Essays on Food Choices and Food Safety

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Dedication

Familjes –

Me shumë dashuri

To my family –

With much love

Abstract

This dissertation concentrates on demand-side issues on food economics. Specifically, we investigate policy-relevant economic issues related to food safety and food choices in the United States. Due to the rising diet-related health issues in the U.S. population, understanding factors that impact food choices is of major importance. In the first essay we explore the impact of food shopping frequency on the healthfulness of food choices. Using household-level data, we find that a higher food shopping frequency leads to less healthful food purchases for at-home consumption. We further provide evidence that the negative effect is primarily because households purchase increasingly more *temptation foods* – savory and sugary processed items such as snacks and beverages – as they shop more frequently. Based on our results, we conjecture that limiting consumer exposure to temptation foods in grocery stores, and instead, increasing the visibility of fresh fruits and vegetables would lead consumers to purchasing healthier foods.

The second and third essays focus on issues surrounding food safety in the United States, and the private sector's incentive to invest in and enforce food safety standards. Specifically, we investigate consumers' choices in the case of a recall of a branded product due to a food safety concern. If consumers switch to other products, then any losses due to one manufacturer recalling their product are externalized to all manufacturers of that product. This would provide manufacturers with incentives to cooperate in setting and enforcing food safety standards to avoid recalls and hence losses due to decreases in the demand for their product. Alternatively, if consumers switch to purchasing other brands of the recalled product, then losses are incurred only by the manufacturer that is directly

affected by the recall. Manufacturers of other brands of the same product may in fact experience an increase in demand. In this scenario, manufacturers do not have strong incentives to jointly establish and enforce food safety standards. We use two alternative empirical methods to model a system of demand equations that allow measuring demand spillover effects due to a food recall: a multistage budgeting approach and a discrete choice modeling approach. Specifically, in the first approach we estimate an Almost Ideal Demand System (AIDS) and in the second approach we estimate a logit model. The second essay reports the results of the AIDS estimation. These results indicate that all competing brands of the recalled product experience positive spillover effects, hence benefiting from the recall of their rival brand. The third essay reports the results of the logit model estimation. The results from this model suggest that while most competing brands experience positive spillover effects, at least one competing brand is negatively affected. We discuss the advantages and limitations of each of the empirical approaches, and offer implications for food safety policy, specifically focusing on private sector incentives to cooperate in food safety initiatives.

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Chapter 1: Overview

1.1. Introduction

Economic issues surrounding food production, storage, distribution, and consumption in the world are of existential importance. The field of economics has in the past primarily analyzed these issues at an aggregate level, making use of aggregate and usually producer-side data. Yet, in the recent years, household-level food consumption data, mainly from developed countries, have become available to researchers. This has opened up great possibilities in analyzing consumer behavior with respect to food, as well as factors that impact consumer food choices. It has also provided the opportunity to empirically analyze consumers' impact on a variety of issues concerning food production practices, food safety, and agricultural and food policy. The broad field of food economics in recent years focuses on using rich consumer and producer datasets to address questions related to food choices, food labeling, food safety, and food production practices, among others. Such topics are of great interest to the public as well as to policymakers.

Literature on food choices documents that consumer food choices are affected by a series of factors, including lifestyle, demographic, economic, and geographic factors. In turn, food choices affect health outcomes. Preventable chronic and acute diseases affect over half of the U.S. population. Poor nutrition is one of the key factors that causes such chronic diseases. As a result, eating healthful food has increasingly become a long-term goal for many people. Yet health outcome trends continue to show that a large part of the US population falls short of reaching this objective. The U.S. Department of Agriculture (USDA) issues dietary guidelines which provide food-intake recommendation to the U.S.

population. However, recent research shows that the average U.S. household falls very short of following these guidelines (Volpe and Okrent 2012). Thus, understanding factors that affect American households' food choices is crucially important to policymakers' objective of incentivizing healthful eating behavior in the U.S. population. The first essay in this dissertation contributes to this objective.

Food safety is another important public policy issue in the United States and worldwide. Providing safe food to an increasingly larger global population is of great importance. In developed countries, food safety standards have started to appear at the turn of the twentieth century. Yet, there are still enormous challenges in setting and enforcing food safety standards, as well as in integrating such standards across countries. In the United States, millions of Americans each year are affected by food borne diseases, despite the government's increased efforts to mitigate the problem through policy changes such as the Food and Drug Administration (FDA) Food Safety Modernization Act of 2011. Hence, it is important to understand factors that generate market-driven incentives for the private sector to set and enforce food safety standards, beyond those required by government regulations. One such factor is consumer attitude towards safe food. Improving our understanding of consumer attitude towards food safety and how it affects incentives for public and private sectors to establish and enforce food safety standards is of great importance. Two of the essays of this dissertation contribute to this objective.

1.2. Contributions of the first essay

The extant literature on consumer behavior has explored many factors that affect consumer food choices, such as food prices, availability of stores, demographic factors, etc. In the second chapter of this dissertation, we contribute to this literature by exploring the impact of grocery shopping frequency on the healthfulness of food purchases. We argue that the effect of shopping frequency on the healthfulness of food choices is conceptually ambiguous, and hence empirical analysis is necessary to understand the impact of this factor. Most healthful foods, such as fresh fruits and vegetables, have a short shelf life. Thus, going to the grocery store frequently may enable a more healthful diet, as it would facilitate the availability and hence the consumption of fresh fruits and vegetables. Yet, every time consumers visit a grocery store, they are also faced with the temptation to purchase unhealthful foods, such as sugary snacks and beverages. These food items are generally placed in the most accessible or visible areas of grocery stores, such as by checkout lanes, in order to induce consumers to purchase them. If consumers do purchase larger quantities of unhealthful foods with each shopping trip, the impact of grocery shopping frequency on the healthfulness of food purchases is negative.

To address this question, we use U.S. household food purchase data. Given that the decision on shopping trips may be endogenous to food choices, we use an instrumental variables approach in order to identify the causal effect. We find that grocery shopping frequency has a negative and statistically significant effect on the healthfulness of food purchases, which indicates that consumers do purchase more unhealthful foods with each trip to the grocery store. In line with this finding, additional analysis of the impact of shopping frequency by major food groups show that consumers increase their purchases of *temptation foods* – sugary and salty commercially prepared food items - as they shop more frequently. These findings suggest that policies that limit the exposure of consumers to temptation foods when visiting the grocery store could be helpful in reducing their purchases of unhealthful food items.

1.3. Contributions of the second essay

In the third chapter of this dissertation, we explore the extent to which demand spillover effects of food recalls exist in branded food products. We argue that the existence of demand spillover effects determines whether there are demand-driven incentives for private initiatives in food safety. Specifically, if there are positive spillover effects for other brands, this would indicate that manufacturers of other brands benefit from the recall and hence there are no strong incentives to cooperate in setting and enforcing food safety standards beyond those required by the government. Yet, if there are negative spillover effects due to the recall, manufacturers not directly linked to the recall suffer the consequences, and hence market incentives exist for private initiatives in food safety.

The literature on food safety has been expanding in the last two decades. Yet, studies so far have focused primarily on homogeneous products. To our knowledge, our study is the first that investigates spillover effects in a differentiated food market, and makes the link between demand spillover effects and private initiatives in food safety. For our empirical analysis, we explore the case of the *Peter Pan* peanut butter recall of 2007, in order to investigate the existence of spillover effects for other brands of peanut butter. We utilize Homescan data, a household-level dataset with rich information on all food purchases as well as demographic information. In this chapter, we use a multistage budgeting approach to estimate the demand system for closely competing brands, namely the Almost Ideal Demand System (AIDS). The results from the AIDS model estimation indicate that *Peter Pan* is negatively affected by its own recall. The results also indicate that there are positive spillover effects for all the other brands of peanut butter, but that the effect is largest for *Jif*. Positive spillover effects for competing brands indicate that there are no demand-driven market forces to incentivize manufacturers in setting and enforcing food safety standards beyond those required by government regulations.

1.4. Contributions of the third essay

In the fourth chapter of this dissertation, we propose a discrete choice modeling approach to estimate the peanut butter demand system and analyze the impact of the *Peter Pan* recall on competing brands of peanut butter. To the best of our knowledge, this methodology has not been used before in the context of food recalls. When applied to differentiated product markets, the discrete choice modeling approach has a number of advantages over the multistage budgeting approach. For example, the main assumption of the discrete choice framework is that consumers make choices based on product characteristics. That is, consumers derive utility from product characteristics, and not from the products directly. This approach is appropriate in studying demand in differentiated product markets where consumers face many slightly varied options of the same product. Additional advantages of the discrete choice modeling approach over the multistage budgeting approach include: (i) the discrete choice modeling approach is not subject to dimensionality problem that occurs when the number of estimated demand equations is large, and (ii) it could potentially allow for changing consumer choice set across time periods that occurs when a product is recalled. Consequently, in this chapter we use different specifications of the logit model to estimate spillover effects for competing brands and compare results with those of AIDS model.

Results from logit model show that the *Peter Pan* recall resulted in positive spillover effects for some of the competing brands, namely *Jif*, *Store brands*, and to a smaller extent, *Skippy*. Similar to the results of the AIDS model, we find that the biggest gainer is *Jif*, indicating that a large number of formerly *Peter Pan* consumers switch to purchasing *Jif* peanut butter. However, in contrast to the AIDS model, we find that one of the competing brands – *All other brands*, is negatively affected by the *Peter Pan* recall. We also find that the magnitude of the spillover effects for competing brands is smaller than those obtained from the AIDS model. We conclude with discussing the implications of these results for policy, and provide a discussion of potential extensions to the estimated models that could be used to study recalls due to food safety.

Chapter 2: Vice or Virtue: How Shopping Frequency Affects the Healthfulness of Food Choices

2.1. Introduction

In the recent past, there has been an increase in the rate of chronic and acute diseases in the American population (Just and Payne 2009). Poor diet quality is linked to four major causes of death in the United States: coronary heart disease, cancer, stroke and type 2 diabetes (Chiuve et al. 2012). Additionally, the Center for Disease Control and Prevention (CDC) estimates that 38 percent of adults and 21 percent of adolescents are obese (CDC). Literature finds that 20.6 percent of U.S. national expenditures on health, amounting to $209.7 billion annually, is spent on treating obesity-related illness (Cawley and Meyerhoefer 2011). Hence, improving Americans' diet quality is a major public policy issue. For example, as part of the nutrition education policies of the U.S. Department of Agriculture (USDA) and the Department of Health and Human Services, the Dietary Guidelines for Americans is published every five years to provide information on the amount and distribution of different types of foods to be consumed each day (U.S. Department of Agriculture & U.S. Department of Health and Human Services, Dietary Guidelines for Americans, 2015-2020).[1] While such policies might be effective, the extant literature has shown that there are many factors that impact consumer food choices ranging from socio-demographic and economic factors to environmental factors. In this study, we

[1] Other institutions, such as the World Health Organization (WHO) in conjunction with the Food and Agriculture Organization of the United Nations (FAO) and the National Health Service in the United Kingdom, also provide dietary guidelines and recommendations.

contribute to this literature by investigating the causal effect of the frequency of grocery store visits on the healthfulness of food purchases.

The impact of grocery shopping frequency on the healthfulness of food choices is conceptually ambiguous. The effect may be positive because the most healthful foods (i.e., fresh fruits and vegetables) have short shelf lives. This implies that purchasing fresh produce in bulk is not a good strategy as the food may quickly spoil, hence not allowing the consumer to consume fresh produce on a continuous basis. However, consumers with a higher shopping frequency may purchase fresh produce often, consume these foods on a continuous basis, and thus have healthier diets. Alternatively, the impact of shopping frequency on the healthfulness of food purchases may be negative if consumers tend to purchase *temptation foods* with each visit to the grocery store. Temptation foods are commercially prepared sweet and savory items as well as sugary drinks—all of which are recommended for decreased consumption based on their high content of sodium and sugar (U.S. Department of Agriculture & U.S. Department of Health and Human Services, Dietary Guidelines for Americans, 2015-2020). In most grocery stores, in addition to a designated aisle, temptation foods are placed in end-of-aisle displays or by checkout lanes so as to attract the consumers' attention. Hence, consumers who make more frequent trips to a grocery store are exposed to such temptations more frequently, which may lead to a lower healthfulness of food purchases. In this chapter, we explore these two mechanisms through which shopping frequency may affect the healthfulness of food purchases.

Exploring how shopping frequency affects the healthfulness of food purchases for American households has important implications for policy. If the effect is positive so that a higher shopping frequency leads to more healthful food purchases, then policies that facilitate frequent trips to grocery stores may directly increase people's diet quality. Such policies may include providing incentives luring grocery stores to open in locations where there is limited store availability, in order to allow households easier access to grocery stores. It may also include incentivizing stores to offer shuttle services to pick up and drop off customers, in order to ease the transaction and transportation costs of visiting a grocery store. Also, business policies that facilitate customer commitment to future store visits might be effective. For example, stores could offer promotions of fresh produce such that part of the purchase is made at a later date (e.g., buy one today, get one free next week). Alternatively, if the effect is negative such that a higher shopping frequency leads to less healthful food purchases, then policies that limit the convenience and visibility of unhealthful foods in stores would likely be most effective in improving people's diet quality. Examples of such policies may include designing "healthful aisles" that display healthful food items, or limiting in-store featuring and display of temptation foods. Furthermore, nutrition education programs that raise awareness about unhealthful foods and how to reduce the temptations to purchase such items might be effective.

To measure the effect of shopping frequency on the healthfulness of food purchases we estimate a multivariate regression model using data on food purchases from a panel of U.S. households. The econometric model incorporates a rich set of control variables including food prices, which are largely ignored in the prior studies of the healthfulness of food purchases. In our estimation we control for household heterogeneity using panel data techniques and account for the endogeneity of shopping frequency to household purchase decisions using an instrumental variables method. Also, we perform a number of robustness checks to measure the sensitivity of the results to alternative model specifications and to alternative measures of purchase frequency and healthfulness of food purchases.

Our main finding is that, on average, grocery shopping frequency negatively impacts the healthfulness of food purchases. The negative sign is robust across all model specifications, and persists throughout robustness checks to alternative measures of purchase frequency and healthfulness of food purchases. The effect is both statistically and economically significant. A plausible explanation behind this result is that an average consumer does not commit to a shopping list and spends relatively more on temptation foods as he or she makes more shopping trips. In fact, a breakdown of the analysis by major food groups indicates that, on average, a household's food expenditure shares of temptation foods increase with more frequent shopping trips, whereas the share of food expenditures on fruits and vegetables decreases with more frequent shopping trips. In light of these results, a combination of policies that increase consumer awareness on purchases of temptation foods, limit the exposure of consumers to temptation foods, and provide incentives to purchase healthful foods would be most effective in improving diet quality.

The remainder of this chapter is structured as follows. Section 2.2 discusses the literature on factors that impact food choices. Section 2.3 describes the empirical model and the identification strategy. Section 2.4 provides information on the data used to implement the analysis. Section 2.5 provides the results from the various model specifications and discusses the sensitivity of the results. Finally, section 2.6 concludes with a discussion of the results and their policy implications.

2.2. Literature Review

The literature on factors that impact individuals' food choices is abundant and addresses many different factors. One strand of the literature addresses the impact of income on diet quality. Closely related, a second strand of the literature addresses the impact of prices on food choices, distinguishing between prices for healthful versus unhealthful foods. In a third strand of the literature, time availability and time use are also explored as factors determining food choices, with particular focus on the time availability of poor households. A fourth strand of the literature explores how demographics are correlated with food choices. Availability of food stores is explored extensively in a fifth strand of the literature, with a special focus on food deserts. Finally, a sixth strand of the literature focuses on marketing strategies used to induce purchases of temptation foods, and the strategies consumers may use in order to avoid purchasing such food items.

The effect of income on food choices has been studied from multiple perspectives. Chandon and Wansink (2011) list income as one of the key factors determining food choices. Xie et al. (2003) analyze how household income affects individuals' consumption of various nutrients. The authors find that the intake of nutrients such as protein, folate, calcium, and iron – all increase with family income. In addition, they find that high income households are more likely to consume the recommended level of dairy products, whereas low income households are more likely to consume foods with added sugar, generally categorized as unhealthful (Xie et al. 2003). Blaylock et al. (1999) review a set of economic factors that influence food choices. They argue that rising income has two potential channels through which it affects food choices. First, rising income expands the set of foods that can be purchased. Second, because earning income takes time, it leads to higher demand of pre-prepared foods and food away from home. For low-income households, prior studies focus on how government food assistance programs affect food choices. For example, Wilde, McNamara, and Ranney (1999) find that food stamp participation increases the consumption of meats, added sugars, and total fats. Yet, the authors find that the Women, Infants, Children (WIC) program has an opposite effect specifically for added sugars. That is, participants of WIC were found to decrease their consumption of added sugar. In a study at a more macro level, a recent article by Beatty, Lin, and Smith (2014) shows that while diet quality of the U.S. households is slowly improving, poor households and households with very poor diet quality show significantly less improvements than the rest of the population.

Prior research has often studied the impact of income jointly with that of food prices and promotions. For example, Cooke (2007), and Neslin and Van Heerde (2009) find that prices, promotions, and quantity discounts have significant effects on consumer food choices. Other studies also show that lower prices for healthful foods increase consumption of such items (Drewnowski and Darmon 2005; French 2003; Monsivais, Mclain, and Drewnowski 2010). Drewnowski and Darmon (2005) document that foods high in added sugars and fat provide the highest dietary energy at the lowest cost. Hence, they argue that encouraging low-income households to consume more healthful foods may not be an effective policy because it disregards the fact that such foods are also more costly. Furthermore, Leonardt (2009) indicates that processed foods with high concentrations of fat and sugar have experienced the steepest price declines in the last three decades. Whereas, around the same time period, prices of fruits and vegetables have increased faster than inflation. To a certain extent, these trends explain why consumption of processed foods is more prevalent than consumption of fresh produce. In fact, prior studies that examined food price elasticities found that consumers are responsive to food prices, both to prices of healthful as well as unhealthful food items (Andreyeva, Long, and Brownell 2010; Chou et al. 2004; French 2003). Hence, making healthful foods more affordable may be an effective strategy to induce purchases of healthful items.

