0.09)	(0.24)	(0.15)	(0.03)
Prepared	-0.26	1.43	-0.78	-0.51	0.03	-0.54	0.54	0.66	-1.13	-0.74	0.11
	(0.10)	(1.99)	(0.25)	(0.12)	(0.13)	(0.27)	(0.64)	(0.31)	(0.71)	(0.38)	(0.07)
Snacks	-0.62	3.21	-0.39	0.01	0.27	-0.58	-1.39	0.40	-4.59	-0.29	-0.14
	(0.09)	(3.56)	(0.26)	(0.10)	(0.22)	(0.20)	(0.51)	(0.25)	(1.37)	(0.39)	(0.13)
Sugars	0.05	-0.61	0.19	-0.09	-0.01	-0.18	-0.33	-0.12	0.13	-0.26	-0.02
	(0.02)	(0.68)	(0.06)	(0.07)	(0.03)	(0.10)	(0.17)	(0.06)	(0.17)	(0.22)	(0.02)
Vegetables	0.22	-5.11	-0.35	-0.12	-0.13	-0.10	-0.45	0.17	-0.43	-0.20	-0.85
	(0.05)	(5.53)	(0.13)	(0.07)	(0.12)	(0.11)	(0.27)	(0.12)	(0.43)	(0.17)	(0.06)

Cluster-bootstrapped standard errors reported in parentheses
Standard errors clustered at the store-availability level

Table B5: Product Category Key

Product Category	Description
Dairy	Milk & Milk Substitutes, Cheese, Yogurt, Cream Cheese
Drinks	Non-Alcoholic Beverages, Water, Soda, Juice
Fruit	Fresh, Dried and Frozen Fruits
Grains	Rice, Pasta, Bread, Cereal, Oatmeal
Meat	Beef, Poultry, Seafood, Eggs, Beans, Legumes
Oils	Butter, Mayonnaise, Salad Dressings, Vegetable Oils
Other	Flour, Gravy, Seasonings, Baking Items
Prepared	Rice Mixed Dishes, Pizza, Macaroni, Soups
Snacks and Sweets	Chips, Crackers, Granola Bars, Cakes, Candy, Ice Cream
Sugar	Sugar, Honey, Jams, Syrups
Vegetables	Fresh & Frozen Vegetables

Table courtesy of Harris (2019)

Table B6: First Stage Estimates

	$\ln(p_{Dairy})$	$\ln(p_{Drink})$	$\ln(p_{Fruit})$	$\ln(p_{Grain})$	$\ln(p_{Meat})$	$\ln(p_{Oil})$
$\ln(c_{Dairy})$	0.878***	-0.139	0.0791	0.0693**	-0.00643	0.0179
	(0.0707)	(0.136)	(0.0556)	(0.0339)	(0.0400)	(0.0539)
$\ln(c_{Drink})$	0.142**	1.035***	0.0538	0.117***	0.0681	0.129**
	(0.0633)	(0.0727)	(0.0416)	(0.0321)	(0.0405)	(0.0533)
$\ln(c_{Fruit})$	-0.180**	-0.0894	0.464***	0.00449	0.0149	-0.0537
	(0.0817)	(0.0942)	(0.0523)	(0.0334)	(0.0374)	(0.0576)
$\ln(c_{Grain})$	-0.122	0.714***	-0.201*	0.432***	-0.00960	0.185*
	(0.145)	(0.210)	(0.0994)	(0.0639)	(0.0724)	(0.0981)
$\ln(c_{Meat})$	0.0773	-0.260*	0.126**	0.138***	0.742***	0.240***
	(0.0798)	(0.150)	(0.0566)	(0.0487)	(0.0737)	(0.0856)
$\ln(c_{Oil})$	0.122	0.233*	0.0161	0.0335	0.120***	0.485***
	(0.0813)	(0.133)	(0.0483)	(0.0229)	(0.0336)	(0.0587)
$\ln(c_{Other})$	-0.0500*	-0.190***	-0.0385*	-0.0256**	0.00562	-0.0417*
	(0.0280)	(0.0515)	(0.0191)	(0.0125)	(0.0166)	(0.0230)
$\ln(c_{Prepared})$	0.496***	1.023***	0.321***	0.0995	0.0213	0.196
	(0.120)	(0.271)	(0.0676)	(0.0639)	(0.0797)	(0.120)
$\ln(c_{Snack})$	0.0162	0.348*	-0.123*	0.0117	-0.00889	0.139
	(0.144)	(0.198)	(0.0694)	(0.0555)	(0.0562)	(0.0889)
$\ln(c_{Sugar})$	-0.0473	0.0408	-0.0439*	0.0201	0.0150	0.0365
	(0.0347)	(0.0576)	(0.0231)	(0.0235)	(0.0283)	(0.0337)
$\ln(c_{Veg})$	-0.0267	0.0150	0.155***	0.00974	0.0427	0.0534
	(0.0527)	(0.0640)	(0.0399)	(0.0238)	(0.0390)	(0.0523)
1{OnlineAvail}	-0.00227	-0.0109	0.00336	0.00116	-0.00327	0.000540
	(0.00918)	(0.00900)	(0.00419)	(0.00411)	(0.00341)	(0.00433)
Constant	X	X	X	X	X	X
Linear Time Trend	X	X	X	X	X	X
Month Indicators	X	X	X	X	X	X
HH Dem.	X	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157	616,157
R-squared	0.017	0.023	0.017	0.022	0.025	0.022

Robust standard errors in parentheses
Standard errors are clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table B7: First Stage Estimates

	$\ln(p_{Other})$	$\ln(p_{Prep})$	$\ln(p_{Snack})$	$\ln(p_{Sugar})$	$\ln(p_{Veg})$	$1\{Online\}$
$\ln(c_{Dairy})$	-0.818***	0.00410	0.0865**	-0.489***	0.110**	-1.840***
	(0.234)	(0.0456)	(0.0365)	(0.148)	(0.0457)	(0.540)
$\ln(c_{Drink})$	0.0233	0.0890*	0.0704	0.0533	0.0968**	1.762**
	(0.118)	(0.0473)	(0.0423)	(0.117)	(0.0469)	(0.830)
$\ln(c_{Fruit})$	-0.174	0.0104	0.0439	-0.138	-0.0537	1.484***
	(0.182)	(0.0352)	(0.0363)	(0.107)	(0.0610)	(0.540)
$\ln(c_{Grain})$	0.516	-0.0901	-0.165**	0.494*	-0.0845	-1.321
	(0.321)	(0.0947)	(0.0800)	(0.280)	(0.0997)	(1.981)
$\ln(c_{Meat})$	-0.113	0.284***	0.0744	0.0682	0.190**	-1.792
	(0.240)	(0.0765)	(0.0595)	(0.183)	(0.0806)	(1.286)
$\ln(c_{Oil})$	0.0247	0.101***	0.0556*	0.214	-0.0327	1.103
	(0.201)	(0.0322)	(0.0286)	(0.133)	(0.0418)	(0.854)
$\ln(c_{Other})$	0.254***	-0.0219	-0.00641	-0.0515	-0.0368	-0.330
	(0.0729)	(0.0147)	(0.0165)	(0.0569)	(0.0278)	(0.235)
$\ln(c_{Prepared})$	1.216***	0.833***	0.140**	0.679**	0.271***	3.083**
	(0.424)	(0.0890)	(0.0652)	(0.305)	(0.0954)	(1.214)
$\ln(c_{Snack})$	1.535***	0.0416	0.767***	0.647***	-0.0253	-0.359
	(0.298)	(0.0685)	(0.0865)	(0.227)	(0.0765)	(1.263)
$\ln(c_{Sugar})$	0.161*	0.0328	-0.00974	0.419***	-0.0375	1.364***
	(0.0797)	(0.0296)	(0.0185)	(0.0649)	(0.0341)	(0.285)
$\ln(c_{Veg})$	0.290***	-0.0263	-0.0431**	0.194***	0.642***	0.548
	(0.100)	(0.0399)	(0.0208)	(0.0690)	(0.0620)	(0.732)
1{OnlineAvail}	-0.0583*	0.00550	-0.00129	-0.0195	0.0114**	1.428***
	(0.0292)	(0.00531)	(0.00404)	(0.0162)	(0.00436)	(0.108)
Constant	X	X	X	X	X	X
Linear Time Trend	X	X	X	X	X	X
Month Indicators	X	X	X	X	X	X
HH Dem.	X	X	X	X	X	X
Est. Price Residuals						X
Observations	616,157	616,157	616,157	616,157	616,157	616,157
R-squared	0.026	0.031	0.021	0.025	0.023	

Robust standard errors in parentheses
Standard errors are clustered at the store-availability level
Standard errors for the Probit regression, 1{Online}, are cluster bootstrapped
Bootstrapped standard errors are generated from 250 replications
*** p<0.01, ** p<0.05, * p<0.1

Table B8: Demand Estimates - Online Households

Budget Shares	(1) Dairy	(2) Drink	(3) Fruit	(4) Grain	(5) Oil
Constant	0.227***	0.155**	-0.0383	0.110*	0.0918***
	(0.0573)	(0.0623)	(0.107)	(0.0567)	(0.0354)
$\ln(p_{Dairy})$	0.0188	0.0302***	0.0508***	-0.0144	0.0134**
	(0.0183)	(0.00786)	(0.0149)	(0.00973)	(0.00527)
$\ln(p_{Drink})$	0.0302***	-0.0867***	0.0574***	0.0118**	-0.00256
	(0.00786)	(0.0110)	(0.0106)	(0.00474)	(0.00343)
$\ln(p_{Fruit})$	0.0508***	0.0574***	0.0345	-0.0397***	0.0323**
	(0.0149)	(0.0106)	(0.0288)	(0.0127)	(0.0139)
$\ln(p_{Grain})$	-0.0144	0.0118**	-0.0397***	0.0916***	0.0182
	(0.00973)	(0.00474)	(0.0127)	(0.0218)	(0.0119)
$\ln(p_{Meat})$	0.0186	-0.0295**	0.0284	0.0175	-0.0144
	(0.0188)	(0.0129)	(0.0361)	(0.0172)	(0.0124)
$\ln(p_{Oil})$	0.0134**	-0.00256	0.0323**	0.0182	0.0319**
	(0.00527)	(0.00343)	(0.0139)	(0.0119)	(0.0132)
$\ln(p_{Other})$	0.00818**	0.00971***	-0.000802	-0.00756**	0.000289
	(0.00410)	(0.00244)	(0.00821)	(0.00341)	(0.00325)
$\ln(p_{Prep})$	-0.0526**	-0.00917	-0.0986***	-0.0581***	-0.0305**
	(0.0206)	(0.0108)	(0.0285)	(0.0140)	(0.0145)
$\ln(p_{Snack})$	-0.126***	-0.0223*	-0.0448	0.00402	-0.0327***
	(0.0195)	(0.0129)	(0.0329)	(0.0112)	(0.0107)
$\ln(p_{Sugar})$	0.00997***	0.00408	0.0238***	-0.00930	-0.00990*
	(0.00362)	(0.00278)	(0.00717)	(0.00815)	(0.00568)
$\ln(p_{Veg})$	0.0434***	0.0369***	-0.0433***	-0.0140*	-0.00600
	(0.0106)	(0.00781)	(0.0148)	(0.00816)	(0.00618)
$\ln(\frac{M}{P})$	0.00248***	-0.0150***	0.00390***	-0.00213***	-0.000208
	(0.000406)	(0.000955)	(0.000307)	(0.000262)	(0.000149)
Linear Time Trend	X	X	X	X	X
Month Indicators	X	X	X	X	X
HH Dem.	X	X	X	X	X
Price Residual	X	X	X	X	X
Gen. Residual	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157

Cluster-bootstrapped standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table B9: Demand Estimates - Online Households

Budget Shares	(1) Dairy	(2) Drink	(3) Fruit	(4) Grain	(5) Oil
1{Online}	0.0841***	-0.112***	0.0440***	0.0383***	0.0125***
	(0.00962)	(0.00751)	(0.00811)	(0.00493)	(0.00348)
ln(p_{Dairy})x1{O}	0.0139***	-0.00105**	-0.00173**	-0.00263***	-0.000580***
	(0.00148)	(0.000454)	(0.000690)	(0.000549)	(0.000208)
ln(p_{Drink})x1{O}	-0.00105**	0.00800***	-0.000816	-0.000219	-0.000862***
	(0.000454)	(0.000843)	(0.000599)	(0.000284)	(0.000236)
ln(p_{Fruit})x1{O}	-0.00173**	-0.000816	0.0125***	-0.00134*	-0.000870**
	(0.000690)	(0.000599)	(0.00131)	(0.000751)	(0.000435)
ln(p_{Grain})x1{O}	-0.00263***	-0.000219	-0.00134*	0.0124***	-0.000954*
	(0.000549)	(0.000284)	(0.000751)	(0.00124)	(0.000521)
ln(p_{Meat})x1{O}	-0.00149	-0.00248***	-0.00273***	-0.00117	9.14e-05
	(0.00103)	(0.000550)	(0.000758)	(0.000823)	(0.000445)
ln(p_{Oil})x1{O}	-0.000580***	-0.000862***	-0.000870**	-0.000954*	0.00372***
	(0.000208)	(0.000236)	(0.000435)	(0.000521)	(0.000549)
ln(p_{Other})x1{O}	-0.000446**	-0.000246**	-0.000564***	-0.000310***	-0.000183
	(0.000219)	(0.000115)	(0.000203)	(0.000120)	(0.000139)
Linear Time Trend	X	X	X	X	X
Month Indicators	X	X	X	X	X
HH Dem.	X	X	X	X	X
Price Residual	X	X	X	X	X
Gen. Residual	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157

Cluster-bootstrapped standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table B10: Demand Estimates - Online Households