A third strand of the literature investigates the impact of time on food choices. In an overview paper, Jabs and Devine (2006) outline how time scarcity affects foods choices. They argue that food consumption patterns of American households have changed with a decrease of time dedicated to food preparation, and an increase in the consumption of food away from home and convenience ready-to-eat meals. Consequently, the authors argue that the diet quality in the population has decreased. In another study, Davis and You (2011) analyze the impacts of time and money in reaching the Thrifty Food Plan (TFP) target for single-headed households. They conclude that time, rather than money, is the most binding constraint to satisfying the TFP. Household time constraints can have important implications for household shopping behavior. For example, time-short households may not travel long distances for shopping, shop less frequently, and spend less time shopping. However, the literature on the impact of time is still relatively scarce.

A fourth strand of the literature investigates the role of socio-demographic factors such as gender, race, level of education, health behaviors, poverty status, and food insecurity status, on food purchases and diet quality. In general, studies find that consumers with a higher level of education, white consumers, and females have better diet quality (Rankin et al. 1998, Nayga 1999, Xie et al. 2003, Cullen et al. 2007). For example, Rose (1999) investigates the dietary consequences of food insecurity in U.S. households, and finds that the effects are significant. In another study, Bhattacharya, Currie, and Haider (2004) find that food insecurity and poverty status do not have an impact on nutritional outcomes of children, but do have predictive power for the nutritional outcomes of adults. In terms of health behavior, Nayga (1999) finds that smokers and individuals who exercise less, tend to have less healthful diets than the rest of the population.

Another stream of the literature on food choices is related to food deserts.[2] Studies on food deserts generally focus on the effects of distance to store on diet quality. However, results of these studies are mixed. For example, Rose and Richards (2004) find that higher distance to store is correlated with low consumption of fresh fruits for SNAP participants. Yet, in a more recent study Cummins, Flint, and Matthews (2014) evaluate the opening of a new supermarket in a "food desert" community in Philadelphia and find no changes in respondents' consumption of fresh fruits and vegetables compared to their consumption before the supermarket opening.

[2] The USDA – Agricultural Marketing Service defines food deserts as "urban neighborhoods and rural towns without ready access to fresh, healthy, and affordable food. Instead of supermarkets and grocery stores, these communities may have no food access or are served only by fast food restaurants and convenience stores that offer few healthy, affordable food options."
More information is available at: http://apps.ams.usda.gov/fooddeserts/foodDeserts.aspx

A sixth strand of the literature investigates how marketing strategies and consumer behavior affect food choices. In a series of experimental papers, researchers investigate factors that induce people to making healthier food choices (see for example, Hanks et al. 2012, Laroche et al. 2015). A range of factors including availability, visibility, and easiness of preparation, are all found to affect people's food choices. In addition, the literature investigates the environment and circumstances that induce people to eat more unhealthful foods. Factors such as exposure to television ads, eating as a secondary activity to watching television, the brightness of the room in which consumption takes place, the size and shape of plates and bowls - were found to significantly affect people's food choices as well as the quantity they consume. Chandon and Wansink (2011) provide a thorough review of this literature from many related disciplines, including marketing, psychology, nutrition, food science, and economics.

For about half of the total food consumption – the consumption that takes place at home, the first step that determines the type, quality, and quantity of food consumed is the set of purchasing decisions that occur at the grocery stores. People have different approaches when it comes to shopping for groceries. While very few consumers write down and follow a list when doing grocery shopping, the majority of people only have a mental list and easily concede to temptations to indulge in the purchases of relatively unhealthful food (Baumeister 2002). Shoppers also often fail to accurately estimate how much of each type of food they have at home already, and hence tend to overstock for certain items (Chandon and Wansink 2006). This often leads to spoilage and food waste, and other times it leads to overeating of the overstocked item, so as "to get their money's worth" (Chandon and Wansink 2006, Chandon and Wansink 2011). As in any type of shopping, with grocery shopping as well, consumers are also faced with the issue of self-control (Baumeister 2002). Shoppers face multiple temptations, some of which are internal such as the desire to buy and indulge in chocolate. Other temptations are external, they are the result of marketing actions in stores that attract shoppers to purchasing certain foods that they didn't plan to originally, or in larger quantities than originally planned. Such marketing actions include, but are not limited to, promotions, price and quantity discounts, placement of items in certain parts of the shelf, etc. In fact, research shows that even elements such as the strength of the lights in the store, the music played, and the layout of the store, affect people's purchasing decisions (see for example Stroebele and De Castro 2004; Wansink 2004; and Caldwell and Hibbert 2002). Baumeister (2002) argues that shoppers may exercise self-control when it comes to shopping, but the degree of self-control exercise varies by individuals and circumstances. The author suggests that in order to exercise self-control, a source of energy is used that is similar to the energy used to make any type of decision. Hence, the more of those decisions made, the more the energy is depleted and the harder it gets to exercise self-control. It is likely because of this reason that a lot of the most tempting items are placed by the check-out lane at the grocery store, and consumers give in to the temptation. In order to avoid decision fatigue and be able to exercise more self-control, the author argues that shoppers must take frequent but short shopping trips, and plan their purchases in advance.

In this complex shopping environment with multiple interventions from marketing agents, manufacturers, retailers, policy makers, nutritionists, etc., and with the large set of factors consumers consider when making their purchasing decisions, it becomes empirically challenging to identify the impact of any single factor on food choices. Moreover, any single factor is likely to have a relatively small impact, as it is the sum of all the factors discussed here that dictate food choices. In this chapter, our goal is to identify the impact of shopping frequency on food choices, and the mechanisms through which this effect operates.

2.3. Empirical Methods and Identification Strategy

2.3.1. Measurements of the Healthfulness of Food Purchases

In the recent past, nutritionist have constructed various indices to measure diet healthfulness. Such indices take into account types of foods that are recommended for increased or decreased consumption, as well as factors such as variety, adequacy, balance and moderation (Kim et al. 2003). Some examples of food healthfulness indices include the Healthy Eating Index (HEI), the Diet Quality Index – International (DQI-I), and the Revised Children's Diet Quality Index (RC-DQI) (Guenther, Reedy, and Krebs-Smith 2008; Kranz and McCabe 2013; Kim et al. 2003). The HEI index is constructed from food nutrient information and measures how closely a diet reflects USDA's recommendations included in the Dietary Guidelines for Americans. The DQI-I incorporates diet issues that are typically not faced in the United States, but are major problems in the developing world - such as under-nutrition. Finally, the RC-DQI measures specific nutritional needs of children.

When studying the diet quality of the American population, the HEI is one of the preferred measures to determine how closely the diet reflects USDA's Dietary Guidelines for Americans. However, if nutritional information of specific food products is not available the HEI Score cannot be used. Alternatively, researchers examine diet quality focusing on expenditures on a single product category (e.g., fruits and vegetables) or on expenditure share of healthful foods as they conform to USDA recommendations (Volpe, Okrent, and Leibtag 2013).

For example, in order to assess the healthfulness of food purchases, Volpe, Okrent, and Leibtag (2013) use six measurements, all of which are based on the USDA's Dietary Guidelines for Americans. They use the Quarterly Food-at-Home Price Database (QFAHPD) as the starting point for construction of their measurements. The QFAHPD aggregates UPC level food products reported in the Nielsen Homescan Panel database into 52 food categories. The dataset also provides price indices for each category by Metropolitan Statistical Area (MSA), by year, by quarter. More detailed information on the construction of the QFAHPD is provided by Todd et al. (2010).

Volpe, Okrent, and Leibtag (2013) use the QFAHPD categorization and separate the 52 food categories into "healthful" and "not healthful" based on whether the USDA recommends them for increased consumption or reduced consumption. Then, the first food healthfulness indicator, *HealthExpShare*, measures the expenditure share of healthful foods. The second indicator, *HealthExpShareQ* is similar to the first except it uses quantities instead of prices. However, these indicators do not account for USDA's recommendations on portions for the different types of foods (i.e., variety and balance in the diet). Hence, Volpe, Okrent, and Leibtag (2013) develop three additional scores to take into account USDA's recommendations on expenditure shares for different food categories. Since USDA's aggregation of different foods into categories does not exactly coincide with the food groups in the QFAHPD, the authors aggregate the food groups to make the two sets of categories comparable. Then, they construct three additional scores, *USDAScore1*, *USDAScore2*, and *USDAScore3*, which reflect how closely household expenditures mimic USDA's recommendations. The difference between *USDAScore1* and *USDAScore2* is related to how food groups with no purchases are treated. The authors impute values of zero for the former, but do not do any imputation for the latter. *USDAScore3* is different from the first two in that it separates out the food groups for which households report higher or lower expenditures than recommended by USDA. Finally, the authors construct another score based on the *HEI Score* by combining data on nutrient characteristics of foods (which are not reported in the Nielsen Homescan Panel dataset) from the 2003-2004 National Health and Nutrition Examination Survey.[3]

In this study, we adopt the *HealthExpShare* score to measure the healthfulness of food purchases. This score is defined as follows:

$$HealthExpShare_{it} = \frac{\sum_g exp_{igt} | g \in healthful}{\sum_{g=1}^{52} exp_{igt}}, \tag{2.1}$$

[3] We refer the readers to Volpe and Okrent (2012) and Volpe, Okrent, and Leibtag (2013) for a detailed explanation on the motivation and technical details behind the construction of each of these scores.

where exp denotes expenditures, and $healthful$ denotes the food groups that are recommended for increased consumption by the USDA. Households are denoted with subscript i, the 52 food groups are denoted with subscript g, and t denotes the time frame.

2.3.2. Empirical Model

In order to identify the impact of shopping frequency on healthfulness of food purchases, we employ a regression analysis that accounts for confounding factors suggested by the theory and empirical studies on consumer food choice. For household i and time period t, the benchmark model specification is as follows:

$$H_{itm} = \alpha_0 + \beta_1 F_{it} + \sum_{k=1}^{52} \gamma_k P_{kt} + \delta_g S_{git} + \sum_{j=1}^{J} \theta_j HC_{jit} + \varepsilon_{itm}, \tag{2.2}$$

where H denotes the healthfulness measure of the food purchases, subscript m denotes which food healthfulness measure is utilized, F is a count variable that measures the shopping frequency, and hence β_1 is the main parameter of interest. Other control variables include a set of price indices P for the 52 food categories denoted by k; the share of total food expenditures in different types of stores S indexed by g, and a set of j household characteristics HC. Finally, ε_{itm} denotes the idiosyncratic error term assumed to be normal.

A few issues regarding the model specification need to be addressed before further describing the estimation strategy. First, the model includes a set of price indices for the 52 categories because, in theory, the relative prices of all possible food products would impact consumers' choices (and hence the healthfulness of food purchases). Ideally, a model of consumer food choices should account for prices of all food products. However, estimating effects of all product prices is not feasible due to the large number of products. Instead, we use the price indices for the 52 food categories reported in the QFAHPD. These price indices are constructed using Nielsen Homescan data, and vary by market group.[4] Market groups are categorized as metropolitan and nonmetropolitan markets in the U.S. The market groups reported in QFAHPD, 26 metropolitan and 9 nonmetropolitan markets, do not precisely match the specification of market groups in the Nielsen dataset. Hence, to be able to use the price indices we match the two sets of specifications of the market groups using the geographical market area information from both datasets.

One of the limitations of using QFAHPD price indices is that the prices do not vary by households within a market group, but rather only vary by households across market groups and time. Additionally, some market-year-quarter combinations have missing prices for certain food categories. We impute missing values by linear interpolation using the information from periods for which prices are available.

Prior studies find that store format affects the healthfulness of food purchases (Volpe, Okrent, and Leibtag 2013). To control for the effects of the store format on healthfulness of food purchases, we include food expenditure shares at different types of stores, such as grocery stores, small convenience stores, etc. Also to control for household heterogeneity, we include the following household characteristics in the model: income, education level and employment status for the head(s) of household, race, household size, and presence of young children. The rationale behind including control variables is

[4] Refer to Todd et al. (2010) for a summary of the methodology used to construct these price indices for the 52 food categories.

discussed in Table A.2.1 in the Appendix. Table 2.1 provides a summary of statistics. We use alternative specifications of the model to exploit the panel nature of the data. We estimate the model with household fixed effects, quarter fixed effects to control for seasonality, and year fixed effects. The time invariant demographic variables are necessarily dropped in the specifications of the model with household fixed effects.

In our subsequent analysis we investigate the effect of purchase frequency on expenditure shares of major food categories. This analysis provides insights into the driving forces of the estimated effect of purchase frequency on healthfulness of food purchases. In particular, we specify the dependent variable in equation 2.2 as: (a) the share of expenditures on fruits, (b) the share of expenditures on vegetables, (c) the share of expenditures on commercially prepared items and sugary beverages, and (d) the share of expenditures on all other food items, including meat and dairy products. These major food categories are based on the food category definitions in Table 2.2. Accordingly, fruits correspond to food categories 1-3, vegetables correspond to food categories 4-15, commercially prepared items and sugary beverages correspond to food categories 41-42 and 44-52, and all other food items correspond to food categories 16-40 and 43 listed in Table 2.2. These major food categories are chosen specifically to explore the effect of shopping frequency on expenditure shares of fruits and vegetables and temptation foods.

Table 2.1.: Summary of Sample Statistics (N=3,888,137)

Variable	**Mean**	**St. Deviation**
HealthExpShare	30.19	18.28
Frequency (*t*=1 month)	6.84	3.89
Entropy Function	0.40	0.16
Household Income (Nielsen Bracket)[1]	19.65	5.91
Household Size	2.39	1.29
Child <12 present (%)	11.60	32.03
Male Head Education (Nielsen Bracket)	3.10	2.04
Female Head Education (Nielsen Bracket)	3.76	1.57
Male Head Employment (Nielsen Bracket)	3.56	3.25
Female Head Employment (Nielsen Bracket)	4.72	3.47
White (%)	84.26	36.41
Black (%)	8.83	28.38
Asian (%)	2.33	15.09
Other Race (%)	4.57	20.88
Total Food Expenditures (1 month)	\$80.78	\$54.43
Total Expenditures on Healthful Foods (1 month)	\$23.94	\$21.13
Grocery store Expenditure Share (%)	68.03	33.08
Drug store Expenditure Share (%)	2.34	8.03
Convenience store Expenditure Share (%)	0.37	3.40
Discount store Expenditure Share (%)	19.76	29.55
Dollar store Expenditure Share (%)	1.57	6.72
Warehouse store Expenditure Share (%)	7.94	18.76
Supermarket and Grocery stores, by Zip Code[2]	5.41	6.00
Drug stores, by Zip Code	3.74	3.31
Gas station stores, by Zip Code	7.83	6.24
Convenience stores, by Zip Code	2.40	2.80
Club stores, by Zip Code	0.41	0.71
Severe weather events per month, by FIPS Code[3]	2.03	4.05

Source: Nielsen data and author's calculations.

[1] Table A.2.1 in the Appendix contains information on Nielsen's brackets and variable definitions.

[2] Information on the number of stores, for each store type, by zip code, was obtain from the US Census Bureau, County Business Patterns, using the following NAICS codes: Supermarket and grocery stores (NAICS 445110), Drug stores (NAICS 446110), Club stores (NAICS 452910), Gas station stores (NAICS 447110), and Convenience stores (NAICS 445120).

[3] Information on the number of severe weather event per month, by FIPS code, for the period January 2004 – December 2012 was obtained from National Climatic Data Center – NOAA, Storm Events Database.

Table 2.2.: Average Expenditure Shares for Food Categories

Food Group	Category	USDA Healthful	Mean Expenditure Share
1	Fresh/Frozen fruit	Yes	0.025
2	Canned Fruit	Yes	0.011
3	Fruit Juice	Yes	0.029
4	Fresh/Frozen dark green vegetables	Yes	0.003
5	Canned dark green vegetables	Yes	0.000
6	Fresh/Frozen orange vegetables	Yes	0.002
7	Canned orange vegetables	Yes	0.001
8	Fresh/Frozen starchy vegetables	Yes	0.027
9	Canned starchy vegetables	Yes	0.005
10	Fresh/Frozen select nutrient vegetables	Yes	0.003
11	Canned select nutrients	Yes	0.004
12	Fresh/Frozen other vegetables	Yes	0.013
13	Canned other vegetables	Yes	0.008
14	Frozen/Dried Legumes	Yes	0.000
15	Canned Legumes	Yes	0.001
16	Whole grain bread, rolls, rice, pasta, cereal	Yes	0.035
17	Whole grain flour and mixes	Yes	0.001
18	Whole grain frozen/ready to cook	Yes	0.000
19	Other bread, rolls, rice, pasta, cereal	No	0.064
20	Other flour and mixes	No	0.007
21	Other frozen/ready to cook grains	No	0.018
22	Low fat milk	Yes	0.019
23	Low fat cheese	Yes	0.002
24	Low fat yogurt & other dairy	Yes	0.015
25	Regular fat milk	No	0.016
26	Regular fat cheese	No	0.028
27	Regular fat yogurt & other dairy	No	0.002
28	Fresh/frozen low fat meat	Yes	0.008
29	Fresh/frozen regular fat meat	No	0.032
30	Canned meat	No	0.002
31	Fresh/frozen poultry	Yes	0.007
32	Canned poultry	Yes	0.001
33	Fresh/frozen fish	Yes	0.011
34	Canned fish	Yes	0.006

Continued.