Budget Shares	(1) Dairy	(2) Drink	(3) Fruit	(4) Grain	(5) Oil
	(0.000219)	(0.000115)	(0.000203)	(0.000120)	(0.000139)
$\ln(p_{Prep})$x1{O}	-0.00300***	-0.00125***	-0.000202	-0.000641	-2.46e-05
	(0.000761)	(0.000465)	(0.000491)	(0.000930)	(0.000319)
$\ln(p_{Snack})$x1{O}	-0.00443***	-0.000572	-0.00429***	-0.00293***	-0.000229
	(0.000758)	(0.000798)	(0.000679)	(0.000680)	(0.000542)
$\ln(p_{Sugar})$x1{O}	-0.000512*	0.000249**	0.000167	-0.00107***	-0.000192
	(0.000287)	(0.000125)	(0.000274)	(0.000181)	(0.000158)
$\ln(p_{Veg})$x1{O}	0.00196**	-0.000752	-0.000160	-0.00113	8.63e-05
	(0.000990)	(0.000628)	(0.00101)	(0.000786)	(0.000539)
$\ln(\frac{M}{P})$x1{O}	-0.00842***	0.0132***	-0.00217***	-0.00410***	-0.00205***
	(0.000954)	(0.000828)	(0.000811)	(0.000560)	(0.000325)
Linear Time Trend	X	X	X	X	X
Month Indicators	X	X	X	X	X
HH Dem.	X	X	X	X	X
Price Residual	X	X	X	X	X
Gen. Residual	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157

Cluster-bootstrapped standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table B11: Demand Estimates - Online Households

Budget Shares	(6) Other	(7) Sugar	(8) Snacks	(9) Prep.	(10) Veg.
Constant	-0.0574**	0.0641***	0.00349	-0.0560	-0.0568
	(0.0276)	(0.0210)	(0.0847)	(0.0787)	(0.0684)
$\ln(p_{Dairy})$	0.00818**	0.00997***	-0.126***	-0.0526**	0.0434***
	(0.00410)	(0.00362)	(0.0195)	(0.0206)	(0.0106)
$\ln(p_{Drink})$	0.00971***	0.00408	-0.0223*	-0.00917	0.0369***
	(0.00244)	(0.00278)	(0.0129)	(0.0108)	(0.00781)
$\ln(p_{Fruit})$	-0.000802	0.0238***	-0.0448	-0.0986***	-0.0433***
	(0.00821)	(0.00717)	(0.0329)	(0.0285)	(0.0148)
$\ln(p_{Grain})$	-0.00756**	-0.00930	0.00402	-0.0581***	-0.0140*
	(0.00341)	(0.00815)	(0.0112)	(0.0140)	(0.00816)
$\ln(p_{Meat})$	0.0226**	-0.00225	0.0582	0.00975	-0.0217
	(0.00983)	(0.00615)	(0.0478)	(0.0276)	(0.0250)
$\ln(p_{Oil})$	0.000289	-0.00990*	-0.0327***	-0.0305**	-0.00600
	(0.00325)	(0.00568)	(0.0107)	(0.0145)	(0.00618)
$\ln(p_{Other})$	-0.00644**	-0.00507*	-0.0213***	0.00756	-0.00717
	(0.00306)	(0.00264)	(0.00716)	(0.00938)	(0.00441)
$\ln(p_{Prep})$	0.00756	-0.0136*	0.0451	0.181***	0.0191
	(0.00938)	(0.00703)	(0.0279)	(0.0438)	(0.0130)
$\ln(p_{Snack})$	-0.0213***	-0.00631	0.126**	0.0451	-0.0220
	(0.00716)	(0.00690)	(0.0493)	(0.0279)	(0.0222)
$\ln(p_{Sugar})$	-0.00507*	0.0126***	-0.00631	-0.0136*	-0.00397
	(0.00264)	(0.00372)	(0.00690)	(0.00703)	(0.00304)
$\ln(p_{Veg})$	-0.00717	-0.00397	0.0205	0.0191	0.0188*
	(0.00441)	(0.00304)	(0.0174)	(0.0130)	(0.00979)
$\ln(\frac{M}{P})$	-0.00196***	-0.00144***	-0.0166***	0.00470***	0.00625***
	(0.000130)	(8.17e-05)	(0.000770)	(0.000535)	(0.000456)
Linear Time Trend	X	X	X	X	X
Month Indicators	X	X	X	X	X
HH Dem.	X	X	X	X	X
Price Residual	X	X	X	X	X
Gen. Residual	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157

Cluster-bootstrapped standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table B12: Demand Estimates - Online Households

Budget Shares	(6) Other	(7) Sugar	(8) Snacks	(9) Prep.	(10) Veg.
1{Online}	-0.000565	0.00285*	-0.195***	0.0112	0.0835***
	(0.00188)	(0.00161)	(0.00946)	(0.0124)	(0.00815)
$\ln(p_{Dairy})$x1{O}	-0.000446**	-0.000512*	-0.00443***	-0.00300***	0.00196**
	(0.000219)	(0.000287)	(0.000758)	(0.000761)	(0.000990)
$\ln(p_{Drink})$x1{O}	-0.000246**	0.000249**	-0.000572	-0.00125***	-0.000752
	(0.000115)	(0.000125)	(0.000798)	(0.000465)	(0.000628)
$\ln(p_{Fruit})$x1{O}	-0.000564***	0.000167	-0.00429***	-0.000202	-0.000160
	(0.000203)	(0.000274)	(0.000679)	(0.000491)	(0.00101)
$\ln(p_{Grain})$x1{O}	-0.000310***	-0.00107***	-0.00293***	-0.000641	-0.00113
	(0.000120)	(0.000181)	(0.000680)	(0.000930)	(0.000786)
$\ln(p_{Meat})$x1{O}	-4.38e-05	-0.000646***	0.000283	-0.00108	-0.00453***
	(0.000295)	(0.000248)	(0.000812)	(0.00101)	(0.00108)
$\ln(p_{Oil})$x1{O}	-0.000183	-0.000192	-0.000229	-2.46e-05	8.63e-05
	(0.000139)	(0.000158)	(0.000542)	(0.000319)	(0.000539)
$\ln(p_{Other})$x1{O}	0.00117***	3.84e-05	0.000201	0.000421*	-3.28e-05
	(0.000104)	(8.64e-05)	(0.000180)	(0.000236)	(0.000330)
Linear Time Trend	X	X	X	X	X
Month Indicators	X	X	X	X	X
HH Dem.	X	X	X	X	X
Price Residual	X	X	X	X	X
Gen. Residual	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157

Cluster-bootstrapped standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table B13: Demand Estimates - Online Households

Budget Shares	(6) Other	(7) Sugar	(8) Snacks	(9) Prep.	(10) Veg.
$\ln(p_{Prep})$x1{O}	0.000421*	-7.81e-05	-0.000363	0.00607***	0.000144
	(0.000236)	(0.000237)	(0.00126)	(0.00210)	(0.000707)
$\ln(p_{Snack})$x1{O}	0.000201	0.00112***	0.0144***	-0.000363	-0.00315***
	(0.000180)	(0.000333)	(0.00213)	(0.00126)	(0.00104)
$\ln(p_{Sugar})$x1{O}	3.84e-05	0.000889***	0.00112***	-7.81e-05	2.75e-05
	(8.64e-05)	(0.000218)	(0.000333)	(0.000237)	(0.000204)
$\ln(p_{Veg})$x1{O}	-3.28e-05	2.75e-05	-0.00315***	0.000144	0.00753***
	(0.000330)	(0.000204)	(0.00104)	(0.000707)	(0.00120)
$\ln(\frac{M}{P})$x1{O}	-0.000209	-0.000461**	0.0201***	-0.00256***	-0.00755***
	(0.000179)	(0.000183)	(0.000901)	(0.000869)	(0.000806)
Linear Time Trend	X	X	X	X	X
Month Indicators	X	X	X	X	X
HH Dem.	X	X	X	X	X
Price Residual	X	X	X	X	X
Gen. Residual	X	X	X	X	X
Observations	616,157	616,157	616,157	616,157	616,157

Cluster-bootstrapped standard errors in parentheses
Standard errors clustered at the store-availability level
*** p<0.01, ** p<0.05, * p<0.1

Table B14: Difference in Elasticity Matrices, $\eta_{Instore} - \eta_{Online}$

	Dairy	Drink	Fruit	Grain	Meat	Oil	Other	Prepared	Snacks	Sugars	Vegetables
Dairy	-0.02	4.45	0.22	-0.05	0.02	0.07	0.00	-0.03	-4.15	0.12	0.21
	(0.06)	(4.53)	(0.06)	(0.05)	(0.02)	(0.03)	(0.06)	(0.06)	(0.84)	(0.05)	(0.06)
Drink	0.10	-11.84	0.24	0.06	-0.02	0.00	0.01	0.00	-0.71	0.04	0.19
	(0.02)	(11.88)	(0.05)	(0.02)	(0.01)	(0.02)	(0.08)	(0.01)	(0.42)	(0.04)	(0.05)
Fruit	0.16	8.53	0.04	-0.17	0.03	0.17	0.03	-0.10	-1.54	0.23	-0.23
	(0.05)	(8.42)	(0.11)	(0.07)	(0.03)	(0.07)	(0.02)	(0.11)	(1.09)	(0.14)	(0.08)
Grain	-0.04	1.78	-0.16	0.29	0.02	0.10	0.03	-0.05	0.05	-0.04	-0.07
	(0.03)	(1.98)	(0.06)	(0.11)	(0.02)	(0.06)	(0.06)	(0.06)	(0.35)	(0.11)	(0.04)
Meat	0.05	-4.69	0.14	0.08	-0.14	-0.08	-0.06	0.01	1.87	0.01	-0.10
	(0.06)	(5.30)	(0.15)	(0.08)	(0.05)	(0.06)	(0.17)	(0.03)	(1.68)	(0.06)	(0.13)
Oil	0.04	-0.48	0.14	0.09	-0.01	0.09	0.01	-0.03	-1.05	-0.09	-0.04
	(0.02)	(0.74)	(0.05)	(0.05)	(0.01)	(0.07)	(0.01)	(0.04)	(0.44)	(0.08)	(0.03)
Other	0.03	1.43	0.00	-0.03	0.02	0.00	-0.06	0.00	-0.68	-0.05	-0.04
	(0.01)	(1.53)	(0.03)	(0.02)	(0.01)	(0.02)	(0.04)	(0.01)	(0.28)	(0.04)	(0.02)
Prepared	-0.15	-1.50	-0.41	-0.25	0.01	-0.16	-0.05	0.12	1.43	-0.14	0.09
	(0.06)	(2.06)	(0.11)	(0.07)	(0.02)	(0.07)	(0.07)	(0.20)	(0.88)	(0.11)	(0.07)
Snacks	-0.37	-3.40	-0.16	0.05	0.03	-0.16	0.06	0.04	4.41	-0.11	-0.11
	(0.07)	(3.61)	(0.14)	(0.05)	(0.04)	(0.06)	(0.17)	(0.06)	(1.63)	(0.07)	(0.12)
Sugars	0.03	0.65	0.10	-0.03	0.00	-0.05	0.01	-0.01	-0.17	0.08	-0.02
	(0.01)	(0.69)	(0.03)	(0.04)	(0.01)	(0.03)	(0.04)	(0.02)	(0.21)	(0.08)	(0.02)
Vegetables	0.12	5.48	-0.18	-0.06	0.01	-0.04	0.01	0.02	0.57	-0.05	0.05
	(0.04)	(5.55)	(0.06)	(0.04)	(0.02)	(0.03)	(0.05)	(0.02)	(0.54)	(0.03)	(0.05)

Cluster-bootstrapped standard errors reported in parentheses
Standard errors clustered at the store-availability level

Figure B3: Budget Allocation & Prices

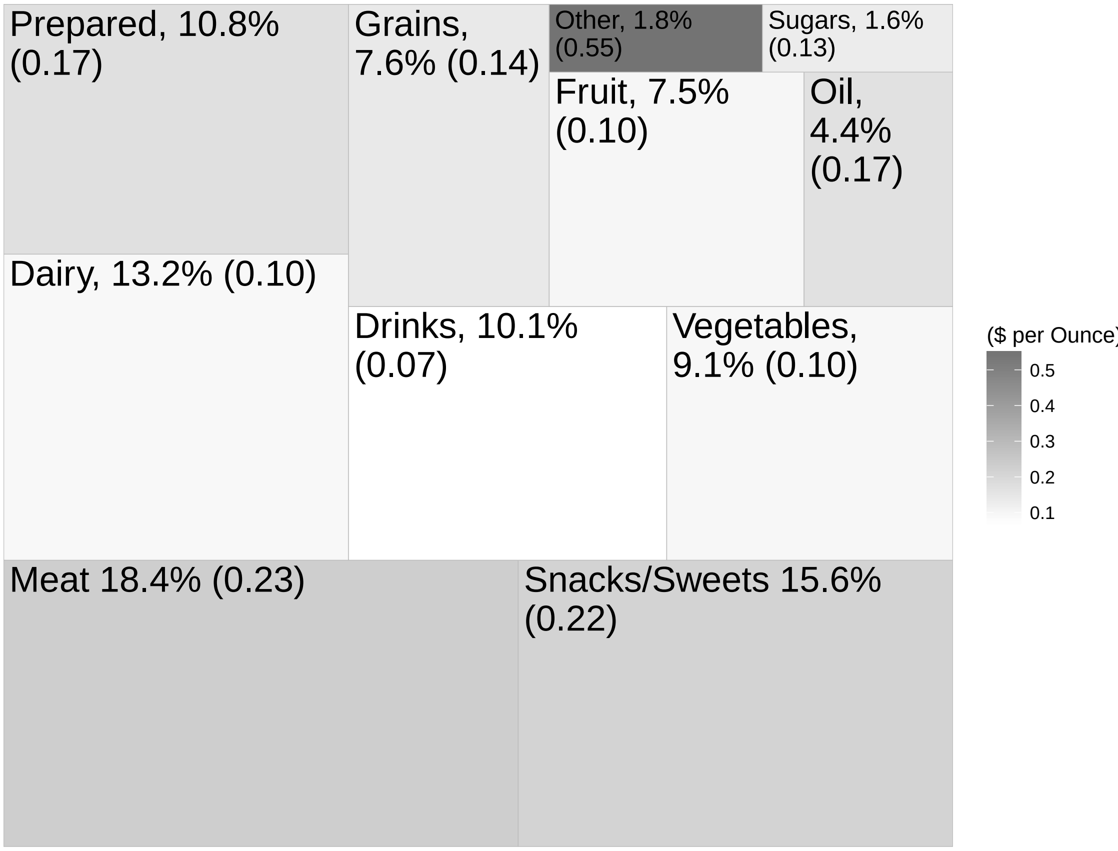

Figure B3 presents the average budget allocation, of the online households, in the six months before the online service was ever available to any household (i.e. before March 2015). The size of each box corresponds to the average budget share amount and the shade of the each box corresponds to how expensive the product category is in terms of price per ounce. Darker shade indicate more expensive product categories and lighter shades represent less expensive product categories.