Table 2.2.: Continued			
Food Group	Category	USDA Healthful	Mean Expenditure Share
35	Raw nuts and seeds	Yes	0.031
36	Processed nuts, seeds and nut butters	Yes	0.006
37	Eggs	Yes	0.005
38	Oils	Yes	0.009
39	Solid fats	No	0.016
40	Raw sugars	No	0.007
41	Non-alcoholic carbonated beverages	No	0.122
42	Non-carbonated caloric beverages	No	0.024
43	Water	Yes	0.014
44	Ice cream and frozen desserts	No	0.035
45	Baked good mixes	No	0.008
46	Packaged sweets/baked goods	No	0.044
47	Bakery items, ready to eat	No	0.026
48	Frozen entrees and sides	No	0.130
49	Canned soups, sauces, prepared foods	No	0.011
50	Packaged snacks	No	0.071
51	Ready to cook meals and sides	No	0.023
52	Ready to eat deli items (hot and cold)	No	0.012

Source: Food categories (QFAHPD), USDA Healthful (Volpe et al. 2013), Mean Expenditures (Author's calculations using Nielsen data).

In subsequent analysis we check the robustness of the estimated results to an alternative way of measuring purchase frequency. Following Beatty (2008), we measure shopping frequency as a distribution of shopping trips in the duration of one month using an entropy function defined as:

$$H(x)_{it} = -\sum_{f=1}^{F} \left(\frac{x_f}{X}\right) * \ln\left(\frac{x_f}{X}\right), \quad (2.3)$$

where f denotes each shopping trip and F is the total number of shopping trips, and x_f denotes total expenditures in trip f, whereas X denotes total expenditures over the course of a month. This function is equal to zero if all food expenditures are made in one shopping trip per one-month period, and takes a maximum value of $log(F)$ when all food expenditures are distributed evenly in the course of the one-month period. For ease of interpretation, we follow the approach suggested by Beatty (2008) to divide the function by $log(F)$ in order to modify the range of values to be between 0 and 1. We also adopt the approach of letting $0 * ln(0) = 0$. In this form, the function of the dispersion of expenditures takes values between 0 and 1, with higher values indicating a higher dispersion of expenditures over the one-month period. We then use this function, instead of the shopping frequency count variable, in equation 2.2 in order to explore the impact of the dispersion of food expenditures over time on the healthfulness of food purchases.

2.3.3. Instrumental Variables

The estimator in equation 2.2 assumes that the purchase frequency is exogenous to healthfulness of household food purchases. However, it could be the case that consumers' healthful food choices might dictate how often they visit a grocery store. For example, consumers who prefer to purchase healthier foods, such as fruits and vegetables, may visit a grocery store more frequently. That is, there could be a reverse causality problem in equation 2.2 that would impose a threat to the identification of the effect of purchase frequency. To address the reverse causality problem we take an instrumental variable, IV, approach to estimate the effect of shopping frequency on healthfulness of food purchases. Ideally, variables that are correlated with purchase frequency but not correlated with consumer food choices could be used as instruments for purchase frequency. To this end, we use the number of stores and the number of severe weather events in an area as instruments. Note that the data on the instrumental variables is at the zip code level. In terms of the number of stores, we use an instrument that measures the number of supermarket and grocery stores and another instrument that measures the number of supercenter and warehouse stores in an area. A maintained assumption under this IV strategy is that the number of stores is predetermined, thereby exogenous to household food purchase decisions. Presumably, an increase in the number of supermarket and grocery stores would increase the options available to the households living in an area. Also, an increase in the number of these stores would likely decrease the average distance to the nearest store. Consequently, we expect the number supermarket and grocery stores to be positively correlated with grocery shopping frequency.

The other instrument that measures the number of warehouse and supercenter stores in an area would likely make it easier for households to purchase more foods in bulk. Hence, we expect this instrument to be negatively correlated with shopping frequency. The first stage regression results, which are reported in the appendix table A.2.2, confirm the expected sign of the correlations.

In addition to the number of stores, we use the number of severe weather events in an area as an instrument for shopping frequency. The rationale for this instrument is that, the number of severe weather events is exogenous to households' healthful food purchases, however, presumably, an increase in severe weather events would make it harder to visit a grocery store, indicating a negative correlation with shopping frequency. The estimates of the first stage regression confirm this expectation, and are reported in table A.2.2.

We formally investigate the relevance of the instrumental variables by testing if $Cov(F, G_i) \neq 0$, and if $Cov(F, SW) \neq 0$, where G denotes the number of stores variable, and i specifies the type of the store; and SW denotes the number of severe weather events. From the first stage regressions, the F statistic for all IVs is above the commonly-used threshold of 10, hence indicating that we do not have a problem of weak instruments.

2.4. Data

We use 2004-2010 Nielsen Homescan data which includes information on food purchases reported by a panel of households. To participate in the panel, consumers who are at least 18 years old register online and provide their demographic information. Based on their demographics Nielsen picks a subset of consumers and provides them with a scanner to record barcodes of the purchased items in each shopping trip (Einav, Leibtag, and Nevo 2009). The incentive to participate is the accumulation of points, which can be redeemed for merchandise (Einav, Leibtag, and Nevo 2009). The sample of households covers 52 metropolitan markets in the United States. The resulting dataset includes information on price and quantity of products, product characteristics, type of store, and date of purchase. In addition to purchase information, the dataset includes information on household demographics, such as household size and composition, presence of children, and income. The heads of households also report their age, gender, level of educational attainment, hours worked, and occupation. Except for gender, which is a binary variable, the rest of the variables on household characteristics are categorical.

The benchmark sample includes 108,739 unique households.[5] Households remain in the sample for an average of 53.01 (out of 84 possible) months. For the purpose of this study, we create the shopping frequency variable as the number of shopping trips that resulted in non-zero expenses during the course of a timeframe t. Using information on household expenditures and store type information available in the Nielsen Homescan database, we calculate the share of purchases in various types of stores by household and time frame. Table 2.1 provides the summary of statistics for the full benchmark sample.

Together with the Nielsen Homescan dataset we use the USDA's QFAHPD to measure the healthfulness score of food purchases. In particular, we aggregate the UPC level purchase information reported by the Nielsen Homescan dataset into one of the 52 food categories as specified by the QFAHPD.[6] We also use price information for each of the food categories reported in the QFAHPD. Table 2.2 reports the aggregate food categories, USDA recommendations for each group, and the mean household expenditure shares for each category for the households in the sample.

We supplement the main dataset with additional data on the instrumental variables. The data on the number of stores are obtained from the U.S. Census Bureau, County Business Patterns. This dataset includes information on the number of supermarket grocery stores and club and supercenter stores. The data are annual and at the county level. Data on

[5] The dataset includes information on food purchases for 132,170 households. However, for the purpose of our analysis which involves using household fixed effects, we eliminate households that remain in the panel for less than six months. In addition, we eliminate data outliers as will be discussed in the empirical section. Finally, we eliminate observations with missing values for the control variables and/or instrumental variables. This brings down the total number of households to 108,739.

[6] The authors are grateful to the USDA-ERS staff for providing us with information on how each individual product is categorized into one of the 52 QFAHPD categories.

severe weather events are daily, but were aggregated at a monthly-level (the time unit for the benchmark analysis). The data are obtained from the National Climatic Data Center – NOAA, Storm Events Database. The summaries of statistics for the two instrumental variables are included in Table 2.1.

Recall that the food healthfulness variable is measured as indicated in equation 2.2 above. The measurement of food purchase healthfulness, FoodExpShare, takes on values between 0 to 100. For example, FoodExpShare=30 implies that 30 percent of the household's budget is spent on food categories recommended for increased consumption by the USDA. We use the linear form of the shopping frequency variable in our empirical analysis, in order to ease the interpretation of the results. We use price indices from the QFAHPD-2, which provides price indices for food categories by geographical market area, for the time period 2004-2010. Since there are some missing price indices for category/market group/year/quarter combinations, we impute missing values using averages across periods when such prices are available for the specific category/market group.

In estimation of all models we exclude outliers in the frequency of shopping trips and in monthly food expenditures. We do this by identifying the natural breaks in the data, instead of using arbitrary thresholds. For monthly food expenditures, we keep observations that report grocery expenditures between $10 and $400, and drop any observations outside of this range. In terms of grocery shopping frequency, we keep observations that report up to 24 shopping trips per month. Similarly, in order to explore the panel structure of the data, we only keep households that appear in the sample for at least 6 months in the course of the seven-year study period.

2.5. Results

2.5.1. Benchmark Results

Table 2.3 reports the estimates of OLS, Fixed Effects and IV models using the benchmark sample. Models 1a, 1b, and 1c report the basic OLS results with no controls, with the set of control variables as specified in equation 2.2, and with the set of demographic controls and price indices, respectively.[7] Detailed information on all covariates is provided in Table A.2.1. The fixed effects models include model 2a which is similar to 1a, except that household fixed effects are included, model 2b, which includes both household and year fixed effects, and model 2c, which includes both types of fixed effects as well as the prices of the different food categories. The IV models include model 3a in which the number of severe weather events is used as an IV, model 3b in which the number of grocery/supermarket stores, the number of club/supercenter stores, as well as the number of severe weather events are used as IVs, and model 3c in which the number of grocery/supermarket stores and the number of supercenter/club stores in the area are used as IVs. Models 4a, 4b, and 4c, are similar respectively to models 3a, 3b, and 3c – except that they also control for food prices.

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

Table 2.3.: Estimates of Model Coefficients (Dependent Variable: Healthfulness of Food Purchases)[1]

	OLS[2]			Fixed Effect			Instrumental Variables					
	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3a	Model 3b	Model 3c	Model 4a	Model 4b	Model 4c
Shopping Frequency	-0.060***	-0.051***	-0.029***	-0.068***	-0.036***	-0.038***	-3.478***	-2.501***	-2.264***	-6.123***	-2.715***	-1.355**
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.290)	(0.123)	(0.136)	(1.425)	(0.611)	(0.689)
Child under 12		-0.264***	-0.115				0.052	-0.011	-0.026	-0.223**	-0.057	0.010
		(0.075)	(0.074)				(0.066)	(0.058)	(0.057)	(0.109)	(0.066)	(0.062)
Employed		-1.339***	-0.944***				-0.435***	-0.553***	-0.582***	-1.131***	-0.657***	-0.468***
		(0.074)	(0.073)				(0.066)	(0.054)	(0.053)	(0.210)	(0.100)	(0.108)
Max Education		1.088***	1.066***				0.061	0.085**	0.091**	0.111**	0.101**	0.097**
		(0.038)	(0.037)				(0.044)	(0.040)	(0.040)	(0.056)	(0.041)	(0.038)
White		-0.295***	-0.343***				-0.345***	-0.209*	-0.176	-0.454**	-0.220*	-0.127
		(0.102)	(0.102)				(0.129)	(0.116)	(0.114)	(0.183)	(0.123)	(0.118)
Household Income		0.133***	0.093***				0.005	0.025***	0.030***	0.026***	0.026***	0.026***
		(0.006)	(0.006)				(0.008)	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)
Household Size		-0.762***	-0.659***				0.410***	0.157***	0.095**	0.791***	0.178	-0.067
		(0.025)	(0.024)				(0.079)	(0.038)	(0.041)	(0.258)	(0.112)	(0.126)
Grocery Store Expenditure Share		-7.838***	-7.741***				-8.764***	-8.417***	-8.333***	-9.875***	-8.516***	-7.974***
		(0.126)	(0.126)				(0.136)	(0.095)	(0.097)	(0.577)	(0.258)	(0.286)
Small Store Expenditure Share		-10.180***	-10.226***				-9.955***	-9.847***	-9.821***	-10.072***	-9.844***	-9.753***
		(0.134)	(0.134)				(0.102)	(0.094)	(0.093)	(0.149)	(0.102)	(0.100)
Price Indices	No	No	Yes	No	No	Yes	No	No	No	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	Yes	Yes	No	No	No	No	No	No
Constant[3]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137
Within/Adjusted R^2 [4]	0.0004	0.1126	0.1051	0.4100	0.4110	0.4120	-0.3670	-0.1840	-0.1490	-1.1600	-0.2170	-0.0450

Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01

[1] The sample excludes outliers in the number of shopping trips and outliers in monthly food expenditures.

[2] Model 1a: Basic OLS; Model 1b: OLS with Demographics; Model 1c: OLS with Demographics and Price Indices; Model 2a: Household Fixed Effects; Model 2b: Household and Year Fixed Effects; Model 2c: Household and Year Fixed Effects, and Price Indices; Model 3a: IV #Severe Weather Events; Model 3b: IV #Grocery/Supermarket stores, #Supercenter/Warehouse stores, and # Severe weather events; Model 3c: IV #Grocery/Supermarket stores, #Supercenter/Warehouse stores, and; Model 4a: IV #Severe Weather Events, and Price Indices; Model 4b: IV #Grocery/Supermarket stores, #Supercenter/Warehouse stores, and # Severe weather events, and Price Indices; Model 4c: IV #Grocery/Supermarket stores, #Supercenter/Warehouse stores, and Price Indices.

[3] The constant for the IV models is not reported when using the XTIVREG2 Stata command, but is reported when using the XTIVREG Stata command.

[4] The within R^2 is either not reported for the IV models (when using the XTIVREG Stata command), or reported and negative (when using the XTIVREG2 Stata command).

The benchmark results suggest that the impact of shopping frequency on the healthfulness of food purchases is negative and statistically significant. The economic significance varies by model specification, with the coefficient ranging from -0.03 to -6.12. For example, in model 3a, in which severe weather events are used as an IV, the results indicate that increasing the number of shopping trips by 1 additional trip per month, at the mean, leads to a decrease in the share of expenditures on healthful foods by 3.48 percentage points. The results from the instrumental variables models suggest that the magnitude of the impact, in absolute value, is larger, than the OLS and fixed effects models. Yet throughout the benchmark results, the coefficient is negative.

Note that, as stated above, the IV estimates of the effect of shopping frequency on healthfulness of purchases are larger in absolute value than OLS estimates. This is plausible because of the difference between the average treatment effect (ATE) and the local average treatment effect (LATE). The benchmark regression results identify the negative impact of shopping frequency on the healthfulness of food purchases, and this is the ATE. In using instrumental variables, we identify the local average treatment effect (LATE), as some households are affected by the instrument, while others are not. In the sample, there are households that carefully plan their purchases and stick to their list of food items to purchase as well as to their planned shopping trips. Let's call these households "planners". The sample also includes households that do not plan shopping trips and do not shop with a list, and hence are more prone to temptations to purchase unhealthful foods. Let's call these households "non-planners". These groups of households cannot be identified in the data, however we conjecture that non-planners are more prone to *temptation* foods. That is, if we were able to identify non-planner households and run the regression only on this sub-sample, the estimated coefficient of shopping frequency would have been even higher, in absolute value.

Now consider the differential effects of the instruments on planners and non-planners. The number of severe weather events is more likely to affect the purchase frequency of non-planners compared to those who plan their shopping trips. Similarly, the number of stores in an area might affect the purchase frequency of non-planners more than that of planners. That is, for non-planners, more stores in an area makes it easier to shop more frequently. If non-planners are more easily tempted to purchase unhealthful foods, this would lead to a greater negative impact of purchase frequency. Hence, these expected differential effects of instruments on household types would explain why the IV estimates of the shopping frequency on healthfulness of food purchases are larger, in absolute value, than the OLS estimates.

The estimated effects of the covariates to a large extent confirm the findings of previous studies. The results suggest that income and education are positively correlated with healthfulness of food purchases. Similarly, ceteris paribus, households with employed household head(s) have lower scores of healthfulness of food purchases, compared to households with unemployed household head(s). This is expected since employed households are likely to be more time constrained, consequently, more likely to rely on pre-prepared and processed foods. The impacts of the household size and the presence of children younger than 12 years old change magnitude and sign across empirical model specifications, and are ambiguous. The estimates indicate that being white is correlated with a less healthful diet, compared to minorities. Also, a higher share of expenditures in grocery stores and small stores such as convenience stores is associated with a lower healthfulness of food purchases, compared to purchases made in warehouse stores.

Next, we investigate the effect of purchase frequency on expenditure shares of major food categories: fruits, vegetables, commercially prepared items and sugary beverages, and all other foods. We consider commercially prepared items and sugary beverages to be the temptation foods. Table 2.4 reports the empirical results from this exercise using the preferred model specification in which the number of stores variables are used as IVs. Models 1a and 1b report the results for vegetables, models 2a and 2b report the results for all fruits, models 3a and 3b report the results for commercially prepared items and sugary beverages,[8] and models 4a and 4b report the results for all other foods. We exclude the same outliers as in the benchmark sample, such that the analysis is conducted with the same set of households.

The results indicate that a higher shopping frequency leads to a lower share of expenditures for fruits and vegetables. The results however suggest that a higher shopping frequency leads to more purchases of *temptation* foods, as the share of expenditures on commercially prepared items and sugary beverages goes up. This indicates that the second mechanism, that of temptation, also is supported by the data. As a whole, these results suggest that going to grocery store more often decreases the share of expenditures on healthful foods, but increases the share of expenditures on unhealthful foods.

[8] Commercially prepared items include items such as ice cream, frozen dessert, muffin and cake mixes, cookies, candy bars, pizzas, French fries, etc.

Table 2.4.: Estimates of Model Coefficients (Dependent Variable: Expenditure Shares)

	Vegetables[1]		Fruits		Commercially Prepared Food & Sugary Beverages		All Other Food	
	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b	Model 4a	Model 4b
Shopping Frequency	-0.266***	-0.711**	-0.796***	-0.473	2.899***	3.181***	-1.836***	-1.996***
	(0.058)	(0.317)	(0.073)	(0.387)	(0.155)	(0.819)	(0.142)	(0.755)
Child under 12	-0.015	-0.031	0.127***	0.139***	-0.149**	-0.067	0.038	-0.040
	(0.023)	(0.028)	(0.029)	(0.033)	(0.067)	(0.079)	(0.060)	(0.071)
Employed	-0.092***	-0.145***	-0.121***	-0.087	0.747***	0.930***	-0.534***	-0.698***
	(0.023)	(0.050)	(0.028)	(0.060)	(0.061)	(0.129)	(0.056)	(0.118)
Max Education	0.040**	0.040**	0.025	0.029	-0.166***	-0.184***	0.102**	0.115***
	(0.017)	(0.018)	(0.020)	(0.020)	(0.046)	(0.047)	(0.042)	(0.042)
White	-0.133***	-0.158***	0.108*	0.127**	0.505***	0.498***	-0.480***	-0.466***
	(0.048)	(0.054)	(0.060)	(0.063)	(0.131)	(0.143)	(0.120)	(0.130)
Household Income	0.009***	0.010***	0.011***	0.011***	-0.030***	-0.034***	0.010*	0.014***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.006)	(0.006)	(0.006)	(0.005)
Household Size	0.003	0.084	0.080***	0.017	-0.459***	-0.480***	0.376***	0.379***
	(0.017)	(0.058)	(0.021)	(0.070)	(0.047)	(0.149)	(0.043)	(0.138)
Grocery Store Expenditure	-0.105**	-0.294**	-3.743***	-3.610***	3.357***	3.483***	0.492***	0.421
Share	(0.042)	(0.132)	(0.053)	(0.161)	(0.108)	(0.340)	(0.100)	(0.313)
Small Store Expenditure	-2.135***	-2.198***	-4.456***	-4.403***	7.621***	7.643***	-1.030***	-1.041***
Share	(0.040)	(0.046)	(0.050)	(0.055)	(0.104)	(0.118)	(0.097)	(0.109)
Price Indices	No	Yes	No	Yes	No	Yes	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137
R^2	-0.007	-0.067	-0.063	-0.015	-0.189	-0.229	-0.079	-0.093
First stage statistics:								
F statistic	974.88	38.33	974.88	38.33	974.88	38.33	974.28	38.33
RMSE	2.552	2.534	2.552	2.534	2.552	2.534	2.552	2.534
ARW F Test	10.69	2.83	64.28	3.94	209.28	10.58	91.8	3.86

Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01

[1] Models 1a, 1b: In these models, the dependent variable is the share of expenditures on vegetables; Models 2a, 2b: The dependent variable is the share of expenditures on fruits; Models 3a, 3b: The dependent variable is the share of expenditures on all commercially prepared items and sugary beverages; and Models 4a, 4b: The dependent variable is the share of expenditures on all other food categories. All models correspond to models 3c and 4c in Table 2.3.

2.5.2. Robustness Checks

The analysis of robustness checks is conducted with all the model variations described above. Yet, for brevity, we only report the results from the equivalent of models 3c and 4d, that is, the model in which the number of grocery/supermarket stores and club/supercenter stores are used as instrumental variables, and prices are not included in one variation and are included in the second variation of the model. First stage results from the estimations reported in Table A.2.2 show that these two models perform best in terms of the strength of instruments as measured by the significance of the coefficients and the F-test. The relevant statistics on the tests conducted on the exclusion restriction and strength of the instrumental variables are reported on Table A.2.2.

Table 2.5 reports the results of robustness checks. The first two columns, models 1a and 1b, of Table 1.4 report estimates of equation 2.2 using projection factors. The Nielsen Homescan data includes projection factors for households in the sample. Projection factors make the sample representative of the U.S. population in several segments, including household size, income, race, Hispanic origin, as well as gender, education and occupation of the heads of household and presence of children. The software utilized for the analysis does not allow projection factors to vary by year when panel data is used. Hence, for each household we use the weight given to the household in 2004. If the household does not appear in the data in 2004, we use the weight assigned to the household in the earliest year in which the household appears in the sample. The estimates of the effect of shopping frequency on healthfulness of food purchases are largely consistent with the results reported in Table 2.3. In both models the estimates are negative, and close in magnitude to the models estimated without projection factors. That is, the results indicate that increasing shopping frequency by one time per month, at the mean, decreases the share of expenditures on healthful foods, by 2.37 percentage points. The results for the demographic and other controls follow the same pattern, with the exception of race, which becomes statistically not significant in this case.

Table 2.5.: Estimates of Model Coefficients using Alternative Weights and Samples (Dependent Variable: Healthfulness of Food Purchases)[1]

	Projection Factors		Grocery Store Sample		Single-member Households	
	Model 1a	Model 1b	Model 2a	Model 2b	Model 3a	Model 3b
Shopping Frequency	-2.373***	-0.259	-2.052***	-0.838**	-3.752***	-4.397
	(0.221)	(1.094)	(0.159)	(0.382)	(0.552)	(4.072)
Child under 12	0.006	0.026	-0.068	0.073		
	(0.088)	(0.077)	(0.071)	(0.073)		
Employed	-0.801***	-0.455**	-0.667***	-0.425***	-1.147***	-1.293**
	(0.081)	(0.199)	(0.066)	(0.069)	(0.107)	(0.652)
Max Education	0.143**	0.222***	0.134***	0.110**	0.081	0.095
	(0.067)	(0.068)	(0.049)	(0.048)	(0.113)	(0.145)
White	-0.095	0.078	-0.179	-0.166	-0.519	-0.427
	(0.169)	(0.178)	(0.139)	(0.137)	(0.440)	(0.641)
Household Income	0.035***	0.031***	0.033***	0.017***	0.046***	0.053**
	(0.008)	(0.007)	(0.006)	(0.006)	(0.013)	(0.025)
Household Size	0.199***	-0.155	-0.099**	-0.197***		
	(0.063)	(0.186)	(0.039)	(0.053)		
Grocery Store	-7.936***	-7.283***			-8.833***	-9.108***
Expenditure Share	(0.143)	(0.360)			(0.304)	(1.625)
Small Store Expenditure	-9.530***	-9.498***			-9.359***	-9.278***
Share	(0.144)	(0.136)			(0.240)	(0.486)
Price Indices	No	Yes	No	Yes	No	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	3,888,137	3,888,137	3,617,545	3,617,523	961,476	961,476
R^2	-0.168	0.008	-0.049	-0.006	-0.233	-0.322
First stage statistics:						
F statistic	362.8	13.91	1664.55	279.94	112.83	2.25
RMSE	2.578	2.558	2.001	1.989	2.155	2.148
ARW F Test[2]	72.59	2.97	88.1	2.86	28.96	0.95

Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01

[1] Model 1a, 1b: In these models, we use the projection factors provided by Nielsen; Models 2a, 2b: In these models, we conduct the analysis using the grocery store sample. Model 3a, 3b: In these models, we limit the sample to single-member households. All models correspond to models 3c and 4c in Table 2.3.

[2] Anderson-Rubin-Wald F-Test for Weak Instruments.

Second, we estimate the model by limiting the sample to only purchases made in grocery stores. The results are reported in table 2.4 models under models 2a and 2b. The results show that the estimated effect of purchase frequency on healthfulness of food purchases remains robust. The impact of shopping frequency is negative and significant. Also, the impact of demographic factors follows the same pattern as reported in the benchmark results.

Third, we estimate the model by limiting the sample to only purchases made by single-member households. These households, if the member is fully employed, tend to have higher time constraints as the task of purchasing and preparing food cannot be shared with other members of the household. The results are reported in Table 2.4 under models 3a and 3b. The results indicate that the effect of purchase frequency on healthfulness of food purchases is negative and significant, but the effect is larger in absolute value compared to the benchmark results. The results show that for single-member households, increasing shopping frequency by 1 time per month decreases the share of expenditures on healthful food by 3.75 percentage points. Also, the estimates of the other covariates largely conform to the benchmark results with the exception of the estimate of the coefficient on education, which losses its statistical significance in the sub-sample of single-member households.

Lastly, we investigate the robustness of the results to an alternative measure of purchase frequency. In particular, we estimate the impact of the dispersion of expenditures over time on the healthfulness of food purchases. The entropy function that is used in this estimation is discussed at greater length in the empirical methods section, and is defined in equation 2.3.[9] In order to ease the interpretation of the results, we take the logarithm of the entropy function. Table 2.6 reports the estimates of the preferred IV models equivalent to models 3a and 3b in Table 2.3. In both models the results indicate that the effect of the dispersion of expenditures over time on the healthfulness of food purchases is negative. However, the effect is not statistically significant in the model that includes price indices. Compared to benchmark results the magnitude of the effect is more negative. A one percent increase in the entropy function (a higher dispersion of food expenditures) leads to a 9.06 percentage point decrease in the healthfulness of food purchases, at the mean.

[9] Note that the mean value of the entropy function in our sample is 0.40, with values ranging from 0 to 0.92. The shopping frequency variable and the dispersion of food expenditures variable (entropy function) are positively correlated, with a coefficient of correlation at 0.84. For observations for which the entropy function is between 0 and 0.25 the average shopping frequency is 2.63 trips per month; for observations for which the entropy function is between 0.25 and 0.50 the average shopping frequency is 5.89 shopping trips per month; for observations for which the entropy functions is between 0.50 and 0.75 the average shopping frequency is 11.14; finally, for observations for which the entropy function is between 0.75 and 1.00 the average shopping frequency is 19.98 shopping trips per month.

Table 2.6.: Selected Results of Estimating the Impact of Expenditure Dispersion on the Healthfulness of Food Purchases

	Model 1a	Model 1b
Log Entropy Function[1]	-9.056***	-2.858
	(0.608)	(3.114)
Child under 12	0.297***	0.136
	(0.072)	(0.083)
Employed	-0.448***	-0.352***
	(0.062)	(0.092)
Max Education	0.065	0.089**
	(0.045)	(0.038)
White	-0.253*	-0.105
	(0.131)	(0.133)
Household Income	0.027***	0.026***
	(0.006)	(0.005)
Household Size	-0.144***	-0.263***
	(0.033)	(0.056)
Grocery Store Expenditure Share	-5.747***	-6.906***
	(0.159)	(0.581)
Small Store Expenditure Share	-7.264***	-8.895***
	(0.192)	(0.841)
Price Indices	No	Yes
Constant	Yes	Yes
N	3,888,137	3,888,137
R^2	-0.482	-0.040
First Stage Statistics:		
F statistic	363.26	10.84
RMSE	1.102	1.098
ARW F Test[2]	159.8	4.11

Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01

[1] The Entropy function is defined in equation 2.3.

[2] Anderson-Rubin-Wald F-Test for Weak Instruments.

2.6. Discussion and Conclusions

In this chapter we have estimated the impact of shopping frequency on the healthfulness of food purchases for American households. Our main result is that a higher frequency of shopping trips leads to less healthful food purchases. The result indicates that consumers buy relatively more temptation foods compared to healthful foods as they shop for foods more frequently. This finding lends support to the findings of prior studies that once at the store, people are influenced in a variety of ways to purchase unhealthful foods. For example, unhealthful foods are often placed in checkout lanes and at the end of the aisles in order to make it easy for customers to pick up such items. Our subsequent analysis of the effects of purchase frequency on expenditure share of major food groups provides further support to this finding. This analysis shows that, on average, the expenditure share of temptation foods increases and the expenditures shares of fruits and vegetables decrease with purchase frequency.

We conduct a number of robustness checks. First, we investigate the impact of shopping frequency on the healthfulness of food purchases for specific sub-samples, such as single-member households. Second, in order to isolate the impact of store types, we conduct the analysis using only grocery shopping done at traditional grocery stores. Results from both of the analyses indicate that the effect of shopping frequency on the healthfulness of food purchases is negative and statistically significant.

Third, we investigate whether the negative impact persists if we look at the effect of the dispersion of expenditures over time rather than the effect of shopping frequency. We measure the dispersion of expenditures using an entropy function approach. We find that increasing the dispersion of food expenditures across time leads to less healthful food purchases. To the extent that a higher food dispersion correspond to a higher shopping frequency, this result tells a consistent story that as households visit the grocery stores more often, they face higher temptations, and end up purchasing less healthful foods. Overall our results suggest that recommendations directed to consumers in terms of shopping trips should take into consideration that shopping foods in bulk might not only help consumers to save money and time, but may also lead to positive results in terms of the healthfulness of food purchases.

The result that shopping frequency has a negative effect on the healthfulness of food purchases has important implications for business and public policy. For example, in January 2016 one of the major retail grocery chains announced that it would introduce “Healthier Checklanes” in select stores (Caruso 2016). Accordingly, the retailer is replacing the temptation foods such as chocolates and candy with healthier alternatives at the checkout lanes to limit unhealthy, impulse buys. Examples of similar efforts exist at the regional level where nonprofit organizations partner with local retailers to promote “healthy aisles” and improve diets in local communities (Can Do Houston – Building Healthy Lives n.d.). Our results suggest that these policies and similar other efforts that limit in-store visibility of and access to temptation foods would be effective in increasing the healthfulness of food purchases. Furthermore, public policies that are targeted to improving diet quality, should account for the effect of purchase frequency. For example, nutrition education programs that raise awareness of temptation foods and how to reduce temptations to purchase such items could be effective.

Our main result is also closely related to the findings in the food desert literature and has implications for public policy on food deserts. The food desert literature focuses on the effects of distance to store on diet quality. The findings in this literature are mixed: while some studies find that higher distance to store is correlated with low consumption of healthful foods, such as fresh fruits and vegetables (Rose and Richards 2004), other studies find no evidence of such a correlation (Cummins, Flint, and Matthews 2014). To the extent that shopping frequency is correlated with the distance to store, our results support the findings of the latter group of studies on food deserts. That is, lower distance to store may not improve people's diet, if it also increases purchase frequency and leads to increased purchases of temptation foods.

Table A.2.1.: Definition of Explanatory Variables and Motivation for Inclusion

Variable	**Definition**	**Motivation for Inclusion**
Household Income	Annual income Nielsen brackets, range from 3- Under $5,000, to 27- Over $100,000.	Studies have shown that household income is positively related to diet quality (see for example, Mushi-Brunt et al. 2007, Xie et al. 2003, Cullen et al. 2007).
Household Size	Number of household members, top-coded at 9 members.	Larger households may have different patterns of grocery shopping frequency and/or preferences for food healthfulness compared to smaller households.
Children <12 yrs old	Binary variable indicating the presence of children under the age of 12 in the household.	Children have different dietary needs compared to adults (Munoz et al. 1997).
Education	Highest education level of male/female head of household. **1** - grade school, **2** - some high school, **3** - graduated high school, **4** - some college, **5** - graduated college, **6 -** post college grad. [1]	Previous studies have established the link between education and diet quality as well as between education and obesity (Cullen et al. 2007, Xie et al. 2007).
Employment Status	Binary variable indicating whether the female and male heads of household are employed, or not.	Employment status and the number of hours worked may be linked to dietary needs. They are also likely highly correlated with the grocery shopping frequency. If one of the household heads is unemployed or working part time, he/she has more time to engage in household activities such as grocery shopping and food preparation.
Race/Ethnicity	Binary variables identifying households as White, Black, Asian or as belonging to another race.	Households of different ethnicities/races exhibit different food preferences and diet qualities (Cullen et al. 2007).

Continued.

Table A.2.1.: Continued

Variable	Definition	Motivation for Inclusion
Supercenter Expenditure Share	The share of food expenditures in club/supercenter stores during the time frame *t*. [3]	Higher share of food expenditures at supercenter stores leads to less healthful food purchases (Volpe et al. 2013).

[1] We keep the same education categories as reported in Nielsen Homescan database. However in regression analysis we control for the highest level of education attained by any of the heads of household.
[2] We control for the minimum hours worked by the head(s) of household. That is, if any of the heads of household have positive work hours, they are coded as "employed." Hence, "unemployed" households in our analysis are households in which both heads do not work.

[3] We calculate the share of expenditures in club/supercenter format stores using information on purchases in the course of a month, as well as store type information provided in the Nielsen Homescan database.

Table A.2.2.: First Stage Regressions - Dependent Variable: Shopping Frequency [1]

	Model 3a [2]	Model 3b	Model 3c	Model 4a	Model 4b	Model 4c
Severe weather events	-0.008***	-0.008***		-0.002***	-0.002***	
	(0.000)	(0.000)		(0.000)	(0.000)	
No. of club/supercenter stores		-0.239***	-0.240***		-0.027*	-0.027*
		(0.014)	(0.014)		(0.014)	(0.014)
No. of supermarket/grocery stores		0.016***	0.016***		0.008***	0.008***
		(0.002)	(0.002)		(0.002)	(0.002)
Child under 12	0.064**	0.057**	0.058**	-0.049*	-0.049*	-0.049*
	(0.026)	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)
Employed	0.121***	0.107***	0.108***	-0.139***	-0.140***	-0.140***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Max Education	-0.025	-0.023	-0.023	0.003	0.003	0.003
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)
White	-0.140***	-0.137***	-0.136***	-0.069*	-0.069*	-0.068*
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Household Income	-0.021***	-0.020***	-0.020***	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Household Size	0.260***	0.257***	0.257***	0.180***	0.180***	0.180***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Grocery Store Expenditure Share	-0.355***	-0.359***	-0.359***	-0.399***	-0.399***	-0.399***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Small Store Expenditure Share	-0.110***	-0.103***	-0.102***	-0.067***	-0.066***	-0.066***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Price Indices	No	No	No	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137	3,888,137
F statistic	535.16	824.41	974.88	34.97	37.21	38.33
RMSE	2.552	2.551	2.552	2.534	2.534	2.534
ARW F Test [3]	194.91	170.71	159.80	39.01	15.73	4.11
R^2	0.003	0.003	0.003	0.017	0.017	0.017

Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01

[1] The sample excludes outliers in the number of shopping trips and outliers in monthly food expenditures.
[2] Model 3a: IV #Severe Weather Events; Model 3b: IV #Grocery/Supermarket stores, #Supercenter/Warehouse stores, and # Severe weather events; Model 3c: IV #Grocery/Supermarket stores, #Supercenter/Warehouse stores, and; Model 4a: IV #Severe Weather Events, and Price Indices; Model 4b: #Grocery/Supermarket stores, #Supercenter/Warehouse stores, and # Severe weather events, and Price Indices; Model 4c: #Grocery/Supermarket stores, #Supercenter/Warehouse stores, and, and Price Indices.
[3] Anderson-Rubin-Wald F-Test for Weak Instruments.