APPENDIX C

CHAPTER 3 APPENDIX

Figure C1: Proportion of Households Using SNAP Benefits

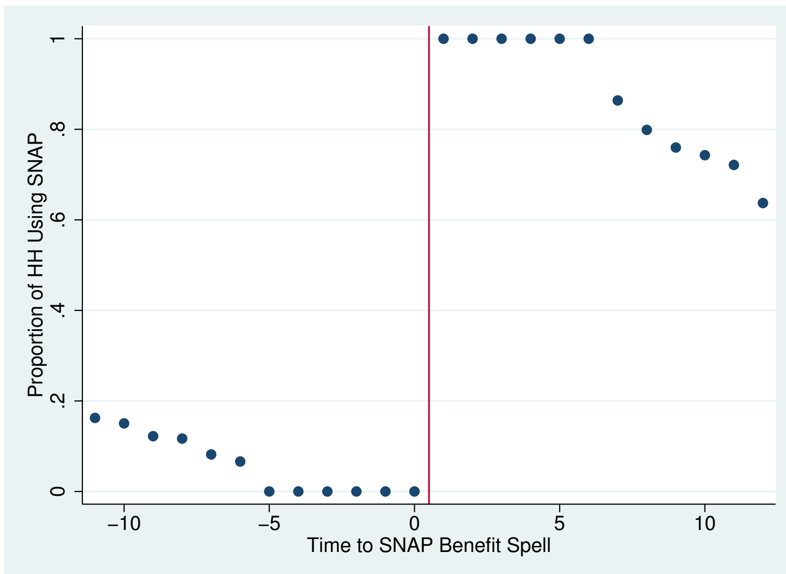

Figure C2: Tender Composition Around SNAP Adoption - Event Study Estimates

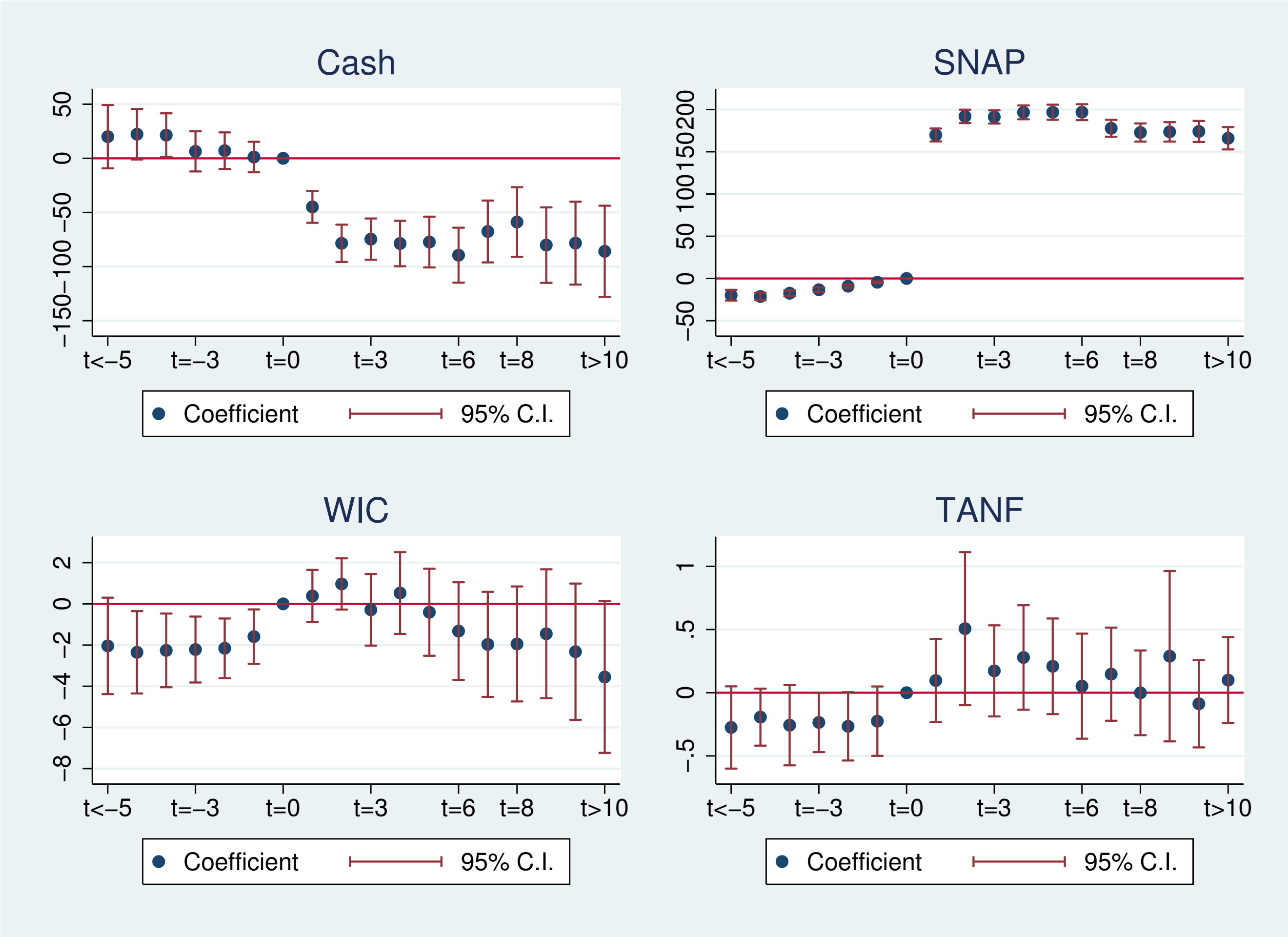

Figure C3: Purchases by SNAP Eligibility Around SNAP Adoption - Event Study Estimates