Chapter 3: Demand Spillovers of Food Recalls in Differentiated Product Markets - Multistage Budgeting Approach to Demand Systems Estimation

3.1. Introduction

Millions of people in OECD countries are affected by food contamination, such as Salmonella, E.coli O157, and campylobacter (Trienekens and Zuurbier 2008). It's estimated that in the United States, each year one in six individuals gets sick due to foodborne illnesses and some 3,000 lives are lost (White 2014). Food product recalls due to pathogen contamination happen frequently in the U.S. economy. The U.S. Food and Drug Administration (FDA)—the institution primarily in charge of notifying consumers of recalls, market withdrawals, and safety alerts—reports food recalls almost on a daily basis.[10] The overall cost of food recalls in the United States exceeds billions of dollars each year (Marsh, Schroeder, and Mintert 2004). Consequently, both public and private organizations continue to devote increasingly more resources to improve the capacity to prevent and address food safety problems. For example, the U.S. government increased the number of inspections in food production plants under the FDA Food Modernization Act in 2011 (U.S. FDA). The rationale for public and private efforts in solving food safety problems and their efficacy depend on a full understanding of the economic consequences of food recalls. This study contributes to the literature on consumer response to food recalls by focusing on demand interrelationships between closely competing brands in a food

[10] Recalls may be initiated by the firm or by FDA's request. There are three classes of recalls based on the likelihood of harm and the severity of harm that exposure to the product may cause. Market withdrawals are initiated by firms typically for minor violations that would not be subject to legal action by the FDA. For extended definitions, see http://www.fda.gov/Safety/Recalls/ucm165546.htm.

product category. In particular, we examine the spillover effects of a recalled brand on demand for other brands in order to improve our understanding of the economic incentives of manufacturers and government for setting and enforcing food safety standards.

A recall of a food product could generate positive or negative spillover effects on demand for its close competitors. Understanding the direction and magnitude of these effects provides important information on economic incentives for private and public initiatives in food safety. To fix ideas, suppose that a brand of a food product is recalled due to safety concerns. Consumers may respond to the recall in one of two ways. On the one hand, buyers of the recalled brand might switch to other brands of the product if they perceive the other brands as “safe”. In this case, there are positive spillover effects of the recall on demand for other brands. Consequently, only the recalled brand is negatively affected, but the competitor brands might benefit and the industry as a whole might not suffer any losses. An implication of the positive spillovers is that manufacturers would only respond to their private incentives when making investment decisions to improve food safety standards in their plants. If private incentives are not strong enough to achieve a socially desired level of food safety standards, then government regulation and enforcement would be necessary for achieving higher standards.

Alternatively, there are negative demand spillovers if consumers perceive the overall product category as “unsafe”, and switch away from the product. Consequently, the industry as a whole would suffer losses as the costs from one manufacturer failing to uphold food safety standards are externalized to all other manufacturers. In this case, it is in the interest of manufacturers to cooperate in setting and enforcing food safety standards, hence adding to government's efforts to mitigate food safety problems.

The principal aim of this and the following chapter, is to empirically test these two scenarios and offer policy insight given the results. To our knowledge, this study is the first to investigate the spillover effects across different brands of a food product, in the case of a large recall in a differentiated product market. In this chapter, we estimate the demand spillover effects for non-recalled brands, and qualify any demand shocks as permanent or transitory. In addition, we qualify the demand shocks as substitutes or complements, where shock substitutes are brands that will see an increase in demand due to the recall, and complements are brands that will see a decrease in demand due to the recall. Given the heterogeneity among consumers - such as consumer preferences, level of information about food safety, and level of risk averseness - we integrate demographic characteristics to investigate differences in the pattern of response from different segments of the population.

The main contribution of this research is that it explores consumer spillover effects due to food safety recalls in differentiated product markets. We use a multistage budgeting approach to estimate a system of demand equations for closely competing products and measure the spillover effects due to a recall of one of the rival products. The estimates of the spillover effects will shed light on the extent to which food recalls affect competing manufacturers that are not directly involved in the recall. Given the increased number of food scares in differentiated markets, this research provides valuable and timely insights for policymakers.

The rest of the chapter is organized as follows. Section 3.2 includes a review of the literature on the effects of product recalls. Section 3.3 provides an overview of food safety issues and government regulation. It also includes a discussion of private sector initiatives in food safety. Section 3.4 includes a detailed review of the recall case studied in this dissertation, namely the *Peter Pan* peanut butter recall of 2007. It also includes a brief overview of the peanut butter industry. Section 3.5 outlines the empirical methods used with emphasis on the demand systems estimation. Section 3.6 includes information on the data used for the analysis. Section 3.7 outlines the results of the demand systems estimation, and the last section concludes with a discussion of the implications of the results for private initiatives in food safety in differentiated product markets.

3.2. Literature Review

The literature on consumer response to food recalls has been expanding in the last decade due to an increase in the number of recalls and more data availability. Early studies on the economic impacts of recalls have analyzed financial market outcomes such as the stock prices of affected manufacturers. As data availability increased over the last two decades, especially the availability of household panel data and supermarket scanner data, more studies have estimated demand systems or used reduced form approaches to investigate the impact of recalls on demand.

This study is closely related to three strands of the literature. The first strand of the literature investigates impact of information shocks on the consumption of different types of foods. Information shocks exist when there are changes in healthfulness or quality of food products that are transmitted to consumers through popular TV shows or other types of media coverage. Researchers investigate how such information shocks affect demand for the affected product as well as for other closely related products. In one of the earliest empirical studies in this area, Brown (1969) investigates the impact of an announcement that cranberries contained harmful residues from herbicide use on the demand for cranberries. Using a relatively small dataset of households from Atlanta, the author finds that the demand decreased temporarily due to the food scare, but prices were not affected. Piggott and Marsh (2004) investigate whether food safety concerns with meat products that are highly covered in media outlets affect the demand for beef, pork, and poultry. The authors collect information on media coverage of contaminated meat and other issues surrounding meat, such as Bovine Spongiform Encephalopathy (BSE). The authors estimate a Generalized AIDS model to investigate own- and cross-demand response to information shocks. They find that the effects of information shocks vary by meat type and pre-committed level of meat consumption, and that the average effects on demand are economically small. In a related study, Schlenker and Villas-Boas (2009) analyze whether consumer response to food scares differs based on the information received from independent media versus the government agencies. The authors investigate the impact of the following two events on cattle futures prices and beef sales. The first event is an episode of the Oprah Winfrey show, in which she talks about the hazardous effects of the consumption of beef affected by the mad cow disease. The show was aired in 1997, seven years before the first discovery of an infected cow in the United States. The second event is the actual discovery of an infected cow in the U.S., in December 2003, and the news coverage it received. Using a DID approach, the authors find that both events had a significant negative impact on beef sales as well as cattle futures prices. However, the impact on sales due to the Oprah Winfrey show was lower than the impact of actual discovery of the mad cow disease in the United States. The financial markets also experienced a dip in both cases but the effect lasted longer in response to the 2003 event.

Similarly, Adhikari et al. (2006) study the impact of low-carbohydrate diets' increased media attention, on the demand for meat. Brown and Schrader (1990) investigate the impact of cholesterol information on egg consumption. Dahlgran and Fairchild (2002) investigate the impact of TV and print media coverage of the bacterial contamination of chicken products on demand for chicken in the United States. Shimshack, Ward, and Beatty (2007) investigate the effect of an FDA-issued methyl-mercury fish advisory on household consumption of canned fish products. The general finding of these studies is that negative information adversely affects demand for a product, however the effects are relatively short lived.

A second strand of the related literature investigates the impact of food recalls on demand for the affected and related products. For example, Marsh, Schroeder, and Mintert (2004) analyze the impact of meat recalls on the demand for beef, pork, and poultry. Estimating a Rotterdam demand model, they find that meat recalls have positive effects on demand for their substitutes. However, the effect is offset by an overall decrease in the demand for meat in favor of other foods, indicating a general loss to the industry. In another study, Arnade, Calvin, and Kuchler (2009) investigate consumer response to the outbreak of *E.coli* O157:H7 in spinach. Estimating a two-stage AIDS model, the authors find that consumers switched away from bagged spinach (the product affected by the recall) to other leafy greens, such as bulk spinach, bulk iceberg, and bulk lettuce. However, the overall demand for the group of leafy greens was not significantly adversely affected. In a working paper, Toledo and Villas-Boas (2013) investigate the impact of an eggs' recall (due to *Salmonella* contamination) on the demand for eggs in California. The authors find that a 9 percent decrease in the demand for eggs. Interestingly, the study finds that consumers simply reduced their demand for eggs, rather than switching to other types of eggs not affected by the recall, such as organic eggs. Moghadam et al. (2013) investigate the impact of the recall due to *E.coli* O157:H7 in beef products on nearby cattle futures prices. Using event based methods, they find that futures prices are adversely affected by the recall, but that the effect is short lived.

These two strands of literature have improved our understanding of how consumers respond to food scares and food recalls. The general finding is that consumers move away from the affected product and often switch to its substitutes. Furthermore, the changes in consumption levels are generally transitory and in many cases are economically small. A limitation of the extant literature is that the studies generally focus on homogeneous product categories, such as meat, milk, fresh produce, and eggs, for which branding may not be a strong feature. As a result, consumer response to food scares and recalls is evaluated at the aggregate, product category level. However, contemporary food markets are highly differentiated and the majority of recalled food products are branded. In this study, we fill this void by analyzing consumer response to food recalls across branded products within a food category. While this is the first study focusing on consumer response to branded food products, there are important lessons to be drawn from recalls in non-food branded products, the focus of the third strand of literature.

The third strand of literature is concerned with investigating the impact of recalls on non-recalled brands, in non-food differentiated product markets. In an application to the drug and automobile industries, Jarrell and Peltzman (1985) estimate direct and indirect costs of recalls. Direct costs associated with recalls include costs of destroying affected drugs, costs of repairing defective cars, etc., whereas indirect costs include lost sales, liability suits, etc. The authors find that indirect costs significantly exceed direct costs. The authors also investigate the impact of recalls on the competition. They find that in both industries competitors also suffer from the consequences of the recall (Jarrell and Peltzman 1985). Other studies focus on the impact of product recalls on the wealth of the owners, as measured by changes in stock prices. Such studies include Hoffer, Pruitt, and Reilly (1988) and Rupp and Taylor (2002) – automobile industry; Dranove and Olsen (1994) and Ahmed, Gardella, and Nanda (2002) – pharmaceutical industry; and Chu, Lin, and Prather (2005) – a variety of products excluding automobile recalls.

In a recent study, Freedman, Kearney, and Lederman (2012) use the case of toy recalls to analyze product spillover effects and manufacturer spillover effects. Own-manufacturer spillover effects are defined as the changes in demand for products produced by manufacturer m when manufacturer m recalls one of its products. Cross-manufacturer spillover effects are defined as the changes in demand for similar products that are produced by other manufacturers at the time of the recall. The authors find that there are negative spillover effects at the product level. That is, consumers reduced the overall demand for infant/preschool toys at the time of the recall. However, they do not find evidence for negative manufacturer spillover effects. The authors argue that this may be due to the fact that consumers often have insufficient information to connect the recalled toy brands with the manufacturer. This literature provides important background for our study. It indicates that in branded products, industry structure, level of competition, and the severity of the issue causing the recall – all affect consumer behavior and ultimately, safety standards and regulation. This is the first study that accounts for brand competition and investigates brand spillover effects in the context of recalls in differentiated markets in the food industry.

3.3. Food Safety Issues and Regulation

According to Holleran, Bredahl, and Zaibet (1999), "the assurance of food safety is a guarantee that the food is safe from causing harm." Food safety is a credence attribute, an attribute that is not observable by the consumers, because information on food safety is imperfectly distributed among the consumers (Starbird 2005). Loader and Hobbs (1999) argue that consumers may not be able to determine the quality of food safety even after consumption of the good, because they do not have the expert knowledge.[11] However, food producers have information on food safety because they know the steps they have taken, or failed to take, in order to ensure a safe product. Due to this information asymmetry, consumers may not be willing to pay for food safety, an attribute that they cannot observe.

[11] This is different from "search goods" – whose quality may be determined before purchase through visual inspection, and "experience goods" – whose quality may be determined after consumption (Loader and Hobbs 1999).

Therefore, private sector incentives to provide this attribute independently are not very high, given that it takes resources to provide food safety (Roberts 2005a, Starbird 2005). Institutional guarantees become necessary in order to counteract the effects of the information asymmetry and ensure safety in the food supply (Holleran, Bredahl, and Zaibet 1999). Government regulations impose safety rules on producers, as well as mandate producers to provide information to consumers in the form of food package labels. At the global level, food safety is currently primarily ensured through government intervention.

Foodborne illnesses are a significant concern at the global level (Hoffmann 2010). It is estimated that in developing countries over 2.2 million people die from causes related to water and foodborne illnesses (Hoffmann 2010). Developed countries fare better in this regard, however there is still a significant number of lives lost. The Center for Disease Control and Prevention estimates that in addition to approximately 3,000 lives lost each year in the United States, approximately 128,000 people are hospitalized due to foodborne illnesses (CDC). However, according to Hoffmann (2009), there is great uncertainty about the exact number of cases of foodborne illnesses. There are many difficulties with collecting this information, even in the developed countries. The difficulties arise due to several factors. Most cases of foodborne illnesses are relatively mild, such that the affected persons never visit a doctor, although they may miss work or school due to the illness. In cases when an affected person visits the doctor, attributing the problem to a foodborne pathogen is a long and complex procedure. Generally, individuals are not good at recalling the food consumed, so identifying which food caused the illness is a difficult process (Hoffmann 2009). Laboratory tests take time and resources, and in most cases are not conducted unless it is necessary for a patient's treatment. At the macro scale, several cases need to be reported and linked to a food in order for government institutions to test for the existence of pathogens, and if necessary, work with the manufacturers and retailers to recall the product (Hoffmann 2009). Several initiatives, such as OutbreakNet, PulseNet, and FoodNet, have been taken in order to gather information quickly and provide this information to appropriate government agencies, so that any recalls may happen on a timely manner.

Food safety is ensured through a complex set of rules and regulations involving public and private institutions, and international agencies. At the international and national levels, there are several initiatives to design policies and integrate food safety regulations across countries. For example, *Codex Alimentarius* includes a set of standards and guidelines which are in line with the General Agreement in Trade and Tariffs (GATT) and are applied across borders. The Codex standards cover a wide range of issues, such as guidelines for preventing consumer fraud, standards on food additives, and tolerance levels for pesticides (Hoffmann 2010). The European Union has sought to integrate food safety regulations across member countries through the General Food Law that was adopted in 2002. The General Food Law serves as the foundation for regulations regarding food and feed law, including issues such as feed production, primary production, food processing, food storage and transportation, and retail (European Commission). Hoffmann (2010) and Loader and Hobbs (1999) offer in-depth reviews and comparisons across food safety regulations in several developed countries, including the United States.

One of the consequences of the increasingly integrated global food market is that food pathogens may cross borders. For example, the United States imports an increasingly larger quantity of food from middle income countries, such as Mexico, Chile, and China (Buzby and Regmi 2009). In order to ensure safety of the food products imported, the U.S. needs to rely on a good set of regulations and enforcement from its importing partners, as well as on the food inspections at the border. However, with current technology, inspections at the border cover only a small portion of the food imports. According to Nganje et al. (2009), FDA currently inspects about 1% of the foods imported, down from 8% in 1992 when the level of food imports was much smaller. Furthermore, given a long history of countries using stricter food safety regulations as barriers to trade, under the Uruguay Round of trade talks, countries cannot impose food safety regulations beyond those included in the *Codex Alimentarius* (Hoffmann 2009). If they do, such regulations must be supported by scientific evidence (which takes time and resources), or else they risk being imposed trade sanctions (Henson and Caswell 1999, Hoffmann 2009). This twofold challenge emerging from trade of food products has been an important push to integrate food safety regulations. However while some initiatives are in place as discussed above, most countries still have different systems in place to ensure food safety, as well as to prevent and manage foodborne illnesses (Garcia Martinez, Fearne, and Caswell 2007).

In the United States, the four main government agencies in charge of food safety regulations and enforcement include, the U.S. Department of Agriculture (for meat, poultry and processed egg products), the U.S. Department of Commerce (for seafood), the FDA (for all other foods), and the Environmental Protection Agency (for setting pesticide tolerance levels) (Hoffmann 2010). One of the early efforts to provide regulation for food safety standards in the food processing industry came in the 1950s when the National Aeronautics and Space Administration (NASA) officials asked a U.S. food processing firm to develop reliable food products to meet the needs of manned space crafts. The idea was to adopt a failure control system used in rocket sciences to the food manufacturing process. This led to the development of hazard analysis and critical control point systems (HACCP). In the decades that followed, the HACCP system was adopted by the food industry in the United States. Since 1993, HACCP is also included in the recommendations of the *Codex Alimentarius*. The HACCP includes a guideline of systematically identifying and assessing food safety throughout critical points where foodborne hazards are most likely to occur in the food production chain (Hoffmann 2010). Food safety standards set by the government authorities in the U.S. take three forms, depending on the level of intervention required. Target standards impose manufacturers' criminal liability for harmful consequences of their products. Performance standards require certain level of safety to be supplied, but give the manufacturers freedom to choose the mechanisms through which they may do so. Specification standards specify both product and process standards (Henson and Caswell 1999).

In addition to government efforts in food safety, the private sector plays an important role in this regard. The private sector has to comply with government regulations in food safety because otherwise they would face the consequences of not obeying the law. However, in some cases the private sector creates new industry standards in addition to the minimum standards set by regulations. Henson and Hooker (2001) identify three sources of private sector incentives for supplying safe food products: market forces, food safety regulations, and product liability law. In summary, these forces are a combination of reputation, brand equity, market share, sales revenue, penalties and fines associated with product recalls, and costs associated with product liability cases in case consumers suffer harm. Businesses implement strategies based on incentives that emerge from the interplay of these factors (Henson and Hooker 2001). Henson and Caswell (1999) qualify private systems in food safety as self-regulation and certification by third parties. Self-regulation includes control systems that are internally defined and implemented. Certification involves quality standards that are set and monitored through a third party. Such certification may be sought voluntarily by the company or it may be requested by those with which the company conducts business. Trienekens and Zuurbier (2008) argue that quality is not just related to the product, but also to production and distribution processes. Hence, quality certifications are increasingly sought after by the retailers.