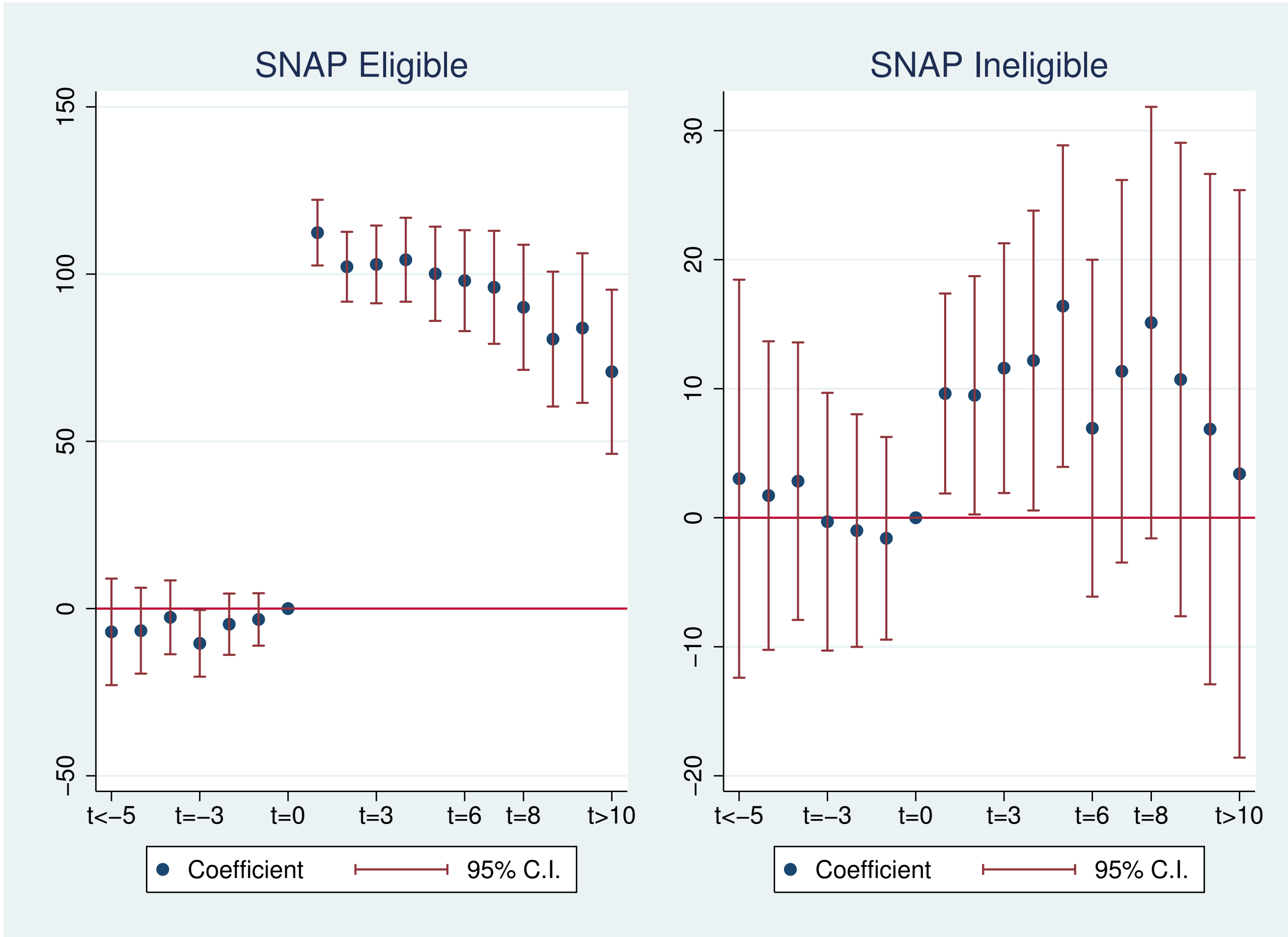

Figure C4: Store Brand Share of Sales - Event Study Estimates

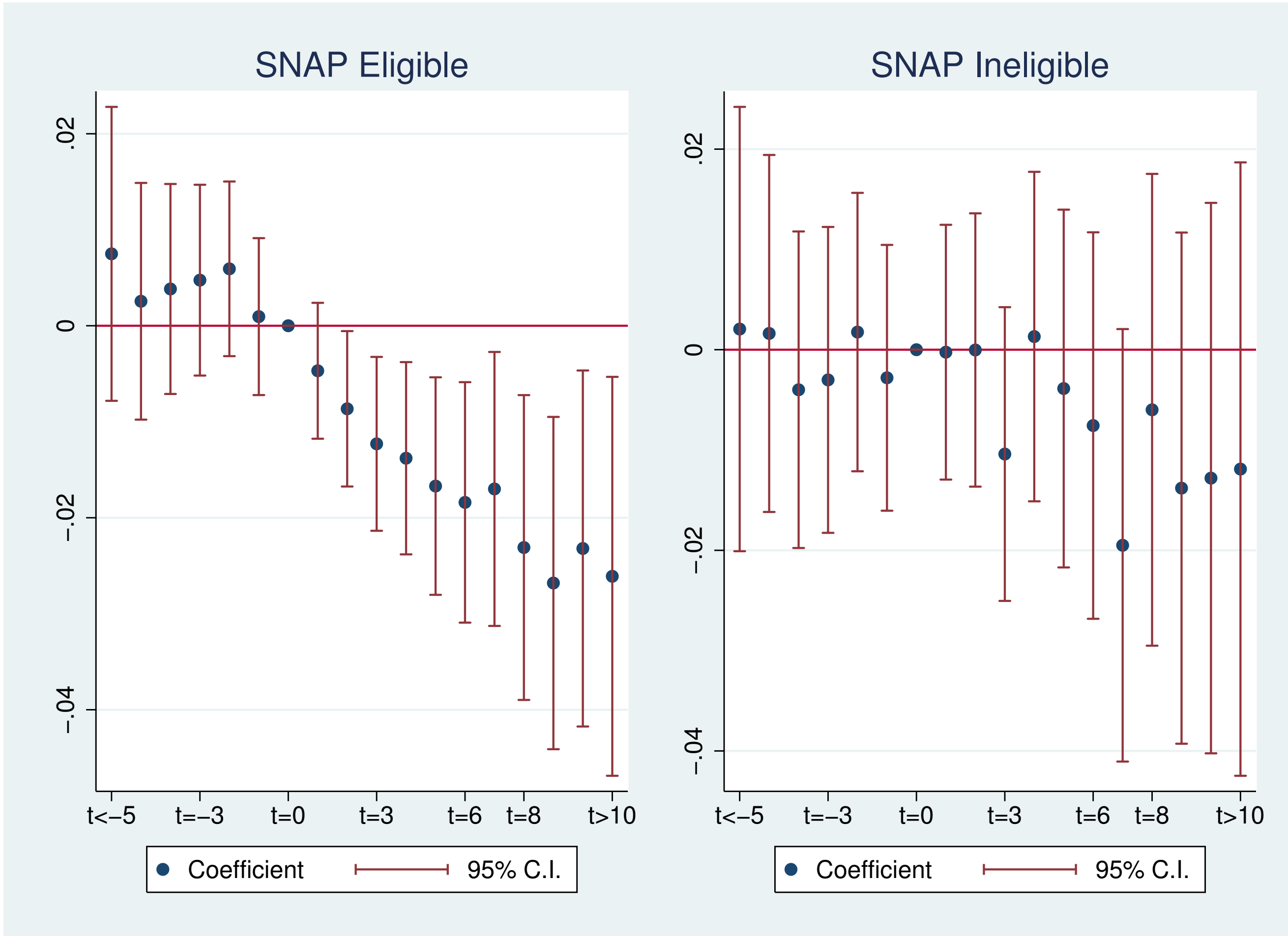

Figure C5: Grocery Purchases Around SNAP Adoption - Event Study Estimates

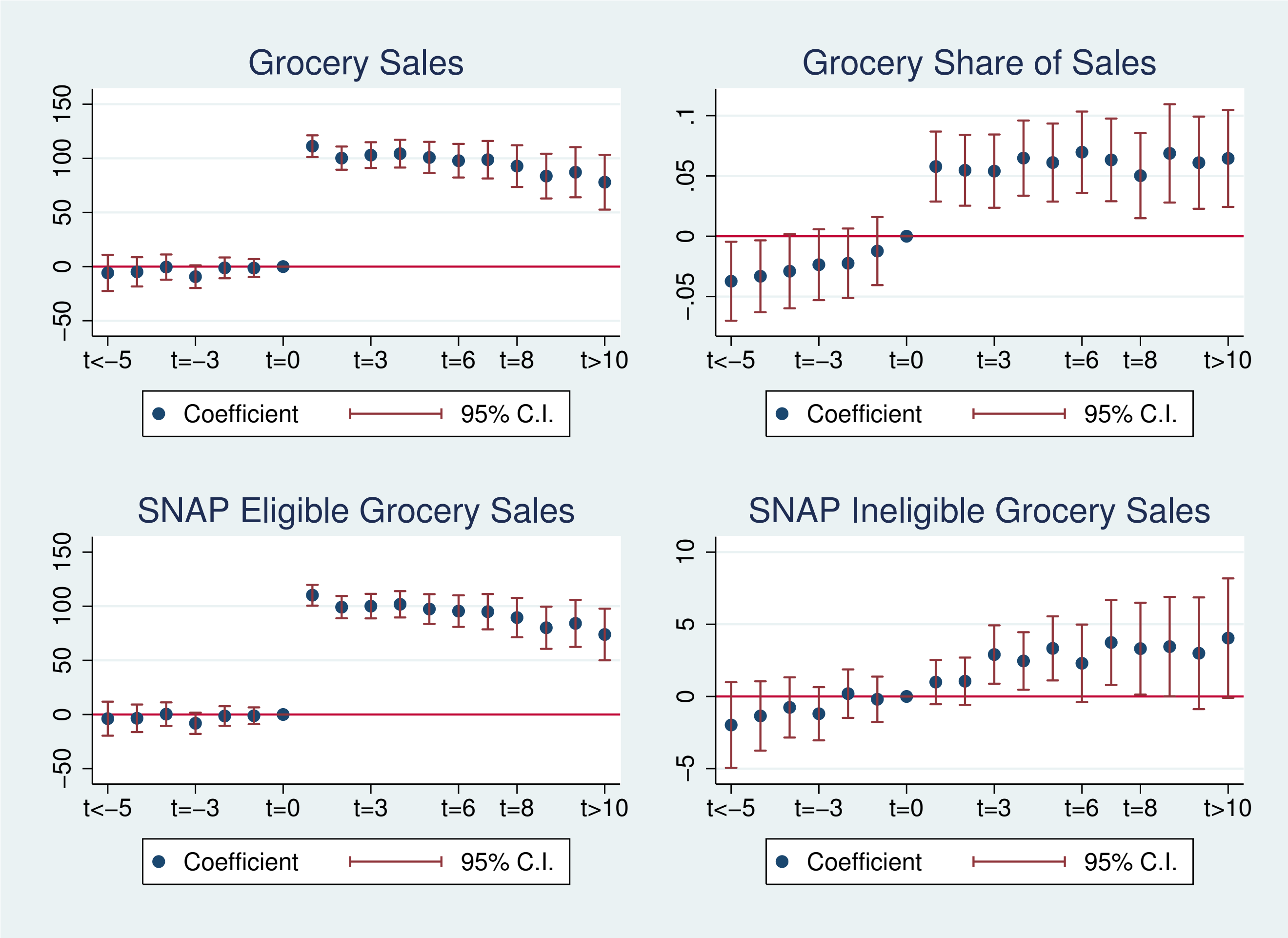

Figure C6: Grocery Budget Shares by Product Category Around SNAP Adoption - Event Study Estimates

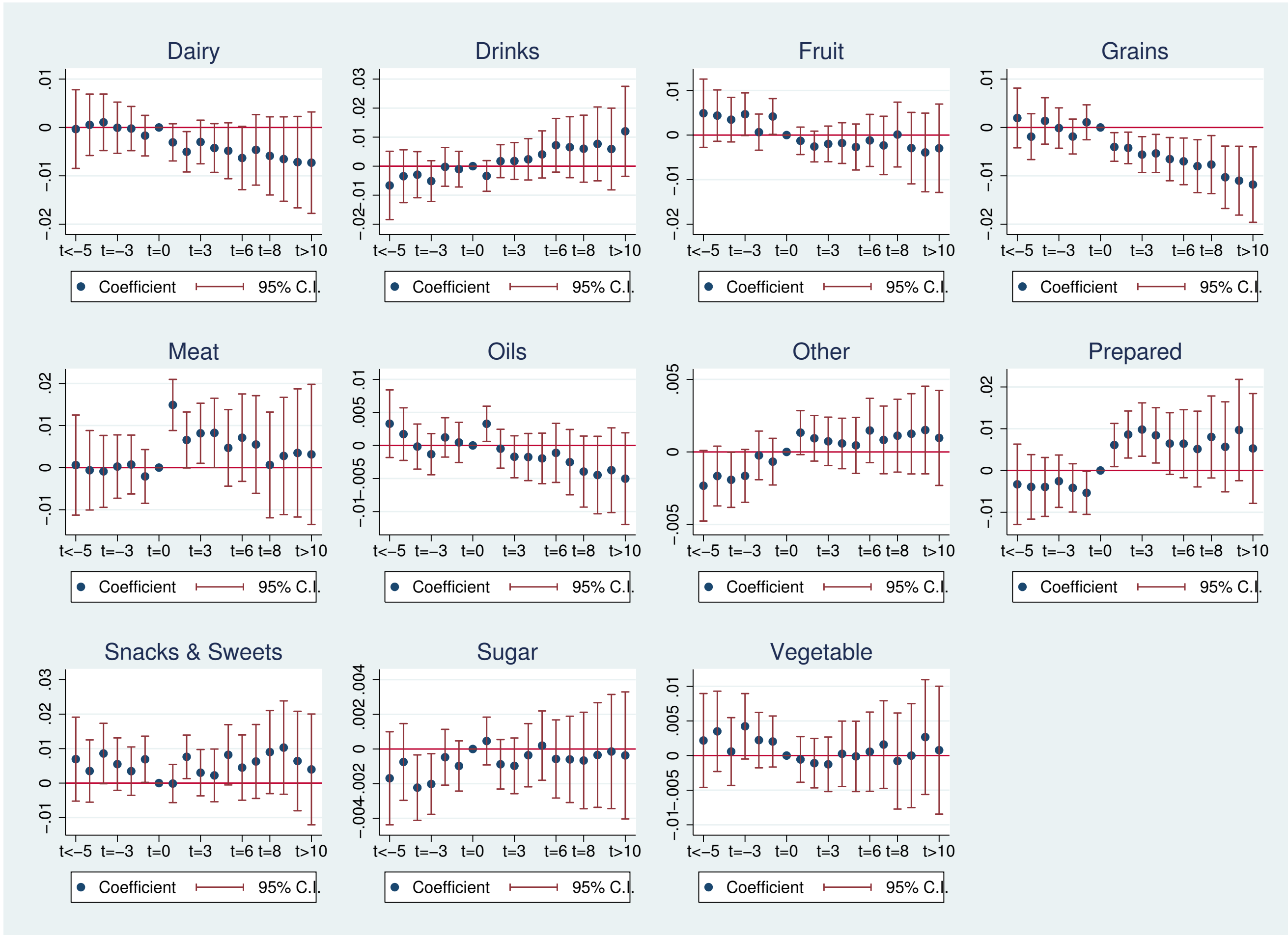

Figure C7: Baby Sales Around SNAP Adoption - Event Study Estimates

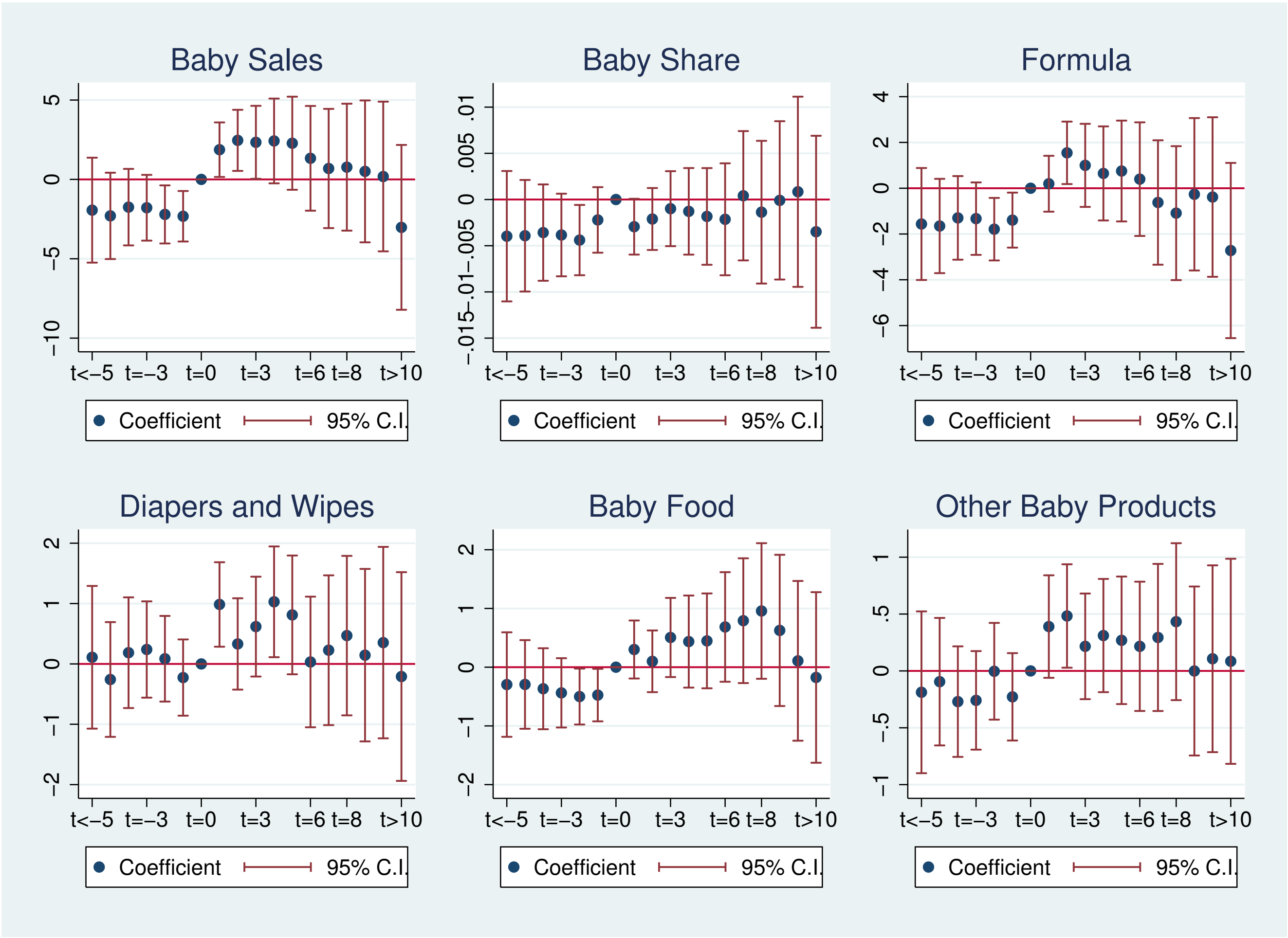

Figure C8: Vice Sales Around SNAP Adoption - Event Study Estimates

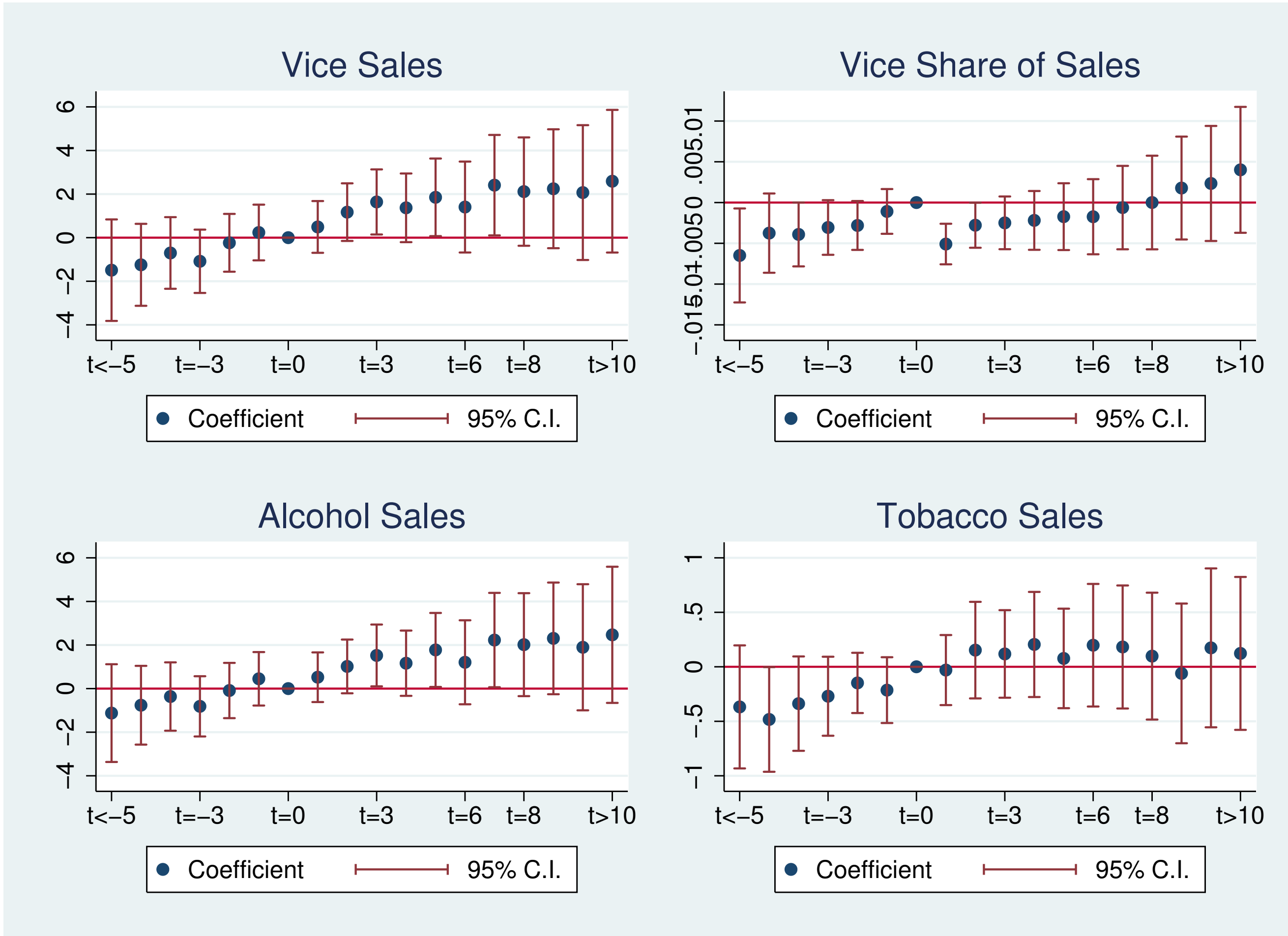

Table C1: Comparison of Tender Composition and Supermarket Purchases - Before and After SNAP Adoption