One of the greatest success stories of the private sector's initiatives in food safety involves the Lion quality scheme in the United Kingdom (Fearne and Garcia Martinez 2005). During the 1980s and early 1990s, there was an increase in the number of *salmonellosis* cases in the United Kingdom. In the beginning of the 1990s, it was determined that the issue was due to *Salmonella enteritidis* which invades the reproductive tract of chickens, hence affecting eggs. Consumer confidence had greatly declined resulting in a decrease in demand for eggs. In response, the British Egg Industry Council (BEIC) developed the so-called Lion Code of Practice in order to reduce the *Salmonella* contamination of eggs. Fearne and Garcia Martinez (2005) report that as a result of this scheme, developed and implemented by the private sector, the occurrence of Salmonella contamination of eggs had practically been eliminated by 1999.

However, private safety initiatives have a higher probability of succeeding in certain industry settings compared to others. For example, in the UK the egg, poultry, and pig industries are relatively more integrated than other industries, and have a smaller number of suppliers. It is easier to reach agreements and to check on compliance when an industry has a smaller number of suppliers. Hence, there are more food safety initiatives in these industries. In contrast, beef and lamb sectors are more complex and include a larger number of suppliers, hence hampering the chances of successful initiatives for private safety standards (Fearne and Garcia Martinez 2005). In the United States, private initiatives in food safety across the food industry include adoption of quality assurance programs, such as Total Quality Management and ISO 9000 (Holleran, Bredahl, and Zaibet 1999). Holleran, Bredahl, and Zaibet (1999) provide an overview of food safety and quality assurance programs in several developed countries including the United States as well as a discussion on the various internal and external factors that affect farms' and manufacturers' adoption of such systems.

The private sector faces several challenges with regard to setting and enforcing safety standards. Starbird (2005) argues that there are at least two challenges that directly affect the private sector: the lack of a precise definition of safety and the lack of a standard way to measure safety without being subject to a significant error. He argues that the lack of consensus on these issues is due in part to the incompatibility of interests between consumers, producers, processors, and retailers; and in part due to the lack of unambiguous scientific evidence. These challenges limit manufacturers' ability to calculate the costs and benefits of different measures and compute the return to food safety investments (Starbird 2005). However, Roberts (2005) paints a more positive picture arguing that with newly available pathogen tests, improvements in detection technologies, as well as current government regulations – the private sector faces increased incentives for pathogen controls. Improvements in the technology to quickly and efficiently detect harmful pathogens is the focus for not just the private sector, but also for the government. In 2014, the FDA extended an invitation to outside parties to submit solutions that would target *Salmonella* detection. In the so-called "First Food Safety Challenge," the agency hoped to incentivize scientists, academics, innovators, engineers and others, to find ways to detect *Salmonella* contamination, especially in produce, before the products reach to the consumers, hence helping eliminate "one of our most pervasive food-safety problems today" (White 2014).

An additional challenge for both governmental institutions and the private sector is the difficulty with conducting cost-benefit analysis to determine the optimal level of investment in food safety. In particular, there is a lack of consensus on how to address the cost of lives lost due to foodborne illnesses, which is an important philosophical question that emerges often in policy debates (Henson and Caswell 1999). Governmental regulations are also affected by industry lobbyist and consumer groups so that the decisions are often not based on a systematic and consistent methodology to evaluate the costs and benefits of each policy initiative (Henson and Caswell 1999).

Despite these challenges, the literature identifies several success stories in private and public cooperation in food safety standards (Garcia Martinez et al. 2007). However, in order to design policy solutions an analysis of market and consumer behavior should be performed. The literature on consumer response to food safety has concentrated exclusively in markets of relatively homogeneous goods. This is the first study that seeks to understand consumer behavior in the case of a product recall, in differentiated product markets. The primary goal of this study is to understand whether consumers prefer to purchase the same product from unaffected brands, or whether they switch away from the product category hence lowering the sales of the affected product for all manufacturers. The direction of the demand spillover effect has important implications for private initiatives in food safety in differentiated product markets.

3.4. Peanut Butter Industry Structure and Recalls

To examine demand spillover effects we focus on a national recall of a brand in the U.S. peanut butter market. On February 14, 2007, ConAgra Foods Inc. recalled its entire stock of Peter Pan and part of the Great Value peanut butter, due to *Salmonella Tennessee* infection. Investigations indicated that at least 700 people across 44 states had been affected by the contaminated product. Approximately 20% of the affected individuals were hospitalized (Flynn 2015). Prior to the recall, the illnesses were being reported for more than six months, from August 1, 2006, to February 16, 2007 (CDC 2007). The recall included all Peter Pan peanut butter purchased between May 2006 and February 2007, and Great Value peanut butter with a product code “2111”. All the affected Peter Pan peanut butter products were produced at the Sylvester plant in Georgia. Great Value peanut butter is produced in several plants throughout the country, therefore only a small fraction of its products were affected (FDA 2007). The affected Peter Pan products had been distributed throughout the country as well as internationally. After addressing all the safety concerns, Peter Pan peanut butter reappeared in the market a few months after the recall in August 2007.

The U.S. peanut butter market is a highly concentrated market with the top three companies accounting for 82 percent of all sales in 2014 (IBISWorld 2014). The three leading brands of peanut butter are Jif, Skippy, and Peter Pan. Jif is the leading brand of J.M. Smucker Company (Smucker's), which also manufactures other peanut butter brands such as Goober Peanut Butter and Smucker's Natural Peanut Butter (IBISWorld 2014). According to 2013 estimates, the J.M. Smucker Company has half of the peanut butter market (IBISWorld 2014). Skippy is the leading brand of Hormel Foods Corporation which has a 20 percent market share in the peanut butter industry. ConAgra Foods Inc. is the third largest producer, with its leading brands Peter Pan and a market share of over 12 percent (IBISWorld 2014). Other brands with relatively smaller market shares include Smucker's and store brands.

In recent years, the peanut butter industry has been affected by several cases of food safety concerns. The 2007 case of ConAgra Foods Inc. was the first case of *Salmonella* in peanut butter. Across food items, *Salmonella* is the pathogen with the highest incidence rate (Lutter 2015). It is estimated that 1.2 million illnesses each year are attributed to *Salmonella* infection, resulting with 23,000 hospitalizations and 450 deaths (White 2014).

In the beginning of 2009, another case of *Salmonella* in peanut butter was discovered. It affected peanut butter products produced by many manufacturers who used peanut butter or peanut paste produced by the Peanut Corporation of America (PCA). The costs of the PCA recall, both in terms of human lives lost and health problems, as well as the monetary costs to the industry, were enormous.[12] A search through the FDA website for *Recalls, Market Withdrawals & Safety Alerts* reveals that in the years since the PCA peanut butter recall, there have been at least six more cases of peanut butter recalls due to *Salmonella* contamination and one case due to *Listeria monocytogenes*, albeit these recalls have been smaller in magnitude.[13]

3.5. Empirical Methods

3.5.1. Multistage Budgeting Approach

The main goal of this study is to investigate consumer response to food recalls in differentiated product markets. We focus on the U.S. peanut butter industry—a typical oligopolistic, differentiated product industry that is marked with concentration and branding. Specifically, we investigate the consumer response to the 2007 recall of *Peter Pan* peanut butter brand produced by ConAgra Foods Inc. During the recall period,

[12] An estimated 22,000 people got sick and nine people lost their lives due to consuming peanut butter products whose ingredients (produced by PCA) were contaminated with *Salmonella* (Sklamberg and Taylor 2014). It is estimated that the total loss to the peanut butter industry reached $1 billion, with close to 4,000 products and many manufacturers affected by the recall (Doering 2009).

[13] The peanut butter recalls due to *Salmonella* contamination in the recent years include the following manufacturers: Unilever United States, Inc. (Mar. 4, 2011); J. M. Smucker (Nov. 16, 2011); Falcon Trading Company, Inc. / SunRidge Farms of Royal Oaks, CA (Oct. 8, 2012); Sunland, Inc. (announced on Sep. 24, 2012), Trader Joe's (Sep. 24, 2012), and nSPIRED Natural Foods, Inc. (Aug. 19, 2014). Due to Listeria monocytogenes contamination: Parkers Farm Acquisition, LLC (Mar. 22, 2014). Some of the recalls were national and some were regional. The recalls involve multiple peanut butter brands.

February-August 2007, the product was removed from supermarket shelves. Presumably, consumers could respond one of the two ways. They could keep purchasing other brands of peanut butter, or they could perceive all peanut butter products as unsafe and substitute with other products. We seek to distinguish between these two cases by utilizing a system of demand equations for peanut butter products.

We employ a two-stage demand system estimation approach similar to the approach used by Hausman, Leonard, and Zona (1994). The first stage corresponds to the overall demand for the product, peanut butter. The second stage corresponds to the demand for each specific brand of peanut butter. Implicitly, this approach assumes multistage budgeting by the households (Gorman 1971). Specifically, households first choose the budget to be spent on peanut butter. Then, in a second step, they allocate the peanut butter budget to the peanut butter brands.

We estimate the model starting with the second stage. To investigate the demand for each specific brand of peanut butter, we employ Deaton and Muellbauer's (1980) AIDS model. An advantage of the AIDS model is that the results may be interpreted in light of economic models of consumer behavior both when estimated with aggregated macroeconomic data, as well as when estimated with disaggregated data, such as household surveys. The functional form of the AIDS model is given as follows:

$$s_{iht} = \alpha_i + \sum_{j=1}^{n} \beta_{ij} \ln\left(P_{jht}\right) + \gamma_i \ln\left(\frac{x_{ht}}{P}\right), \tag{3.1}$$

where s_i represents the expenditure share of product i, $\ln(P_j)$ include log prices for all the j products, x is total expenditures, and P is a price index given as: $\ln(P) = \alpha_0 +$

$\sum_j \alpha_j \ln(P_j) + \frac{1}{2}\sum_j \sum_i \beta_{ij} \ln(P_i)\ln(P_j)$. Indices h and t are used to denote household and time period, respectively. For simplicity of notation, we do not use these two indices in the equations that follow.

We conduct the analysis for five peanut butter brands purchased for at-home consumption. We use disaggregated household data, as will be outlined in the next section. Shares for each of the brands of peanut butter are calculated as: $s_i = \frac{P_i * q_i}{x}$, where x is total peanut butter expenditures for at-home consumption. Note that in line with the multistage budgeting approach, we use peanut butter expenditures, rather than total food expenditures, at this stage (Hausman, Leonard, and Zona, 1994).

Next, we expand the AIDS model given in equation 3.1, in order to estimate demand spillovers for non-recalled peanut butter brands and qualify any demand shocks as permanent or transitory. The basic specification of the AIDS model comprises regression of expenditure shares for each brand of peanut butter, on a function of prices, total peanut butter expenditures, and a price index. In addition, we include demographic variables and time trends in the model specification. Furthermore, following Arnade, Calvin, and Kuchler (2009), we use a number of time-varying demand shifters in order to characterize the type of the demand shock. Specifically, we estimate the following demand system:

$$s_i = \alpha_i + \sum_{j=1}^{n} \beta_{ij} \log(P_j) + \gamma_i \log\left(\frac{x}{P}\right) + \delta_{if} D_f + \zeta_i t + \eta_i d + \theta_i v_l + \vartheta_i c v_l + \varepsilon_i, \quad (3.2)$$

where D_f is a set of demographic factors including household income, race, presence of children 12 years old or younger, and the education level and employment status of household heads. In addition, we control for time trends by including a time variable – t, and for December trends by including a binary variable d indicating whether it is the month of December. We do so because trends in the google search engine show evidence that there are spikes in searches for peanut butter in the month of December due to the end of the year holidays.[14] The variable v captures the effect of the *Peter Pan* recall on the shares of different peanut butter brands. The effect on competing peanut butter brands may be linear or non-linear, and permanent or transitory. To explore each of these possibilities, we estimate the equation in turn with each of the four specifications of the v variable. Additional details on the specifications of the v variable is provided below. Finally, we include an interaction term between the v variable and the demographic variable c – presence of children 12 years old or younger, in the household. We do so in order to identify whether households with children follow a different pattern in terms of their choices of peanut butter brands compared to households without children. Under the assumption that households with young children are more risk averse than other households, we hypothesize that due to the Peter Pan recall more households with young children will stay away longer from this brand. We apply the model given in equation 3.2 to estimate peanut butter brand level demand. The system comprises demand equations for the peanut butter brands Jif, Skippy, Peter Pan, Store Brands, and all other brands.

The demand response due to the recall of *Peter Pan* may be permanent or transitory. To capture the longevity of the effects we estimate the model including one v variable from

[14] This is likely due to increased web searches for recipes for peanut butter pastries during the time of the end-of-the-year holidays. See the trend in google searchers for the term "peanut butter" at: https://www.google.com/trends/explore?date=all&geo=US&q=peanut%20butter

a set of four variables v_l in the AIDS model. Using the week as the time unit in our analysis, consider the following three periods: $p = 0$ is the pre-recall period that includes 58 weeks starting on January 1, 2006 and ending on Feb 10, 2007; $p = 1$ is the recall period stretching from the announcement of the Peter Pan recall up to the time when Peter Pan once again becomes available in the shelves. This period includes 27 weeks, starting on February 11, 2007 and ending on August 18, 2007; and, $p = 2$ is the post-recall period that includes 175 weeks, starting on August 19, 2007 and ending on December 25, 2010.

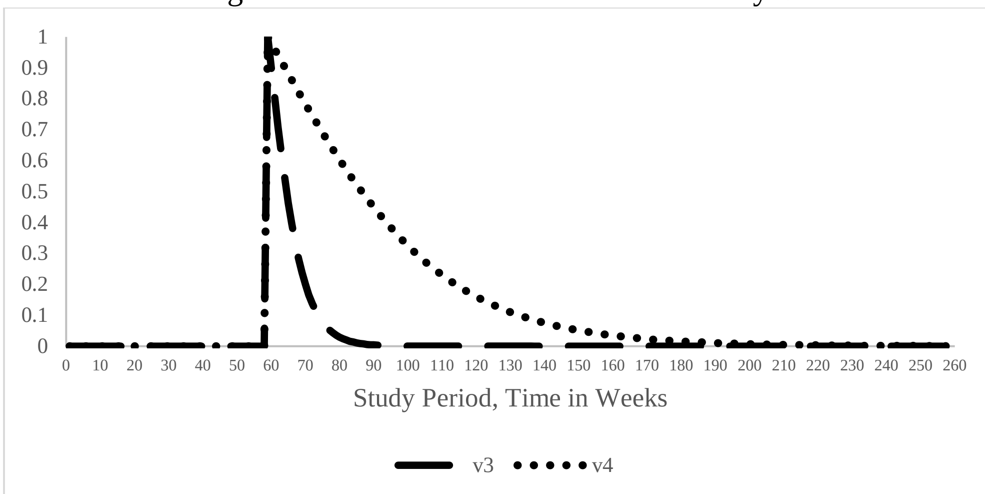
Permanent effects occur when at least some of the consumers permanently change their purchase patterns due to the recall. For example, some of the consumers who used to purchase *Peter Pan* do not purchase *the product* again even when it becomes available after the recall is lifted. We capture this effect by including $v_1 = 0$ for $p = 0$, and $v_1 = 1$ for $p \in \{1,2\}$. If the coefficient on v_{i1} is positive (negative), it would indicate that brand i of peanut butter is a shock substitute (shock complement) to *Peter Pan*. Two products x and y are shock substitutes if when product x is recalled, consumers switch to purchasing product y. Two products x and y are shock complements if when product x is recalled, consumers stop purchasing product y as well. Therefore, if the consumers switch to purchasing other brands permanently, we expect the sign of the coefficient on v_{i1} to be positive in other brands' share equations, and negative for *Peter Pan*.

However, literature on product recalls indicates that most shocks are relatively transitory. Hence, we explore this by including one of the three v variables that capture the transitory effect as described below. First, we include a binary variable $v_2 = 0$ if $p = 0$, $v_2 = 1$ if $p = 1$, and $v_2 = 0$ if $p = 2$. This variable captures the temporary effect of the recall by allowing for an effect only during the recall period, $p = 1$. Contrary to v_1, variable v_2 allows for no effect once the *Peter Pan* brand reappears in the market. Yet, the temporary effect may not necessarily be constant during the recall period and come to an abrupt end once the recalled brand reappears in the market. Instead, the temporary effect may reach a maximum in the week of the recall and then slowly decrease in the weeks after the recall announcement. Hence, we investigate such an alternative adopting an approach used by Arnade, Calvin, and Kuchler (2009). The non-linear transitory effects, v_3 and v_4, differ from each other in the rate in which they converge to zero (see Figure 3.1.). That is, in both cases the effect is the highest on the week of the recall announcement, but it goes down in the weeks following the recall until it reaches pre-recall purchasing patterns. We capture this by defining the two transitory variables as $v_3, v_4 = 0$ at $p = 0$, $v_3, v_4 = 1$ in the week of the recall, and $v_3, v_4 \to 0$ at $p \in \{1,2\}$. The difference between v_3 and v_4 is on how rapidly the consumption pattern on the post-announcement period, p $\in$ {1,2}, converges to the consumption pattern of the pre-announcement period, $p = 0$. While v_3 allows for a more rapid convergence, v_4 allows for a slower convergence.[15] Similarly to v_2, the idea here is that brand loyalty persists despite the recall. For example, *Peter Pan* customers might continue purchasing other brands of peanut butter while their preferred brand – *Peter Pan* - is not available on the shelves. But they gradually return to their preferred brand. The sign on the statistically significant coefficients allows us to qualify

[15] Arnade, Calvin, and Kuchler (2009) construct these two variables as $1 - (1 + e\text{^}(-rt))^{-1}$ and are normalized to 1 at the time of the recall announcement (week 1). For the rapid decay variable, which in our case is v_3, $r = 0.20$. For the slow decay variable, which in our case is v_4, $r = 0.04$.

each brand of peanut butter as a shock substitute or shock complement to *Peter Pan*. Figure 3.1 below offers a graphical depiction of the set of decay variables, υ_3 and υ_4.