Tender Composition ($)	Pre-SNAP Adoption	Post-SNAP Adoption	Difference	|t-stat| Difference
Cash	512.24	459.41	-52.82	8.94
	(4.26)	(4.09)	(5.91)	
SNAP	0.00	173.73	173.73	120.09
	(0.00)	(1.45)	(1.45)	
TANF	0.09	0.49	0.40	4.74
	(0.03)	(0.08)	(0.08)	
WIC	6.04	9.23	3.19	6.81
	(0.29)	(0.37)	(0.47)	
Monthly Purchases ($)	**Pre-SNAP Adoption**	**Post-SNAP Adoption**	**Difference**	**|t-stat| Difference**
SNAP Eligible	288.65	394.54	105.90	29.49
	(2.41)	(2.66)	(3.59)	
SNAP Ineligible	152.62	169.59	16.96	6.91
	(1.68)	(1.79)	(2.45)	
Observations	10,524	10,524		

Standard errors in parenthesis

Table C2: Share of Sales Generated from Store Brand Products - Before and After SNAP Adoption

Store Brand Share	Pre-SNAP Adoption	Post-SNAP Adoption	Difference	|t-stat| Difference
SNAP Eligible Products	0.33	0.32	-0.01	6.26
	(0.00)	(0.00)	(0.00)	
	[10,324]	[10,524]		
SNAP Ineligible Products	0.17	0.17	0.00	0.37
	(0.00)	(0.00)	(0.00)	
	[10,432]	[10,521]		

Standard errors in parenthesis
Number of observations in brackets

Table C3: Grocery Purchases - Before and After SNAP Adoption

Grocery Purchases	Pre-SNAP Adoption	Post-SNAP Adoption	Difference	|t-stat| Difference
Grocery Share of Total Expenditure	0.61	0.66	0.06	16.36
	(0.00)	(0.00)	(0.00)	
Grocery Sales ($)	305.09	402.62	97.53	26.45
	(2.50)	(2.70)	(3.69)	
SNAP Eligible Grocery Sales ($)	285.32	381.65	96.33	27.68
	(2.35)	(2.56)	(3.48)	
SNAP Ineligible Grocery Sales ($)	19.76	20.97	1.20	2.34
	(0.36)	(0.37)	(0.51)	
Grocery Purchases ($) by Product Category	**Pre-SNAP Adoption**	**Post-SNAP Adoption**	**Difference**	**|t-stat| Difference**
Dairy	32.04	40.87	8.83	19.24
	(0.31)	(0.34)	(0.46)	
Drinks	32.88	44.87	11.99	23.88
	(0.34)	(0.37)	(0.50)	
Fruit	19.30	24.58	5.28	15.11
	(0.23)	(0.26)	(0.35)	
Grains	21.28	27.53	6.25	20.34
	(0.21)	(0.23)	(0.31)	
Meat	58.54	78.68	20.15	23.20
	(0.58)	(0.65)	(0.87)	
Oil	12.02	16.17	4.14	20.64
	(0.13)	(0.15)	(0.20)	
Other	3.92	5.50	1.58	15.34
	(0.07)	(0.08)	(0.10)	
Prepared	32.62	46.20	13.58	25.80
	(0.34)	(0.40)	(0.53)	
Snacks & Sweets	44.62	60.19	15.58	23.88
	(0.44)	(0.48)	(0.65)	
Sugars	4.30	5.45	1.15	11.52
	(0.07)	(0.07)	(0.10)	
Vegetables	23.02	29.86	6.84	18.54
	(0.25)	(0.27)	(0.37)	
Observations	10,325	10,522		

Standard errors in parenthesis

Table C4: Grocery Budget Composition - Before and After SNAP Adoption

Grocery Exp. Share by Product Category	Pre-SNAP Adoption	Post-SNAP Adoption	Difference	|t-stat| Difference
Dairy	0.104	0.101	-0.003	2.96
	(0.001)	(0.001)	(0.001)	
Drinks	0.117	0.116	0.000	0.24
	(0.001)	(0.001)	(0.001)	
Fruit	0.064	0.061	-0.003	3.70
	(0.001)	(0.001)	(0.001)	
Grains	0.070	0.069	-0.002	2.32
	(0.001)	(0.000)	(0.001)	
Meat	0.183	0.190	0.008	5.07
	(0.001)	(0.001)	(0.002)	
Oil	0.038	0.040	0.002	3.13
	(0.000)	(0.000)	(0.001)	
Other	0.012	0.013	0.001	4.10
	(0.000)	(0.000)	(0.000)	
Prepared	0.106	0.116	0.010	8.35
	(0.001)	(0.001)	(0.001)	
Snacks & Sweets	0.153	0.153	0.001	0.37
	(0.001)	(0.001)	(0.001)	
Sugars	0.013	0.013	0.000	0.39
	(0.000)	(0.000)	(0.000)	
Vegetables	0.075	0.074	-0.002	1.82
	(0.001)	(0.001)	(0.001)	
Observations	10,325	10,522		

Standard errors in parenthesis

Table C5: Purchases over Baby Products - Before and After SNAP Adoption

Baby Purchases	Pre-SNAP Adoption	Post-SNAP Adoption	Difference	|t-stat| Difference
Baby Share of Total Sales	0.02	0.03	0.00	2.49
	(0.00)	(0.00)	(0.00)	
Baby Sales ($)	13.35	19.02	5.67	8.60
	(0.41)	(0.52)	(0.66)	
Diapers and Wipes ($)	4.96	6.25	1.29	5.86
	(0.15)	(0.16)	(0.22)	
Baby Food ($)	2.08	3.21	1.13	6.47
	(0.11)	(0.14)	(0.17)	
Baby Formula ($)	5.06	7.92	2.86	6.38
	(0.27)	(0.36)	(0.45)	
Baby Products ($)	1.25	1.64	0.39	4.46
	(0.06)	(0.07)	(0.09)	
Observations	10,524	10,524		
Standard errors in parenthesis				

Table C6: Purchases over Alcohol and Tobacco Products - Before and After SNAP Adoption

Vice Purchases	Pre-SNAP Adoption	Post-SNAP Adoption	Difference	|t-stat| Difference
Vice Share of Total Sales	0.03	0.02	0.00	6.02
	(0.00)	(0.00)	(0.00)	
Vice Purchases ($)	13.91	14.74	0.83	2.00
	(0.29)	(0.30)	(0.41)	
Alcohol Purchases ($)	13.12	13.79	0.67	1.70
	(0.28)	(0.28)	(0.40)	
Tobacco ($)	0.79	0.95	0.15	1.64
	(0.07)	(0.07)	(0.09)	
Observations	10,524	10,524		
Standard errors in parenthesis				

Table C7: Product Category Key

Product Category	Description
Dairy	Milk & Milk Substitutes, Cheese, Yogurt, Cream Cheese
Drinks	Non-Alcoholic Beverages, Water, Soda, Juice
Fruit	Fresh, Dried and Frozen Fruits
Grains	Rice, Pasta, Bread, Cereal, Oatmeal
Meat	Beef, Poultry, Seafood, Eggs, Beans, Legumes
Oils	Butter, Mayonnaise, Salad Dressings, Vegetable Oils
Other	Flour, Gravy, Seasonings, Baking Items
Prepared	Rice Mixed Dishes, Pizza, Macaroni, Soups
Snacks and Sweets	Chips, Crackers, Granola Bars, Cakes, Candy, Ice Cream
Sugar	Sugar, Honey, Jams, Syrups
Vegetables	Fresh & Frozen Vegetables

Table courtesy of Harris (2019)

Table C8: Tender Composition - Event Study Estimates

Tender Outcome ($)	Cash Tender			SNAP Tender		
	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	-7.904	-8.960	6.424	-1.410***	-0.782*	-13.34***
	(8.202)	(8.270)	(9.466)	(0.438)	(0.441)	(1.379)
1{t=-2}	-3.277	-3.149	7.070	-1.109***	-0.802**	-9.175***
	(7.667)	(7.725)	(8.629)	(0.303)	(0.330)	(0.944)
1{t=-1}	-4.031	-3.916	1.209	-0.517***	-0.274	-4.474***
	(6.921)	(6.918)	(7.190)	(0.180)	(0.229)	(0.505)
1{t=1}	-38.88***	-39.56***	-44.89***	165.8***	165.7***	169.9***
	(7.187)	(7.187)	(7.491)	(3.764)	(3.760)	(3.912)
1{t=2}	-68.53***	-67.82***	-78.51***	183.3***	183.6***	191.9***
	(8.108)	(8.120)	(8.788)	(3.776)	(3.786)	(4.048)
1{t=3}	-60.72***	-59.20***	-74.64***	178.4***	178.7***	191.2***
	(8.413)	(8.461)	(9.727)	(3.535)	(3.542)	(3.991)
1{t=4}	-60.22***	-58.68***	-78.72***	179.4***	180.1***	196.7***
	(9.033)	(9.108)	(10.72)	(3.532)	(3.562)	(4.178)
1{t=5}	-53.83***	-52.37***	-77.34***	175.2***	176.0***	196.8***
	(9.547)	(9.662)	(11.97)	(3.642)	(3.687)	(4.571)
1{t=6}	-59.90***	-59.64***	-89.48***	171.2***	171.9***	196.9***
	(9.726)	(9.796)	(12.95)	(3.649)	(3.688)	(4.801)
1{t=7}	-34.63***	-33.15***	-67.58***	147.7***	148.6***	177.8***
	(10.53)	(10.62)	(14.58)	(3.642)	(3.680)	(5.121)
1{t=8}	-15.48	-14.76	-58.82***	138.8***	139.6***	172.8***
	(11.29)	(11.41)	(16.39)	(3.766)	(3.839)	(5.495)
1{t=9}	-29.46**	-27.95**	-80.17***	135.4***	136.1***	173.6***
	(12.23)	(12.40)	(17.79)	(3.911)	(3.997)	(5.871)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,511	39,511	39,511	39,511	39,511	39,511
R-squared	0.025	0.030	0.717	0.330	0.330	0.513

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C9: Tender Composition - Event Study Estimates

Tender Outcome ($)	WIC Tender			TANF Tender		
	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	-2.609***	-2.628***	-2.217***	-0.213*	-0.220**	-0.235*
	(0.711)	(0.716)	(0.817)	(0.109)	(0.107)	(0.120)
1{t=-2}	-2.394***	-2.438***	-2.158***	-0.256**	-0.258**	-0.266*
	(0.673)	(0.680)	(0.739)	(0.127)	(0.125)	(0.138)
1{t=-1}	-1.721***	-1.736***	-1.590**	-0.221*	-0.219*	-0.225
	(0.658)	(0.659)	(0.675)	(0.133)	(0.132)	(0.140)
1{t=1}	0.515	0.518	0.383	0.0850	0.0922	0.0965
	(0.625)	(0.627)	(0.647)	(0.169)	(0.169)	(0.168)
1{t=2}	1.236**	1.253**	0.968	0.488	0.502	0.507
	(0.584)	(0.582)	(0.635)	(0.312)	(0.312)	(0.309)
1{t=3}	0.197	0.147	-0.287	0.144	0.166	0.173
	(0.779)	(0.784)	(0.887)	(0.199)	(0.197)	(0.184)
1{t=4}	1.128	1.126	0.527	0.248	0.271	0.279
	(0.888)	(0.891)	(1.014)	(0.220)	(0.217)	(0.211)
1{t=5}	0.344	0.366	-0.407	0.213	0.199	0.209
	(0.888)	(0.890)	(1.079)	(0.221)	(0.220)	(0.193)
1{t=6}	-0.466	-0.401	-1.322	0.0604	0.0384	0.0519
	(0.945)	(0.955)	(1.210)	(0.234)	(0.231)	(0.212)
1{t=7}	-1.029	-0.901	-1.968	0.143	0.131	0.147
	(0.989)	(0.990)	(1.302)	(0.181)	(0.180)	(0.188)
1{t=8}	-0.897	-0.720	-1.946	0.00746	-0.00968	-0.000843
	(1.046)	(1.054)	(1.425)	(0.191)	(0.189)	(0.171)
1{t=9}	-0.330	-0.192	-1.451	0.301	0.281	0.289
	(1.185)	(1.193)	(1.598)	(0.363)	(0.342)	(0.344)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,511	39,511	39,511	39,511	39,511	39,511
R-squared	0.016	0.017	0.483	0.002	0.003	0.163

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C10: Sales by SNAP Eligibility - Event Study Estimates