Figure 3.1.: Values of Non-linear Transitory Variables



An advantage of the AIDS model is that the restrictions from theory— homogeneity of degree zero, symmetry, and adding up[16]—are expressions of the model parameters, hence easily imposed. Homogeneity is ensured by imposing the following restriction on the parameters: $\sum_{j=1}^{n} \beta_{ij} = 0$. Symmetry is ensured by imposing the following restriction: $\beta_{ij} = \beta_{ji}$. And the adding up restriction is imposed by the following restrictions: $\sum_{i=1}^{n} \alpha_i = 1$, $\sum_{i=1}^{n} \beta_{ij} = 0$, $\sum_{i=1}^{n} \gamma_i = 0$, $\sum_{i=1}^{n} \delta_{ih} = 0$, $\sum_{i=1}^{n} \zeta_i = 0$, $\sum_{i=1}^{n} \eta_i = 0$, $\sum_{i=1}^{n} \theta_1 = 0$, and $\sum_{i=1}^{n} \vartheta_i = 0$.

[16] Homogeneity of degree zero is the absence of the money illusion, if income is doubled, and all prices are doubled, consumers will purchase the same quantities as before. Symmetry is the change in Hicksian demand for good i with respect to the change in the price of j, is equal to the change in the Hicksian demand of good j with respect to the change in the price of good i. Adding up is the restriction that the whole budget is used, that is, the total spent in goods is equal to the total available income.

We estimate the non-linear AIDS model using the iterated least squares method outlined in Blundell and Robin (1999). Following Green and Alston (1990), the price elasticities are calculated as follows:

$$E_{ij} = \frac{\beta_{ij} - \gamma_i(\alpha_j + \sum_k \beta_{ik}\log(p_k))}{s_i} - \mu_{ij}, \qquad (3.3)$$

where $\mu = 1$ if $k = j$, and $\mu = 0$ if $k \neq j$, and all the other terms are already defined in this section.

Expenditure elasticities are calculated using the following formula:

$$\eta_{iX} = \frac{\gamma_i}{s_i} + 1. \qquad (3.4)$$

3.5.2. Overall Peanut Butter Demand

The first stage of the estimation approach corresponds to the overall peanut butter demand estimation. We estimate the demand for peanut butter using the following equation:

$$Ln(PBExp_{ht}) = \beta_0 + \beta_1 Ln(TotExp_{ht}) + \beta_2 Ln(PBPrice_{ht}) + \beta_3 v_l + \beta_4 t + \Phi D_f + \varepsilon_{ht}, \qquad (3.5)$$

where $PBExp$ denotes peanut butter expenditures, $TotExp$ denotes total food expenditures, $PBPrice$ is peanut butter price, and the rest of the variables have already been defined above. The coefficient on v, β_3, gives the impact of the *Peter Pan* recall on the peanut butter expenditures. We estimate the regression using OLS and report the results of the estimation both when v_1 is included, as well as when v_2 is included.

3.6. Data

For the empirical analysis, we use purchase data in the U.S. peanut butter market between 2006 and 2010 provided by the Nielsen Company.[17] We use Homescan data comprising purchases made by a panel of households. The dataset includes product level information such as UPC code, price, quantity purchased, type of store, day of the purchase, and availability of promotions. The household panel dataset covers 52 metropolitan markets in the United States. In addition to purchase information, the household panel dataset also includes household demographic information, such as household size and composition, presence of children and income. The heads of households also report their age, gender, level of educational attainment, hours worked, and occupation.

Additional information on the Nielsen Homescan data is reported in Chapter 2. An advantage of using the Nielsen Homescan data is that we are able to conduct our analyses using a rich disaggregate dataset, with important demographic and geographic information. However, using this dataset is not without its limitations. There is evidence that households do not report all their food shopping trips while in the panel. There is also evidence that households fail to report a fraction of their food purchases for each shopping trip that they do report (Einav, Leibtag, and Nevo 2010). Matching Nielsen Homescan data with Scanner data from a major retailer in a metropolitan area in the United States, Einav, Leibtag, and Nevo (2010) provide evidence of discrepancies between household-reported data and

[17] The data source is The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing, Data Center at the University of Chicago - Booth School of Business.

supermarket scanner data.[18] According to their calculations, 53-60 percent of the shopping trips made by the households in the panel that appear on the scanner data, are not reported by the Nielsen Homescan households. In addition, for the trips that households do report, 10-14 percent of the UPC items purchased are not reported. The products for which the error rate in reporting is the highest primarily include: (1) snacks and bottled drinks (which consumers may consume on the way home), and (2) products with very similar UPCs, (e.g. yogurts of different flavors). The first data issue, the under-reporting of food shopping trips – will not lead to a bias in our estimated spillover effects as long as the households randomly choose which trips are reported and which trips are not reported. This issue will lead to an underestimation of the level of total food expenditures, total peanut butter expenditures, and total expenditures on each peanut butter brand. However, since we rely primarily on shares of expenditures, our results are not affected if the reporting of trips is random. The second data issue, the under-reporting of certain products in the shopping trips that are reported, does affect the shares of expenditures on peanut butter. Under the assumption that peanut butter jars are not among the misreported products, the total share of expenditures on peanut butter will appear larger than it actually is. Depending on the size of expenditures that are misreported, the share on peanut butter expenditures as a share of total food expenditures is affected accordingly. To the extent that the total size of unreported expenditures is relatively small, the discrepancy in the share of peanut butter expenditures will be small as well. However, we cannot address this data limitation as we

[18] Refer to Einav, Leibtag, and Nevo (2010) for details on the matching of household data with scanner data, the full set of their results, as well as the limitations of their approach.

do not have a way to know exactly which items the households in our dataset have failed to report.

The study period extends through 260 weeks, starting from January 1, 2006 and ending on December 25, 2010. The recall period extends 27 weeks, starting on February 11, 2007 and ending on August 18, 2007. The data is organized by household and time measured in weeks, such that all observations are at the household/week level. All peanut butter purchases are classified into one of the five brand categories: Jif, Skippy, Peter Pan, store brands, and all other brands. Using UPCs, we identify peanut butter purchases and group all such purchases into one of the five peanut butter brands. We sum purchases of each peanut butter brand by household and week. Then, we eliminate household/week pairs that result with zero peanut butter purchases, hence effectively having a dataset in which each household/week observation has non-zero purchases of peanut butter. We then calculate total food purchases by household and week for household/week observations with non-zero peanut butter expenditures. Since many households have breaks in their participation in the household survey, for each year we calculate the number of weeks in which each household appears in the survey. Then, we sum the number of weeks in the survey throughout the study period for each household, and we also sum total expenditures on food items throughout the study period for each household. Finally, we divide total expenditures by the number of weeks the household appears in the survey, and the resulting number is the average weekly food expenditure. Therefore, weekly food expenditures vary by household, but are averaged across time. We calculate the share of expenditures on each peanut butter brand by dividing the weekly household expenditures on each brand, by the total household food expenditures.

The prices for each brand of peanut butter are calculated using the survey information on prices paid for each UPC item by each household in a given time. Since there are cases in which two or more products with distinct UPCs but of the same brand of peanut butter are purchased by the same household in the same shopping trip, we normalize all prices to be per ounce of peanut butter, and calculate the average price per brand across UPCs. It is often the case that a household only purchases peanut butter product(s) of one brand and hence price information for that observation exists only for the brand purchased. In such cases, we impute the prices for the other brands of peanut butter using averages across households by county and week. Finally, we use the CPI as a price index for the outside good, namely *all other foods*. We obtain the CPI data from the Bureau of Labor Statistics, and use the category "Food and beverages".[19] The resulting dataset includes 86,830 unique households that appear in the sample for an average of 12 weeks. The sample includes 812,869 household/week observations for the entire study period, 2006-2010.

Table 3.1 provides summary statistics of peanut butter expenditures shares by brand before, during, and after the *Peter Pan* recall period. It also provides the overall shares, and the overall average weekly expenditures per household. As expected, the data shows a significant drop in the share of expenditures for *Peter Pan* peanut butter during the recall period. Yet, all other brands experience an increase in the share of expenditures during the

[19] The CPI data is derived from the Bureau of Labor Statistics, at the following link: http://data.bls.gov/cgi-bin/surveymost

Peter Pan recall period, compared to the pre-recall period. These summary statistics indicate that Jif has the biggest gain in the share of expenditures on peanut butter during the *Peter Pan* recall period, increasing the share by almost one percentage point. The summary statistics also show that in the post-recall period, most brands except for *Peter Pan* and *All other brands*, remain at higher share levels than in the pre-recall period, although these shares are slightly lower than during the recall period. The share for *Peter Pan* is 0.03 percentage points lower in the post-recall period compared to the pre-recall period, whereas that difference for *All other brands* is much lower, at 0.003 percentage points. Alternatively, other brands show an increase in their shares of 0.019 (for Skippy) to 0.006 (for Jif) percentage points, when comparing the pre-recall and the post-recall periods. These gains are mainly made at the expense of *Peter Pan* which fails to get back to its pre-recall period share. As expected, peanut butter weekly expenditures per household by brand show the highest expenditures on Jif, and the lowest on Store brands.

Table 3.1.: Share of Expenditures on Peanut Butter by Brand and Period [a]

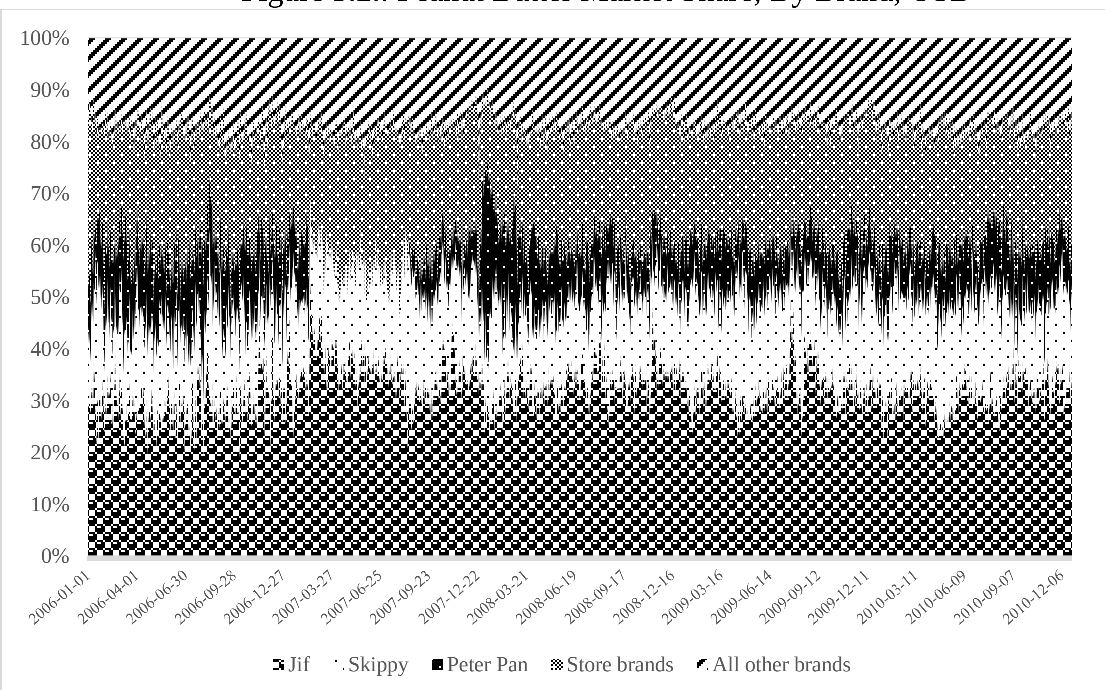
	Pre-recall Period		Recall Period		Post-recall Period		Overall Shares[b]		Weekly Expenditures[b]	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Jif	0.276	0.444	0.328	0.466	0.282	0.447	0.287	0.449	3.945	2.486
Skippy	0.168	0.372	0.205	0.401	0.187	0.387	0.186	0.387	3.528	2.485
Peter Pan	0.151	0.356	0.005	0.067	0.122	0.324	0.112	0.314	2.916	1.962
Store brands	0.275	0.444	0.319	0.463	0.283	0.447	0.286	0.449	2.649	1.834
All other brands	0.129	0.332	0.144	0.347	0.126	0.328	0.129	0.331	3.239	2.072

[a] The pre-recall period includes 58 weeks, from January 1, 2006 to February 10, 2007. The recall period includes 27 weeks, from February 11, 2007 to August 18, 2007. And the post-recall period includes 175 weeks, from August 19, 2007 to December 25, 2010.

[b] Summarized over the entire study period.

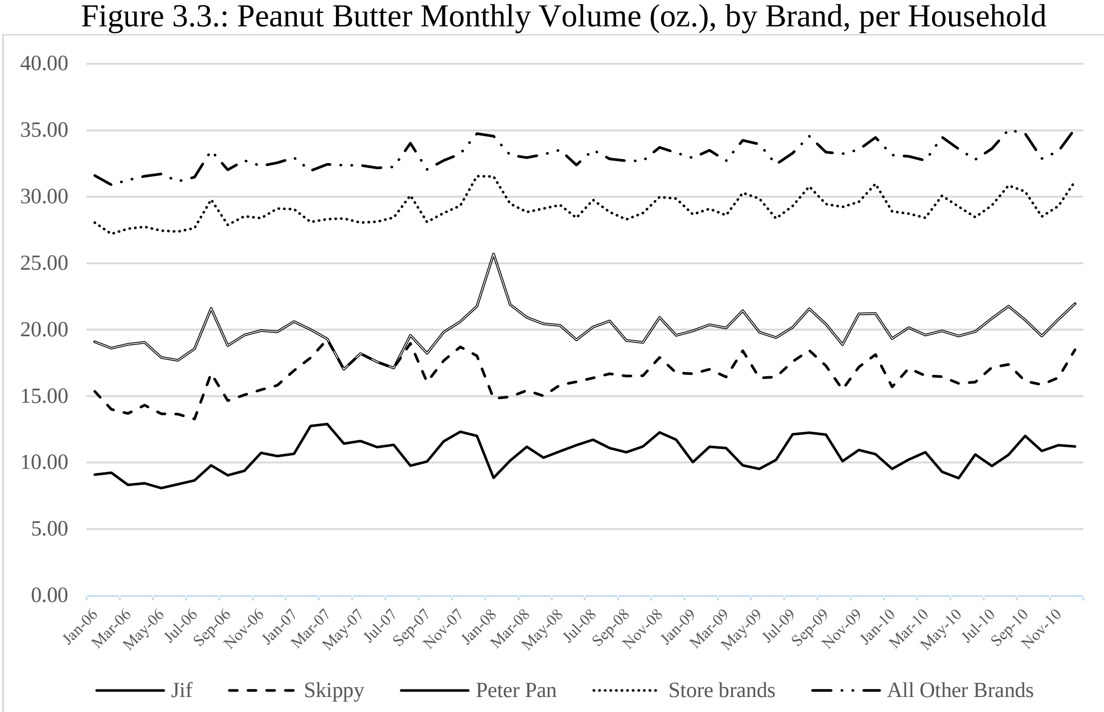
To get a better sense of the share of expenditures for each brand or peanut butter and on the volume of peanut butter sold, we plot peanut butter purchase data per day summed over all households. The results are given in figures 3.2 and 3.3 respectively. Figure 3.2 shows market share trends of peanut butter brands in the period 2006-2010. A visual inspection of the trends suggests that the impact of the recall on the demand for *Peter Pan* peanut butter is transitory. That is, the market share for this brand seems to approach its level during the pre-recall period a few months after it reappears on the supermarket shelves in August 2007. An additional observation from this graph is that some brands, most notably *Jif*, gained market share during the *Peter Pan* recall period.

Figure 3.2.: Peanut Butter Market Share, By Brand, USD



Observing changes in market shares is quite informative because it allows us to notice any substitution effects across brands. However, one way the consumers may respond to the recall, is to switch away from peanut butter in favor of other food products. Potential peanut butter substitutes may be almond butter, and chocolate/hazelnut spread, etc. The household data suggests that there is no clear downward trend in the average volume of peanut butter consumed by households during the recall period (See figure 3.3). Specifically, households on average consume a little over 30 ounces of peanut butter per month, and this volume continues throughout the study period with a slight upward trend. While the share of peanut butter from different brands varies significantly, especially during and immediately after the Peter Pan recall period, the overall volume of peanut butter purchased remains to a significant degree stable throughout the study period.

Figure 3.3.: Peanut Butter Monthly Volume (oz.), by Brand, per Household



3.7. Results

3.7.1. Demand for Peanut Butter

We first report the results from the first stage demand estimation, namely equation 3.5. The results are given in Table 3.2. As expected, an increase in the household total expenditures and increases in peanut butter prices, both are positively correlated with increases in expenditures on peanut butter. The results suggest that there is a positive monthly trend in peanut butter expenditures, indicating that the overall market size of peanut butter increased over time throughout the study period. The coefficient on the binary variable v_1 provides the long-term effect of the recall, since this variable is defined to be equal to 1 for all weeks during and after the recall period. The overall effect on peanut butter is positive and significant, as given by the coefficient on variable v_1. The results indicate that compared to the pre-recall period, expenditures on peanut butter are 0.025 percent higher in the recall and post-recall periods. Note that these results should not be interpreted as causal. In other words, the coefficient on v_1 does not give the causal impact of the *Peter Pan* recall on peanut butter expenditures. Instead, this coefficient indicates that there is a positive correlation between the onset of the *Peter Pan* recall period and peanut butter expenditures. This result is very important because it suggest that the peanut butter market size has not decreased since the onset of the recall period, instead, it has increased. Hence, in conjunction with the AIDS model results from the second stage, it will allow us to identify the spillover effects of the *Peter Pan* recall.