Sales by SNAP Eligibility	SNAP Eligible Purchases (1)	(2)	(3)	SNAP Ineligible Purchases (1)	(2)	(3)
1{t=-3}	-9.975**	-9.779**	-10.40**	-3.165	-3.749	-0.309
	(4.506)	(4.535)	(5.086)	(4.308)	(4.334)	(5.096)
1{t=-2}	-4.756	-4.226	-4.673	-3.043	-3.320	-0.998
	(4.294)	(4.327)	(4.673)	(4.054)	(4.067)	(4.599)
1{t=-1}	-3.342	-3.032	-3.254	-2.641	-2.770	-1.596
	(3.874)	(3.873)	(4.003)	(3.865)	(3.858)	(4.007)
1{t=1}	112.6***	112.3***	112.4***	11.22***	10.84***	9.626**
	(4.797)	(4.797)	(5.009)	(3.775)	(3.769)	(3.953)
1{t=2}	101.2***	102.0***	102.2***	11.90***	11.95***	9.486**
	(4.968)	(4.989)	(5.327)	(4.263)	(4.261)	(4.711)
1{t=3}	101.2***	102.3***	102.9***	14.77***	15.14***	11.59**
	(5.173)	(5.222)	(5.929)	(4.175)	(4.183)	(4.937)
1{t=4}	101.7***	103.4***	104.3***	16.31***	16.74***	12.18**
	(5.495)	(5.551)	(6.403)	(4.767)	(4.791)	(5.928)
1{t=5}	96.88***	98.80***	100.1***	21.87***	22.09***	16.40***
	(5.851)	(5.928)	(7.184)	(4.702)	(4.739)	(6.358)
1{t=6}	95.19***	96.32***	98.05***	13.91***	13.72***	6.936
	(6.122)	(6.183)	(7.696)	(4.474)	(4.504)	(6.661)
1{t=7}	92.18***	93.71***	96.05***	18.84***	19.12***	11.35
	(6.434)	(6.486)	(8.622)	(4.753)	(4.791)	(7.562)
1{t=8}	88.62***	89.92***	90.08***	25.55***	25.44***	15.12*
	(7.053)	(7.135)	(9.542)	(4.955)	(5.018)	(8.530)
1{t=9}	79.93***	81.49***	80.57***	22.71***	22.96***	10.71
	(7.507)	(7.617)	(10.29)	(5.306)	(5.375)	(9.360)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,511	39,511	39,511	39,511	39,511	39,511
R-squared	0.050	0.054	0.705	0.035	0.038	0.537

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C11: Summary of Store Brand Expenditure Shares - Event Study Estimates

Store Brand	SNAP Eligible Products			SNAP Ineligible Products		
Share	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	0.000172	-0.000203	0.00475	-0.00451	-0.00440	-0.00301
	(0.00429)	(0.00431)	(0.00507)	(0.00669)	(0.00671)	(0.00778)
1{t=-2}	0.00281	0.00258	0.00593	-0.000166	0.000589	0.00176
	(0.00417)	(0.00420)	(0.00464)	(0.00658)	(0.00658)	(0.00708)
1{t=-1}	-0.000430	-0.000549	0.000953	-0.00387	-0.00324	-0.00280
	(0.00401)	(0.00402)	(0.00417)	(0.00652)	(0.00653)	(0.00676)
1{t=1}	-0.00366	-0.00342	-0.00469	0.000386	0.000654	-0.000247
	(0.00339)	(0.00341)	(0.00361)	(0.00617)	(0.00618)	(0.00648)
1{t=2}	-0.00598	-0.00588	-0.00865**	0.000836	0.00150	-2.64e-05
	(0.00367)	(0.00369)	(0.00413)	(0.00627)	(0.00631)	(0.00695)
1{t=3}	-0.00806**	-0.00796**	-0.0123***	-0.00872	-0.00826	-0.0104
	(0.00374)	(0.00377)	(0.00462)	(0.00630)	(0.00634)	(0.00747)
1{t=4}	-0.00770**	-0.00790**	-0.0138***	0.00343	0.00418	0.00131
	(0.00374)	(0.00377)	(0.00511)	(0.00662)	(0.00662)	(0.00838)
1{t=5}	-0.00904**	-0.00935**	-0.0167***	-0.00111	-0.000358	-0.00387
	(0.00390)	(0.00393)	(0.00578)	(0.00648)	(0.00649)	(0.00910)
1{t=6}	-0.00914**	-0.00947**	-0.0184***	-0.00316	-0.00337	-0.00756
	(0.00386)	(0.00390)	(0.00639)	(0.00634)	(0.00638)	(0.00983)
1{t=7}	-0.00600	-0.00664	-0.0170**	-0.0145**	-0.0146**	-0.0195*
	(0.00427)	(0.00430)	(0.00728)	(0.00648)	(0.00650)	(0.0110)
1{t=8}	-0.0109**	-0.0114***	-0.0231***	-0.00108	-0.00108	-0.00599
	(0.00433)	(0.00437)	(0.00810)	(0.00652)	(0.00654)	(0.0120)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,075	39,075	39,075	39,306	39,306	39,306
R-squared	0.010	0.011	0.358	0.003	0.005	0.153

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C12: Summary of Grocery Purchases - Event Study Estimates

	Grocery Share of Total Expenditure			Grocery Sales		
	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	-0.0137	-0.0132	-0.0236	-7.345	-6.897	-9.327*
	(0.0142)	(0.0145)	(0.0150)	(4.773)	(4.803)	(5.351)
1{t=-2}	-0.0158	-0.0155	-0.0224	0.725	1.464	-1.204
	(0.0141)	(0.0144)	(0.0147)	(4.581)	(4.621)	(4.908)
1{t=-1}	-0.00950	-0.00921	-0.0123	-1.084	-0.672	-1.389
	(0.0140)	(0.0142)	(0.0144)	(4.149)	(4.148)	(4.222)
1{t=1}	0.0532***	0.0535***	0.0578***	108.1***	107.8***	111.2***
	(0.0142)	(0.0143)	(0.0148)	(4.958)	(4.958)	(5.133)
1{t=2}	0.0463***	0.0467***	0.0547***	95.68***	96.47***	100.2***
	(0.0143)	(0.0143)	(0.0150)	(5.119)	(5.144)	(5.469)
1{t=3}	0.0420***	0.0424***	0.0540***	97.60***	98.71***	103.0***
	(0.0145)	(0.0145)	(0.0155)	(5.329)	(5.378)	(6.074)
1{t=4}	0.0487***	0.0494***	0.0648***	97.50***	99.08***	104.3***
	(0.0144)	(0.0145)	(0.0159)	(5.604)	(5.665)	(6.537)
1{t=5}	0.0410***	0.0418***	0.0611***	93.04***	94.88***	100.8***
	(0.0145)	(0.0146)	(0.0165)	(5.950)	(6.027)	(7.355)
1{t=6}	0.0464***	0.0468***	0.0697***	90.43***	91.40***	97.82***
	(0.0144)	(0.0148)	(0.0172)	(6.263)	(6.325)	(7.922)
1{t=7}	0.0378***	0.0370**	0.0633***	90.88***	92.23***	98.72***
	(0.0145)	(0.0146)	(0.0175)	(6.596)	(6.649)	(8.832)
1{t=8}	0.0202	0.0196	0.0502***	87.49***	88.53***	92.83***
	(0.0145)	(0.0144)	(0.0180)	(7.218)	(7.295)	(9.837)
1{t=9}	0.0350**	0.0342**	0.0687***	79.22***	80.52***	83.60***
	(0.0175)	(0.0172)	(0.0208)	(7.624)	(7.743)	(10.54)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,069	39,069	39,069	39,069	39,069	39,069
R-squared	0.018	0.020	0.256	0.045	0.049	0.712

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C13: Summary of Grocery Purchases - Event Study Estimates

	SNAP Eligible Grocery Sales			SNAP Ineligible Grocery Sales		
	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	-6.725	-6.364	-8.128	-0.621	-0.533	-1.199
	(4.493)	(4.523)	(5.017)	(0.786)	(0.786)	(0.940)
1{t=-2}	0.0738	0.780	-1.397	0.651	0.684	0.193
	(4.323)	(4.361)	(4.616)	(0.749)	(0.751)	(0.857)
1{t=-1}	-1.089	-0.652	-1.191	0.00554	-0.0198	-0.198
	(3.893)	(3.892)	(3.958)	(0.771)	(0.767)	(0.802)
1{t=1}	107.5***	107.2***	110.2***	0.574	0.580	0.994
	(4.748)	(4.746)	(4.916)	(0.756)	(0.759)	(0.782)
1{t=2}	95.29***	96.01***	99.17***	0.387	0.456	1.055
	(4.917)	(4.938)	(5.251)	(0.765)	(0.768)	(0.836)
1{t=3}	95.59***	96.60***	100.1***	2.016**	2.106**	2.904***
	(5.069)	(5.116)	(5.778)	(0.931)	(0.935)	(1.031)
1{t=4}	96.16***	97.64***	101.8***	1.343	1.434*	2.459**
	(5.342)	(5.394)	(6.210)	(0.849)	(0.856)	(1.017)
1{t=5}	91.04***	92.79***	97.42***	2.000**	2.092**	3.330***
	(5.697)	(5.771)	(7.008)	(0.864)	(0.870)	(1.133)
1{t=6}	89.61***	90.55***	95.53***	0.827	0.858	2.297*
	(5.942)	(5.998)	(7.452)	(0.968)	(0.972)	(1.370)
1{t=7}	88.87***	90.10***	94.98***	2.005*	2.138**	3.738**
	(6.218)	(6.269)	(8.326)	(1.064)	(1.067)	(1.501)
1{t=8}	85.82***	86.74***	89.52***	1.670	1.792*	3.312**
	(6.860)	(6.936)	(9.266)	(1.050)	(1.054)	(1.623)
1{t=9}	77.51***	78.69***	80.15***	1.709	1.832	3.453**
	(7.239)	(7.345)	(9.949)	(1.121)	(1.137)	(1.757)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,069	39,069	39,069	39,069	39,069	39,069
R-squared	0.046	0.050	0.707	0.015	0.016	0.580

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C14: Summary of Grocery Budget Shares - Event Study Estimates

Grocery Shares	Dairy Budget Share (1)	(2)	(3)	Drink Budget Share (1)	(2)	(3)
1{t=-3}	-0.00240	-0.00247	-5.68e-05	-0.00220	-0.00213	-0.00514
	(0.00229)	(0.00230)	(0.00270)	(0.00297)	(0.00297)	(0.00358)
1{t=-2}	-0.00182	-0.00177	-0.000229	0.00142	0.00157	-0.000242
	(0.00208)	(0.00210)	(0.00233)	(0.00304)	(0.00306)	(0.00341)
1{t=-1}	-0.00255	-0.00247	-0.00169	-0.000229	-0.000134	-0.00104
	(0.00203)	(0.00204)	(0.00214)	(0.00302)	(0.00302)	(0.00313)
1{t=1}	-0.00247	-0.00234	-0.00308	-0.00388	-0.00367	-0.00337
	(0.00188)	(0.00189)	(0.00196)	(0.00260)	(0.00262)	(0.00270)
1{t=2}	-0.00362*	-0.00352*	-0.00503**	0.000437	0.000536	0.00172
	(0.00193)	(0.00194)	(0.00213)	(0.00261)	(0.00262)	(0.00290)
1{t=3}	-0.000986	-0.000763	-0.00300	-0.000230	-0.000375	0.00177
	(0.00191)	(0.00194)	(0.00230)	(0.00269)	(0.00270)	(0.00324)
1{t=4}	-0.00129	-0.00116	-0.00425*	-0.000692	-0.000722	0.00235
	(0.00194)	(0.00196)	(0.00257)	(0.00271)	(0.00272)	(0.00363)
1{t=5}	-0.00103	-0.000956	-0.00482	6.11e-05	2.88e-05	0.00404
	(0.00210)	(0.00211)	(0.00295)	(0.00280)	(0.00280)	(0.00414)
1{t=6}	-0.00198	-0.00173	-0.00631*	0.00250	0.00222	0.00719
	(0.00210)	(0.00212)	(0.00334)	(0.00305)	(0.00305)	(0.00471)
1{t=7}	0.000400	0.000725	-0.00463	0.000922	0.000636	0.00654
	(0.00223)	(0.00224)	(0.00372)	(0.00309)	(0.00310)	(0.00536)
1{t=8}	5.83e-05	0.000349	-0.00588	-5.16e-05	-0.000354	0.00601
	(0.00228)	(0.00230)	(0.00412)	(0.00313)	(0.00314)	(0.00589)
HH Dem.	X	X		X	X	
Yr.-Mo. f.e.		X	X		X	X
HH f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Obs.	39,069	39,069	39,069	39,069	39,069	39,069
R-squared	0.009	0.010	0.316	0.008	0.009	0.318

Robust standard errors in parenthesis

Standard errors clustered at the household level

Table C15: Summary of Grocery Budget Shares - Event Study Estimates

Grocery Shares	Fruits Budget Share (1)	Fruits Budget Share (2)	Fruits Budget Share (3)	Grains Budget Share (1)	Grains Budget Share (2)	Grains Budget Share (3)
1{t=-3}	0.00343*	0.00341*	0.00468*	-0.00234	-0.00213	-0.000124
	(0.00202)	(0.00203)	(0.00244)	(0.00183)	(0.00185)	(0.00213)
1{t=-2}	0.000101	-0.000112	0.000657	-0.00334**	-0.00318*	-0.00188
	(0.00180)	(0.00181)	(0.00207)	(0.00167)	(0.00168)	(0.00184)
1{t=-1}	0.00388**	0.00384**	0.00417**	0.000205	0.000316	0.00107
	(0.00196)	(0.00195)	(0.00205)	(0.00177)	(0.00177)	(0.00184)
1{t=1}	-0.000878	-0.000874	-0.00129	-0.00367**	-0.00355**	-0.00403***
	(0.00149)	(0.00149)	(0.00157)	(0.00144)	(0.00145)	(0.00151)
1{t=2}	-0.00166	-0.00180	-0.00257	-0.00333**	-0.00307**	-0.00423**
	(0.00156)	(0.00156)	(0.00176)	(0.00149)	(0.00150)	(0.00166)
1{t=3}	-0.000691	-0.000839	-0.00198	-0.00395**	-0.00376**	-0.00561***
	(0.00164)	(0.00164)	(0.00204)	(0.00158)	(0.00159)	(0.00189)
1{t=4}	-0.000358	-0.000305	-0.00180	-0.00307**	-0.00284*	-0.00537***
	(0.00179)	(0.00178)	(0.00233)	(0.00157)	(0.00157)	(0.00201)
1{t=5}	-0.000831	-0.000823	-0.00268	-0.00354**	-0.00331**	-0.00655***
	(0.00171)	(0.00170)	(0.00263)	(0.00165)	(0.00165)	(0.00228)
1{t=6}	0.00106	0.000969	-0.00120	-0.00328**	-0.00304*	-0.00701***
	(0.00176)	(0.00176)	(0.00298)	(0.00158)	(0.00159)	(0.00246)
1{t=7}	0.000159	4.51e-05	-0.00232	-0.00361**	-0.00327**	-0.00800***
	(0.00188)	(0.00187)	(0.00334)	(0.00162)	(0.00163)	(0.00279)
1{t=8}	0.00284	0.00270	0.000117	-0.00262	-0.00221	-0.00767**
	(0.00197)	(0.00196)	(0.00371)	(0.00179)	(0.00181)	(0.00306)
HH Dem.	X	X		X	X	
Yr.-Mo. f.e.		X	X		X	X
HH f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Obs.	39,069	39,069	39,069	39,069	39,069	39,069
R-squared	0.019	0.019	0.341	0.005	0.006	0.264

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C16: Summary of Grocery Budget Shares - Event Study Estimates

Grocery	Meats Budget Share			Oils Budget Share		
Shares	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	0.000150	0.000545	0.000258	-0.00243*	-0.00248*	-0.00132
	(0.00328)	(0.00329)	(0.00384)	(0.00136)	(0.00137)	(0.00159)
1{t=-2}	0.000896	0.00130	0.000735	0.000434	0.000380	0.00122
	(0.00327)	(0.00329)	(0.00357)	(0.00142)	(0.00142)	(0.00152)
1{t=-1}	-0.00247	-0.00228	-0.00209	8.06e-05	4.68e-05	0.000463
	(0.00315)	(0.00316)	(0.00326)	(0.00150)	(0.00150)	(0.00155)
1{t=1}	0.0144***	0.0143***	0.0149***	0.00367***	0.00365***	0.00328**
	(0.00295)	(0.00296)	(0.00310)	(0.00128)	(0.00128)	(0.00136)
1{t=2}	0.00590**	0.00588**	0.00657*	0.000303	0.000290	-0.000488
	(0.00299)	(0.00300)	(0.00339)	(0.00133)	(0.00133)	(0.00150)
1{t=3}	0.00734**	0.00739**	0.00817**	-0.000623	-0.000561	-0.00171
	(0.00293)	(0.00295)	(0.00364)	(0.00130)	(0.00130)	(0.00162)
1{t=4}	0.00710**	0.00735**	0.00826**	-0.000211	-0.000158	-0.00175
	(0.00315)	(0.00318)	(0.00420)	(0.00133)	(0.00133)	(0.00182)
1{t=5}	0.00345	0.00369	0.00469	3.01e-05	3.18e-05	-0.00196
	(0.00309)	(0.00312)	(0.00464)	(0.00124)	(0.00125)	(0.00195)
1{t=6}	0.00608*	0.00617*	0.00712	0.00128	0.00124	-0.00112
	(0.00334)	(0.00337)	(0.00530)	(0.00144)	(0.00144)	(0.00228)
1{t=7}	0.00454	0.00461	0.00550	0.000248	0.000237	-0.00252
	(0.00341)	(0.00343)	(0.00592)	(0.00146)	(0.00146)	(0.00252)
1{t=8}	-0.000356	-0.000263	0.000648	-0.000673	-0.000696	-0.00395
	(0.00342)	(0.00346)	(0.00641)	(0.00154)	(0.00154)	(0.00274)
HH Dem.	X	X		X	X	
Yr.-Mo. f.e.		X	X		X	X
HH f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Obs.	39,069	39,069	39,069	39,069	39,069	39,069
R-squared	0.007	0.008	0.354	0.004	0.005	0.172

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C17: Summary of Grocery Budget Shares - Event Study Estimates

Grocery Shares	Other Budget Share (1)	Other Budget Share (2)	Other Budget Share (3)	Prepared Budget Share (1)	Prepared Budget Share (2)	Prepared Budget Share (3)
1{t=-3}	-0.000955	-0.000986	-0.00165*	-0.00141	-0.00149	-0.00256
	(0.000820)	(0.000820)	(0.000929)	(0.00279)	(0.00281)	(0.00320)
1{t=-2}	0.000148	0.000149	-0.000239	-0.00337	-0.00333	-0.00416
	(0.000802)	(0.000802)	(0.000855)	(0.00273)	(0.00274)	(0.00295)
1{t=-1}	-0.000455	-0.000453	-0.000669	-0.00552**	-0.00497*	-0.00535**
	(0.000793)	(0.000791)	(0.000820)	(0.00255)	(0.00255)	(0.00263)
1{t=1}	0.00104	0.00106	0.00133*	0.00607**	0.00603**	0.00610**
	(0.000749)	(0.000748)	(0.000773)	(0.00254)	(0.00254)	(0.00264)
1{t=2}	0.000402	0.000443	0.000941	0.00817***	0.00832***	0.00862***
	(0.000759)	(0.000759)	(0.000802)	(0.00259)	(0.00259)	(0.00287)
1{t=3}	-8.68e-05	9.27e-06	0.000732	0.00947***	0.00933***	0.00981***
	(0.000746)	(0.000745)	(0.000850)	(0.00267)	(0.00268)	(0.00326)
1{t=4}	-0.000404	-0.000351	0.000586	0.00774***	0.00761***	0.00842**
	(0.000733)	(0.000731)	(0.000886)	(0.00263)	(0.00263)	(0.00338)
1{t=5}	-0.000709	-0.000713	0.000451	0.00525**	0.00540**	0.00645*
	(0.000734)	(0.000735)	(0.000984)	(0.00267)	(0.00268)	(0.00377)
1{t=6}	1.56e-05	7.63e-05	0.00148	0.00476*	0.00521*	0.00642
	(0.000814)	(0.000816)	(0.00113)	(0.00267)	(0.00269)	(0.00416)
1{t=7}	-0.000859	-0.000816	0.000828	0.00309	0.00383	0.00514
	(0.000759)	(0.000759)	(0.00119)	(0.00280)	(0.00280)	(0.00463)
1{t=8}	-0.000787	-0.000789	0.00112	0.00541*	0.00620**	0.00803
	(0.000748)	(0.000750)	(0.00128)	(0.00287)	(0.00289)	(0.00501)
HH Dem.	X	X		X	X	
Yr.-Mo. f.e.		X	X		X	X
HH f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Obs.	39,069	39,069	39,069	39,069	39,069	39,069
R-squared	0.022	0.023	0.172	0.014	0.016	0.330

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C18: Summary of Grocery Budget Shares - Event Study Estimates

Grocery Shares	Snack/Sweets Budget Share (1)	(2)	(3)	Sugar Budget Share (1)	(2)	(3)
1{t=-3}	0.00575*	0.00555*	0.00550	-0.00178**	-0.00174**	-0.00202**
	(0.00318)	(0.00320)	(0.00388)	(0.000733)	(0.000738)	(0.000892)
1{t=-2}	0.00350	0.00341	0.00347	-0.000338	-0.000331	-0.000475
	(0.00326)	(0.00326)	(0.00358)	(0.000748)	(0.000750)	(0.000821)
1{t=-1}	0.00763**	0.00732**	0.00691**	-0.000900	-0.000901	-0.000979
	(0.00328)	(0.00327)	(0.00342)	(0.000701)	(0.000701)	(0.000739)
1{t=1}	0.000615	6.05e-05	-0.000129	0.000345	0.000309	0.000460
	(0.00268)	(0.00268)	(0.00282)	(0.000669)	(0.000673)	(0.000703)
1{t=2}	0.00849***	0.00780***	0.00762**	-0.00108*	-0.00113*	-0.000882
	(0.00289)	(0.00290)	(0.00322)	(0.000644)	(0.000643)	(0.000728)
1{t=3}	0.00345	0.00312	0.00302	-0.00137**	-0.00133**	-0.000973
	(0.00279)	(0.00279)	(0.00343)	(0.000656)	(0.000656)	(0.000820)
1{t=4}	0.00296	0.00233	0.00223	-0.000895	-0.000818	-0.000359
	(0.00294)	(0.00295)	(0.00390)	(0.000679)	(0.000676)	(0.000930)
1{t=5}	0.00897***	0.00829***	0.00821*	-0.000369	-0.000366	0.000196
	(0.00302)	(0.00303)	(0.00446)	(0.000655)	(0.000657)	(0.00102)
1{t=6}	0.00484	0.00446	0.00450	-0.00128*	-0.00124*	-0.000575
	(0.00301)	(0.00302)	(0.00483)	(0.000689)	(0.000689)	(0.00115)
1{t=7}	0.00635**	0.00611*	0.00627	-0.00151**	-0.00137**	-0.000600
	(0.00318)	(0.00317)	(0.00547)	(0.000667)	(0.000666)	(0.00127)
1{t=8}	0.00843**	0.00824**	0.00900	-0.00171**	-0.00155**	-0.000663
	(0.00331)	(0.00333)	(0.00615)	(0.000683)	(0.000684)	(0.00142)
HH Dem.	X	X		X	X	
Yr.-Mo. f.e.		X	X		X	X
HH f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Obs.	39,069	39,069	39,069	39,069	39,069	39,069
R-squared	0.012	0.013	0.305	0.004	0.006	0.183

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C19: Summary of Grocery Budget Shares - Event Study Estimates

Grocery Shares	Vegetables Budget Share (1)	(2)	(3)
1{t=-3}	0.00405*	0.00409*	0.00423*
	(0.00211)	(0.00213)	(0.00241)
1{t=-2}	0.00215	0.00203	0.00223
	(0.00183)	(0.00184)	(0.00204)
1{t=-1}	0.00219	0.00206	0.00203
	(0.00182)	(0.00183)	(0.00188)
1{t=1}	-0.000773	-0.000748	-0.000557
	(0.00160)	(0.00160)	(0.00168)
1{t=2}	-0.00131	-0.00136	-0.00110
	(0.00164)	(0.00165)	(0.00182)
1{t=3}	-0.00141	-0.00154	-0.00126
	(0.00164)	(0.00165)	(0.00201)
1{t=4}	3.63e-05	-4.49e-05	0.000252
	(0.00186)	(0.00187)	(0.00241)
1{t=5}	-0.000441	-0.000449	-0.000118
	(0.00171)	(0.00172)	(0.00259)
1{t=6}	0.000135	0.000171	0.000559
	(0.00184)	(0.00187)	(0.00292)
1{t=7}	0.00114	0.00106	0.00159
	(0.00191)	(0.00193)	(0.00323)
1{t=8}	-0.00132	-0.00136	-0.000788
	(0.00186)	(0.00188)	(0.00354)
HH Dem.	X	X	
Yr.-Mo. f.e.		X	X
HH f.e.			X
Seasonal f.e.	X		
Year f.e.	X		
Obs.	39,069	39,069	39,069
R-squared	0.009	0.010	0.363

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C20: Summary of Baby Purchases - Event Study Estimates

	Overall Baby Sales			Diaper Sales		
	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	-2.347***	-2.317***	-1.786*	-0.0656	-0.0759	0.239
	(0.887)	(0.888)	(1.057)	(0.352)	(0.356)	(0.407)
1{t=-2}	-2.550***	-2.567***	-2.206**	-0.104	-0.127	0.0858
	(0.835)	(0.841)	(0.934)	(0.336)	(0.340)	(0.362)
1{t=-1}	-2.501***	-2.511***	-2.321***	-0.330	-0.336	-0.226
	(0.778)	(0.777)	(0.812)	(0.312)	(0.312)	(0.322)
1{t=1}	2.071**	2.050**	1.873**	1.108***	1.095***	0.985***
	(0.840)	(0.844)	(0.877)	(0.343)	(0.343)	(0.357)
1{t=2}	2.805***	2.814***	2.462**	0.567	0.545	0.331
	(0.894)	(0.897)	(0.982)	(0.356)	(0.359)	(0.386)
1{t=3}	2.850***	2.873***	2.338**	0.936**	0.936**	0.618
	(1.033)	(1.036)	(1.173)	(0.384)	(0.385)	(0.422)
1{t=4}	3.061***	3.146***	2.423*	1.440***	1.450***	1.029**
	(1.133)	(1.136)	(1.363)	(0.401)	(0.404)	(0.468)
1{t=5}	3.072***	3.212***	2.280	1.325***	1.347***	0.812
	(1.162)	(1.169)	(1.496)	(0.406)	(0.409)	(0.502)
1{t=6}	2.243*	2.462*	1.330	0.657	0.687	0.0321
	(1.271)	(1.276)	(1.683)	(0.420)	(0.424)	(0.552)
1{t=7}	1.699	1.998	0.689	0.942**	0.988**	0.227
	(1.408)	(1.414)	(1.916)	(0.466)	(0.469)	(0.633)
1{t=8}	1.983	2.328	0.772	1.334***	1.383***	0.469
	(1.441)	(1.450)	(2.040)	(0.470)	(0.476)	(0.674)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,511	39,511	39,511	39,511	39,511	39,511
R-squared	0.018	0.018	0.499	0.014	0.015	0.512

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C21: Summary of Baby Purchases - Event Study Estimates

	Baby Food Sales			Baby Formula Sales		
	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	-0.548**	-0.550**	-0.437	-1.527**	-1.480**	-1.329
	(0.261)	(0.265)	(0.301)	(0.666)	(0.664)	(0.808)
1{t=-2}	-0.588***	-0.575**	-0.500**	-1.876***	-1.892***	-1.789**
	(0.224)	(0.228)	(0.243)	(0.625)	(0.626)	(0.697)
1{t=-1}	-0.515**	-0.516**	-0.475**	-1.432**	-1.446**	-1.393**
	(0.221)	(0.224)	(0.228)	(0.591)	(0.586)	(0.613)
1{t=1}	0.332	0.336	0.301	0.258	0.245	0.196
	(0.242)	(0.243)	(0.252)	(0.595)	(0.597)	(0.623)
1{t=2}	0.150	0.167	0.100	1.635***	1.650***	1.547**
	(0.243)	(0.241)	(0.268)	(0.627)	(0.627)	(0.696)
1{t=3}	0.574*	0.604*	0.506	1.187	1.165	0.999
	(0.313)	(0.313)	(0.344)	(0.785)	(0.788)	(0.926)
1{t=4}	0.527	0.568	0.436	0.864	0.878	0.647
	(0.346)	(0.349)	(0.400)	(0.858)	(0.862)	(1.049)
1{t=5}	0.584*	0.617*	0.448	0.985	1.056	0.752
	(0.334)	(0.338)	(0.412)	(0.841)	(0.842)	(1.124)
1{t=6}	0.848**	0.888**	0.685	0.631	0.764	0.397
	(0.380)	(0.388)	(0.476)	(0.916)	(0.915)	(1.267)
1{t=7}	1.021**	1.021**	0.792	-0.438	-0.196	-0.623
	(0.422)	(0.433)	(0.542)	(0.949)	(0.946)	(1.387)
1{t=8}	1.226***	1.240***	0.957	-0.891	-0.618	-1.088
	(0.436)	(0.446)	(0.589)	(0.981)	(0.984)	(1.493)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,511	39,511	39,511	39,511	39,511	39,511
R-squared	0.011	0.011	0.448	0.011	0.012	0.371

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C22: Summary of Baby Purchases - Event Study Estimates

	Baby Product Sales		
	(1)	(2)	(3)
1{t=-3}	-0.207	-0.211	-0.259
	(0.187)	(0.186)	(0.221)
1{t=-2}	0.0170	0.0272	-0.00324
	(0.196)	(0.197)	(0.217)
1{t=-1}	-0.224	-0.213	-0.228
	(0.185)	(0.186)	(0.196)
1{t=1}	0.373*	0.374*	0.390*
	(0.221)	(0.222)	(0.230)
1{t=2}	0.452**	0.453**	0.483**
	(0.219)	(0.219)	(0.232)
1{t=3}	0.153	0.169	0.216
	(0.207)	(0.208)	(0.237)
1{t=4}	0.231	0.249	0.311
	(0.200)	(0.200)	(0.254)
1{t=5}	0.179	0.191	0.269
	(0.210)	(0.210)	(0.286)
1{t=6}	0.108	0.124	0.216
	(0.198)	(0.198)	(0.290)
1{t=7}	0.175	0.185	0.294
	(0.212)	(0.214)	(0.330)
1{t=8}	0.314	0.323	0.433
	(0.207)	(0.209)	(0.352)
HH Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Seasonal f.e.	X		
Year f.e.	X		
Observations	39,511	39,511	39,511
R-squared	0.005	0.005	0.171

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C23: Summary of Vice Purchases - Event Study Estimates

	All Vice Sales		
	(1)	(2)	(3)
1{t=-3}	-0.763	-0.715	-1.084
	(0.630)	(0.628)	(0.741)
1{t=-2}	-0.0202	0.00928	-0.236
	(0.588)	(0.590)	(0.677)
1{t=-1}	0.376	0.353	0.236
	(0.622)	(0.619)	(0.652)
1{t=1}	0.395	0.378	0.492
	(0.587)	(0.590)	(0.606)
1{t=2}	0.922	0.951	1.171*
	(0.636)	(0.637)	(0.674)
1{t=3}	1.261*	1.296*	1.639**
	(0.686)	(0.687)	(0.762)
1{t=4}	0.860	0.885	1.369*
	(0.700)	(0.706)	(0.804)
1{t=5}	1.202*	1.232*	1.851**
	(0.708)	(0.713)	(0.908)
1{t=6}	0.664	0.657	1.405
	(0.775)	(0.777)	(1.064)
1{t=7}	1.453*	1.511*	2.409**
	(0.841)	(0.844)	(1.176)
1{t=8}	1.282	1.327	2.114*
	(0.853)	(0.859)	(1.268)
HH Demographics	X	X	
Year-Month f.e.		X	X
Household f.e.			X
Seasonal f.e.	X		
Year f.e.	X		
Observations	39,511	39,511	39,511
R-squared	0.013	0.014	0.578

Robust standard errors in parenthesis
Standard errors clustered at the household level

Table C24: Summary of Vice Purchases - Event Study Estimates

	Alcohol Sales			Tobacco Sales		
	(1)	(2)	(3)	(1)	(2)	(3)
1{t=-3}	-0.544	-0.509	-0.814	-0.219	-0.206	-0.270
	(0.604)	(0.603)	(0.705)	(0.152)	(0.150)	(0.185)
1{t=-2}	0.0961	0.113	-0.0880	-0.116	-0.104	-0.148
	(0.562)	(0.564)	(0.647)	(0.127)	(0.129)	(0.141)
1{t=-1}	0.578	0.548	0.450	-0.202	-0.195	-0.214
	(0.597)	(0.595)	(0.626)	(0.145)	(0.144)	(0.154)
1{t=1}	0.451	0.425	0.522	-0.0559	-0.0470	-0.0299
	(0.560)	(0.564)	(0.581)	(0.164)	(0.162)	(0.164)
1{t=2}	0.828	0.834	1.018	0.0936	0.118	0.153
	(0.585)	(0.588)	(0.629)	(0.232)	(0.225)	(0.226)
1{t=3}	1.228*	1.235*	1.521**	0.0327	0.0610	0.118
	(0.639)	(0.642)	(0.723)	(0.208)	(0.200)	(0.205)
1{t=4}	0.748	0.759	1.164	0.112	0.126	0.205
	(0.658)	(0.664)	(0.764)	(0.236)	(0.231)	(0.246)
1{t=5}	1.235*	1.258*	1.774**	-0.0332	-0.0253	0.0769
	(0.674)	(0.680)	(0.866)	(0.212)	(0.206)	(0.233)
1{t=6}	0.596	0.584	1.207	0.0677	0.0728	0.198
	(0.722)	(0.728)	(0.983)	(0.222)	(0.210)	(0.287)
1{t=7}	1.423*	1.473*	2.227**	0.0302	0.0383	0.182
	(0.800)	(0.806)	(1.104)	(0.213)	(0.202)	(0.288)
1{t=8}	1.323*	1.372*	2.016*	-0.0411	-0.0450	0.0980
	(0.796)	(0.802)	(1.205)	(0.237)	(0.234)	(0.297)
HH Demographics	X	X		X	X	
Year-Month f.e.		X	X		X	X
Household f.e.			X			X
Seasonal f.e.	X			X		
Year f.e.	X			X		
Observations	39,511	39,511	39,511	39,511	39,511	39,511
R-squared	0.014	0.015	0.585	0.002	0.003	0.402

Robust standard errors in parenthesis
Standard errors clustered at the household level

BIBLIOGRAPHY

BIBILIOGRAPHY

- Atkin, D. (2013). Trade, tastes, and nutrition in India. American economic review, 103(5), 1629-63.
- Almond, D., Hoynes, H. W., Schanzenbach, D. W. (2011). Inside the war on poverty: The impact of food stamps on birth outcomes. The Review of Economics and Statistics, 93(2), 387-403.
- Bazerman, M. H., Tenbrunsel, A. E., Wade-Benzoni, K. (1998). Negotiating with yourself and losing: Making decisions with competing internal preferences. Academy of Management Review, 23(2), 225-241.
- Borusyak, K., Jaravel, X. (2017). Revisiting event study designs. Available at SSRN 2826228.
- Bruich, G. A. (2014). The effect of SNAP benefits on expenditures: New evidence from scanner data and the November 2013 benefit cuts. Harvard University. Mimeograph, September.
- Bakos, J. Y. (1997). Reducing buyer search costs: Implications for electronic marketplaces. Management science, 43(12), 1676-1692.
- Brown, J. R., Goolsbee, A. (2002). Does the Internet make markets more competitive? Evidence from the life insurance industry. Journal of political economy, 110(3), 481-507.
- Brynjolfsson, E., Smith, M. D. (2000). Frictionless commerce? A comparison of Internet and conventional retailers. Management science, 46(4), 563-585.
- Chalfant, J. A. (1987). "A globally flexible, almost ideal demand system." Journal of Business Economic Statistics, 5(2), 233-242.
- Chu, J., Chintagunta, P., Cebollada, J. (2008). Research note?a comparison of within-household price sensitivity across online and offline channels. Marketing Science, 27(2), 283-299.
- Chu, J., Arce-Urriza, M., Cebollada-Calvo, J. J., Chintagunta, P. K. (2010). An empirical analysis of shopping behavior across online and offline channels for grocery products: the moderating effects of household and product characteristics. Journal of Interactive Marketing, 24(4), 251-268.
- Clemons, E. K., Hann, I. H., Hitt, L. M. (2002). Price dispersion and differentiation in online travel: An empirical investigation. Management science, 48(4), 534-549.
- Condon, Elizabeth, Susan Drilea, Keri Jowers, Carolyn Lichtenstein, James Mabli, Emily Madden, and Katherine Niland. (2015). Diet Quality of Americans by SNAP Participation Status: Data from the National Health and Nutrition Examination Survey, 2007-2010. Prepared by Walter R. McDonald Associates, Inc. and Mathematica Policy Research for the Food and Nutrition Service.
- Deaton, A., Muellbauer, J. (1980). An almost ideal demand system. The American economic review, 70(3), 312-326.

- East, C. (2015). The Effect of Food Stamps on Children's Health: Evidence from Immigrants' Changing Eligibility.
- Ellison, G., Fisher Ellison, S. (2005). Lessons about Markets from the Internet. Journal of Economic Perspectives, 19(2), 139-158.
- Gibson, D. (2004). Long-term food stamp program participation is differentially related to overweight in young girls and boys. The Journal of nutrition, 134(2), 372-379.
- Greene, W. H. (2012). Econometric analysis, 71e. Stern School of Business, New York University.
- Hales, C. M., Carroll, M. D., Fryar, C. D., Ogden, C. L. (2017). Prevalence of obesity among adults and youth: United States, 2015?2016.
- Hann, I. H., Terwiesch, C. (2003). Measuring the frictional costs of online transactions: The case of a name-your-own-price channel. Management Science, 49(11), 1563-1579.
- Harding, M., Lovenheim, M. (2017). The effect of prices on nutrition: comparing the impact of product-and nutrient-specific taxes. Journal of Health Economics, 53, 53-71.
- Harris, K. (2019). The Effect of Online Shopping on the Nutritional Content of Grocery Purchases. Working Paper.
- Hastings, J. S., Shapiro, J. M. (2017). How Are SNAP Benefits Spent? Evidence from a Retail Panel (No. w23112). National Bureau of Economic Research.
- Hoch, S. J., Loewenstein, G. F. (1991). Time-inconsistent preferences and consumer self-control. Journal of consumer research, 17(4), 492-507.
- Hoynes, H., Schanzenbach, D. W., Almond, D. (2016). Long-run impacts of childhood access to the safety net. The American Economic Review, 106(4), 903-934.
- Hoynes, H. W., Schanzenbach, D. W. (2009). Consumption responses to in-kind transfers: Evidence from the introduction of the food stamp program. American Economic Journal: Applied Economics, 1(4), 109-139.
- Hoynes, H. W., Schanzenbach, D. W. (2015). US food and nutrition programs (No. w21057). National Bureau of Economic Research.
- Huyghe, E., Verstraeten, J., Geuens, M., Van Kerckhove, A. (2017). Clicks as a healthy alternative to bricks: how online grocery shopping reduces vice purchases. Journal of Marketing Research, 54(1), 61-74.
- Just, D. R., Mancino, L., Wansink, B. (2007). Could behavioral economics help improve diet quality for nutrition assistance program participants? (Vol. 43). Washington, DC: US Department of Agriculture, Economic Research Service.
- Kim, J. (2016). Do SNAP participants expand non-food spending when they receive more SNAP Benefits? Evidence from the 2009 SNAP benefits increase. Food Policy, 65, 9-20.
- Laibson, D. (1997). Golden eggs and hyperbolic discounting. The Quarterly Journal of Economics, 112(2), 443-478.

- Laibson, D. (2001). A cue-theory of consumption. The Quarterly Journal of Economics, 116(1), 81-119.
- Loewenstein, G. (1996). Out of control: Visceral influences on behavior. Organizational behavior and human decision processes, 65(3), 272-292.
- Milkman, K. L., Rogers, T., Bazerman, M. H. (2010). I'll have the ice cream soon and the vegetables later: A study of online grocery purchases and order lead time. Marketing Letters, 21(1), 17-35.
- Mischel, W., Ebbesen, E. B., Raskoff Zeiss, A. (1972). Cognitive and attentional mechanisms in delay of gratification. Journal of personality and social psychology, 21(2), 204.
- Murtazashvili, I., Wooldridge, J. M. (2016). A control function approach to estimating switching regression models with endogenous explanatory variables and endogenous switching. Journal of Econometrics, 190(2), 252-266.
- Nielsen & Food Marketing Institute. (2017) The Digitally Engaged Food Shopper.
- Pozzi, A. (2012). Shopping cost and brand exploration in online grocery. American Economic Journal: Microeconomics, 4(3), 96-120.
- Pozzi, A. (2013). The effect of Internet distribution on brick-and-mortar sales. The RAND Journal of Economics, 44(3), 569-583.
- Pozzi, A. (2013). E-commerce as a stockpiling technology: Implications for consumer savings. International Journal of Industrial Organization, 31(6), 677-689.
- Schanzenbach, D. W. (2002). What are food stamps worth? Princeton University Industrial Relations Section. Working chapter No. 468.
- Schelling, T. C. (1984). Self-command in practice, in policy, and in a theory of rational choice. The American Economic Review, 74(2), 1-11.
- Schmeiser, M. D. (2012). The impact of long?term participation in the supplemental nutrition assistance program on child obesity. Health economics, 21(4), 386-404.
- Shiv, B., Fedorikhin, A. (1999). Heart and mind in conflict: The interplay of affect and cognition in consumer decision making. Journal of consumer Research, 26(3), 278-292.
- Shiv, B., Fedorikhin, A. (2002). Spontaneous versus controlled influences of stimulus-based affect on choice behavior. Organizational Behavior and Human Decision Processes, 87(2), 342-370.
- Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. Economics letters, 8(3), 201-207.
- Thaler, R. H., Shefrin, H. M. (1981). An economic theory of self-control. Journal of political Economy, 89(2), 392-406.
- Vartanian, T. P., Houser, L. (2012). The effects of childhood SNAP use and neighborhood conditions on adult body mass index. Demography, 49(3), 1127-1154.

- Wilde, P., Ranney, C. (1996). The distinct impact of food stamps on food spending. Journal of Agricultural and Resource Economics, 174-185.
- Wilde, P. E. (2012). The new normal: The supplemental nutrition assistance program (snap). American Journal of Agricultural Economics, 95(2), 325-331.