Table 3.2.: Stage 1 - Regression on Peanut Butter Expenditures

	Expenditures on Peanut Butter	
Log Household Total Expenditures	0.091***	0.092***
	(0.001)	(0.001)
Log Peanut Butter Price	0.546***	0.546***
	(0.001)	(0.001)
v_1 [a]	0.025***	
	(0.002)	
v_2 [b]		-0.010***
		(0.002)
Monthly Time Trend	0.002***	0.002***
	(0.000)	(0.000)
Income	0.006***	0.006***
	(0.000)	(0.000)
Child under 12	-0.012***	-0.011***
	(0.002)	(0.002)
Max Education	0.015***	0.014***
	(0.001)	(0.001)
Employed	-0.003*	-0.002*
	(0.002)	(0.002)
White	0.048***	0.048***
	(0.002)	(0.002)
Constant	1.732***	1.744***
	(0.006)	(0.006)
N	812869	812869
R^2	0.195	0.195

Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01

[a] Variable v_1 is defined as follows: v_1=0 during the pre-recall period, p=0; v_1=1 during the recall period and during the post-recall period, p$\in\{1,2\}$.

[b] Variable v_2 is defined as follows: v_2=0 during the pre-recall period, p=0; v_2=1 during the recall period, p=1; and v_2=0 during the post-recall period, p=2.

The model which includes variable v_2 provides the temporary effect of the recall on peanut butter expenditures. In this case, as intuitively expected, the results suggest a decrease in total expenditures during the *Peter Pan* recall period. Specifically, compared to periods before and after the recall, peanut butter expenditures decrease by 0.01 percent during the recall period. These results indicate that when considering the period recall only, the market size of peanut butter actually decreases slightly. This suggests that at least some peanut butter consumers switched away from peanut butter to other food products during the *Peter Pan* recall period. We use these results in conjunction with the results from the AIDS model estimation to determine any long-term and short-term spillover effects from the *Peter Pan* recall. To determine such effects, we next turn to the AIDS model results, to understand the impact on the shares of each of the peanut butter brands.

3.7.2. AIDS Model Estimation

Tables 3.3 and 3.3.a report the first set of results from the AIDS model estimation. As a first step, we estimate the AIDS model in its basic theoretical form, without the additional controls, that is, we estimate the model as given in equation 3.1. The parameter estimates for the five brands are reported in table 3.3, whereas table 3.3.a reports the estimated own and cross-price elasticities, as well as expenditure elasticities. The model is estimated using a seemingly unrelated regression (SUR) approach, and we impose all the restrictions from theory as outlined in the empirical strategy section. The results on the elasticities suggest that demand for all peanut butter brands is price elastic. The demand for *Skippy* is the most price elastic with $E_{Skippy} = -1.96$. The least price elastic is the demand for peanut butter of *Store brands*, whereas the price elasticity for *Peter Pan* is in the middle range at -1.78. Most of the cross-price elasticities have the expected positive signs indicating that an increase in the price of a rival brand leads to an increase in the demand for all other brands. In other words, the cross-price elasticities indicate that consumers view products from competing brands of peanut butter to various extents as substitutes. The exception is *Jif*. Our results indicate that increases in prices of *Peter Pan*, *Store Brands*, and *All other brands* lead to small but negative impacts on the demand for *Jif* peanut butter. Yet these results are not statistically significant due to the large standard errors. As expected, the expenditure elasticities show that each of the peanut butter brands are normal goods. Three peanut butter brands – *Jif, Skippy,* and *All other brands* - are estimated to have expenditure elasticities of greater than 1. Hence, these brands of peanut butter are perceived as luxury goods. The estimated expenditure elasticity for *Peter Pan* is 0.64.

Table 3.3.: Estimated Coefficients of Basic AIDS model (Independent Variables: Peanut Butter Shares by Brand)

	Jif	Skippy	Peter Pan	Store Brands	All Other Brands
Log Price of Jif	-0.243***	0.045***	0.037***	0.148***	0.013***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price of Skippy	0.045***	-0.176***	0.028***	0.074***	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price of Peter Pan	0.037***	0.028***	-0.097***	0.022***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price of Store Brands	0.148***	0.074***	0.022***	-0.284***	0.040***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Log Price of All Other Brands	0.013***	0.028***	0.011***	0.040***	-0.092***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log of Peanut Butter Exp. and Price Ratio	0.179***	0.030***	-0.041***	-0.185***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.274***	0.096***	0.241***	0.825***	0.112***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
N	812,869				

Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01

Table 3.3.a.: Price Elasticities and Expenditure Elasticities for Peanut Butter Brands - Estimated Using the Coefficients from Table 3.3.

	Jif	Skippy	Peter Pan	Store Brands	All Other Brands
			Price Elasticities		
Jif	-1.681	0.284	0.211	0.363	0.134
	(0.056)	(0.013)	(0.014)	(0.095)	(0.013)
Skippy	0.079	-1.963	0.291	0.344	0.219
	(0.054)	(0.018)	(0.016)	(0.096)	(0.011)
Peter Pan	-0.044	-0.044	-1.778	0.254	0.058
	(0.055)	(0.055)	(0.022)	(0.095)	(0.010)
Store Brands	-0.016	0.269	0.485	-1.434	0.207
	(0.055)	(0.014)	(0.015)	(0.096)	(0.012)
All Other Brands	-0.045	0.140	0.133	0.234	-1.719
	(0.056)	(0.014)	(0.015)	(0.095)	(0.019)
			Expenditure Elasticities		
	1.628	1.156	0.641	0.353	1.129
	(0.004)	(0.006)	(0.007)	(0.004)	(0.006)

Bootstrap Standard Errors in Parentheses.

The main results from the AIDS model estimation following our model outlined in equation 3.2 are reported in Tables 3.4, and 3.4.a below. Table 3.4 includes the results of estimating equation 3.2 when each of the v-variables is used in turn, to qualify the pattern of any shifts due to the *Peter Pan* recall of 2007. Note that all coefficient estimates for all other variables, are those from the model estimated with including variable v_1. However, the estimated coefficients for each of the other variables included in the model vary too little to warrant the inclusion of each of the sets of results. Instead, we only report the coefficient estimates on the v-variables from the various model estimations. All the v-variables are defined in the empirical section of this chapter. All the restrictions from theory have also been imposed in the estimated models. Table 3.4.a reports the price and expenditure elasticities calculated from the coefficient estimates from equation 3.2. As expected, these estimates are very similar to the estimated price and expenditure elasticities reported in Table 3.3.a.

Table 3.4.: Estimated Coefficients of AIDS Model with *v* Variables [a]

	Jif	Skippy	Peter Pan	Store Brands	All Other Brands
Log Price of Jif	-0.245***	0.044***	0.043***	0.144***	0.014***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price of Skippy	0.044***	-0.174***	0.033***	0.070***	0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price of Peter Pan	0.043***	0.033***	-0.110***	0.023***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Price of Store Brands	0.144***	0.070***	0.023***	-0.279***	0.041***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Log Price of All Other Brands	0.014***	0.027***	0.011***	0.041***	-0.093***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log of Peanut Butter Exp. and Price Ratio	0.177***	0.025***	-0.040***	-0.179***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Income	0.003***	0.005***	0.001***	-0.008***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Max Education	-0.019***	-0.001**	-0.008***	0.009***	0.019***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Employed	0.013***	-0.013***	0.006***	0.017***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
White	0.018***	-0.026***	-0.007***	0.028***	-0.012***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Child under 12	0.023***	-0.010***	-0.008***	0.014***	-0.020***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Child under 12 * v_1	0.006	0.010***	-0.003	-0.014***	0.001
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Time Trend	-0.001***	-0.000**	0.002***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
December Trend	0.004**	-0.010***	0.005***	0.018***	-0.017***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Constant	-0.265***	0.035***	0.287***	0.864***	0.079***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)

Continued.

Table 3.4.: Continued					
	Jif	Skippy	Peter Pan	Store Brands	All Other Brands
V-variables:					
v_1 [b]	0.039***	0.020***	-0.109***	0.040***	0.009***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
v_2 [c]	0.049***	0.031***	-0.126***	0.030***	0.016***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
v_3 [d]	0.119***	0.025***	-0.162***	-0.002	0.020***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
v_4 [e]	0.072***	0.035***	-0.166***	0.037***	0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	812,869				
Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01					

[a] The equation is estimated with each of the *v*-variables in turn. The estimated coefficients of other variables reported here, are those of the estimation using v_1, however, they do not change significantly when the equation is estimated with any of the other three *v*-variables.

[b] Variable v_1 is defined as follows: $v_1=0$ during the pre-recall period, p=0; $v_1=1$ during the recall period and during the post-recall period, $p\in\{1,2\}$.

[c] Variable v_2 is defined as follows: $v_2=0$ during the pre-recall period, p=0; $v_2=1$ during the recall period, p=1; and $v_2=0$ during the post-recall period, p=2.

[d] Variable v_3 is defined as follows: $v_3=0$ during the pre-recall period, p=0; $v_3=1$ in the first week of the recall period, and $v_3\rightarrow0$ during the recall period and during the post-recall period, $p\in\{1,2\}$. Specifically, v_3=1-(1+e^(-r*t))^(-1), where r=0.20, and where v_3 is normalized to be 1 in the first week of the recall period.

[e] Variable v_4 is defined as follows: $v_4=0$ during the pre-recall period, p=0; $v_4=1$ in the first week of the recall period, and $v_4\rightarrow0$ during the recall period and during the post-recall period, $p\in\{1,2\}$. Specifically, v_4=1-(1+e^(-r*t))^(-1), where r=0.04, and where v_4 is normalized to be 1 in the first week of the recall period.

The results on the demographic variables tell a more or less expected picture. Households with higher income tend to purchase more of *Jif*, *Skippy*, and *Peter Pan*, and less of *Store brands*. Interestingly, head of household education is positively correlated with the share of expenditures on *Store brands* and *All other brands,* and negatively correlated with the share of expenditures on national brands. Being employed is positively correlated with the expenditure shares on *Jif*, *Peter Pan,* and *Store brands*. The results also show that households with young children tend to purchase more of *Jif* and *Store brands*. We do not find any evidence to suggest that households with children tend to stay away more from *Peter Pan* than households without children, as we hypothesized in the empirical methods section. Note that while the coefficient is negative, it is not statistically significant. Finally, while the time trends do not show any effect with most coefficients being zero, the December effect is consistently positive for *Jif*, *Peter Pan*, and *Store brands*, and negative for *Skippy* and *All other brands*. Yet, since the dependent variables in these equations are shares rather than volumes, it is not possible to differentiate between an actual decline in sales of *Skippy* and *All other brands* during the end-of-the-year holiday season, or whether simply there is a relatively larger increase in the sales of *Jif, Peter Pan,* and *Store brands*.

Table 3.4.a.: Price Elasticities and Expenditure Elasticities for Peanut Butter Brands - Estimated Using the Coefficients from Table 3.4.

	Jif	Skippy	Peter Pan	Store Brands	All Other Brands
			Price Elasticities		
Jif	-1.872	0.249	0.388	0.566	0.121
	(0.036)	(0.010)	(0.016)	(0.038)	(0.013)
Skippy	0.138	-1.923	0.292	0.314	0.215
	(0.035)	(0.015)	(0.013)	(0.039)	(0.010)
Peter Pan	0.134	0.134	-1.956	0.141	0.098
	(0.034)	(0.034)	(0.023)	(0.039)	(0.011)
Store Brands	0.490	0.390	0.201	-1.914	0.337
	(0.035)	(0.010)	(0.014)	(0.039)	(0.011)
All Other Brands	-0.582	0.014	0.470	0.831	-1.845
	(0.035)	(0.011)	(0.018)	(0.039)	(0.020)
			Expenditure Elasticities		
	1.619	1.139	0.638	0.379	1.117
	(0.004)	(0.006)	(0.008)	(0.004)	(0.006)

Bootstrap Standard Errors in Parentheses.

The results across the slight variations of the model are very consistent. Across the four specifications of the shift due to the *Peter Pan* recall, we notice that the share of purchases for *Peter Pan* takes a significant dip. In all cases, the coefficients are negative and statistically significant. The results for the *Peter Pan* share equation show that the drop in the share of expenditures on *Peter Pan* ranges from -0.11 (the coefficient on v_1) to -0.17 (the coefficient on v_4). On the other hand, the results show a positive and significant effect across all other brands. All model specifications show that the effect of the *Peter Pan* recall is the largest on *Jif*. The coefficients across the four *v* variables show an economically and statistically significant positive shift in the share of *Jif*. In the case of *Jif*, the coefficients on the *v* variables across the four specifications range from 0.119 to 0.039. The remaining brands – *Skippy*, *Store brands*, and *All other brands* – also have positive and statistically significant estimated coefficients on the *v* variables, yet the impact on those is economically smaller.

The estimation of the model in equation 3.2 with each of the *v* variables used in turn, allows us to be agnostic about the nature of the effect in terms of it being permanent or transitory. The results suggest that regardless of whether the effects are permanent or transitory, there is a negative and significant effect on the share of *Peter Pan*, and positive and significant effects on the shares of all other brands. These results, in conjunction with the results reported in Table 3.2 which show that there is an increase in the peanut butter market size over time, indicate that there are positive spillover effects of the *Peter Pan* recall on the competing brands. Based on the magnitude of the coefficients on the *v* variables for each of the share equations, the results indicate that *Jif* experiences the biggest spillover effect. In other words, the largest gainer due to the *Peter Pan* recall, is *Jif*. Using approximate calculations, the permanent effect of the *Peter Pan* recall on *Jif* translates into an increase of $74.1 million in peanut butter sales annually.[20] The magnitude of the effect is similar for *Store brands*. The results indicate that *Skippy*, and *All other brands* also experience positive spillover effects, albeit smaller in magnitude. Back of the envelope calculations indicate that the permanent effect of the *Peter Pan* recall on *Skippy* and *All other brands* annual peanut butter sales is $38 million and $17.1 million, respectively.

3.8. Discussion and Conclusions

This chapter has addressed the question of demand spillover effects due to recalls in differentiated product markets. We utilize the case study of a branded food product, namely, the *Peter Pan* peanut butter recall of 2007. The main goal in our analysis is to understand whether there are spillover effects of the recall to other brands of the same product. The existence of spillover effects is a good indicator of the existence of incentives for private initiatives in food safety. For example, if there are positive spillover effects for other brands, this indicates that manufacturers of other brands benefit from the recall and hence there are no incentives to cooperate in setting and enforcing food safety standards beyond those required by the government. Yet, if there are negative spillover effects due to the recall, manufacturers not directly linked to the recall suffer the consequences, and hence market incentives exist for private initiatives in food safety. Given the significant impact food safety issues have on the economy as well as on the wellbeing of the

[20] This is calculated by multiplying the coefficient on v_1 for the *Jif* equation, which is 0.039, with the annual sales in peanut butter, estimated at $1.9 billion according to Chaker (2015).

population, it is very important to have a deeper understanding of market incentives for private initiatives in food safety.

This chapter provides an in-depth discussion of the literature on food safety, showing that there exists a gap in empirical analysis for recalls in differentiated food product markets. We also provide a broad discussion of the evolution of the food safety regulations in the United States, international food safety regulations and their link to international trade agreements, and a discussion of the existing private initiatives in food safety in the United States as well as abroad.

The specific case of the *Peter Pan* peanut butter recall is used as a case study for our empirical analysis. The recall lasted from February 2006 to August 2006 and affected the entire stock of Peter Pan peanut butter in the United States. In this chapter, we estimate an AIDS model to analyzing the impact of the recall on the demand for five brands of peanut butter – Jif, Skippy, Peter Pan, Store brands, and all other brands. We utilize Nielsen Homescan data – a rich dataset including information on peanut butter purchases at the household level, as well as demographic variables. The results from our AIDS model estimation indicate that Peter Pan lost a statistically and economically significant part of the share of the peanut butter market due to the recall. The equations for all other brands show a positive impact on the shares for each of those brands. These results, in conjunction with regression results that show that peanut butter market size increased during the study period, indicate that there are positive spillover effects for all the other brands of peanut butter. Jif experienced the biggest positive spillover effect, indicating that consumers switch to Jif peanut butter due to the Peter Pan recall. Approximate calculations suggest that Jif’s sales increased by $74.1 million annually due to the Peter Pan recall. Our results suggest that such an effect is permanent in our study period that extends until the end of 2010. This indicates that at least part of the Peter Pan consumers permanently switched to purchasing Jif peanut butter due to the Salmonella contamination that led to the Peter Pan recall. While other brands experience positive spillover effects as well, a smaller part of the gain from the Peter Pan recall is shared among the other brands. The estimated positive spillover effects among competing brands of peanut butter provide evidence that there are no demand-driven market forces to incentivize peanut butter manufacturers to cooperate in setting higher safety standards in the production of peanut butter. Instead, our results indicate that all losses are internalized by the manufacturer directly affected by the recall. This is an important finding as it helps shed light on the lack of strong private initiatives in food safety among manufacturers of differentiated food products. It also contributes to our understanding of the necessity of government intervention in setting and enforcing food safety standards amongst all food producers.

Chapter 4: Demand Spillovers of Food Recalls in Differentiated Product Markets – Discrete Choice Model Approach

4.1. Introduction

Chapter 3 explored demand spillover effects due to food safety recalls using an AIDS model. In this chapter, we expand the analysis using a characteristics space approach to demand estimation to investigate the same research question as outlined in chapter 3. Specifically, we use a discrete choice model to estimate the demand spillover effects, which, to the best of our knowledge, has not been used before in the food recall literature. As we outline below, there are several advantages to using this methodology. This chapter provides the theoretical framework of the discrete choice modeling approach and reports the empirical results obtained applying this empirical method to our data. Additionally, this chapter includes a discussion comparing and contrasting results from the AIDS model reported in chapter 3, with the results from the discrete choice model reported in this chapter. The chapter concludes with a discussion of policy implications springing from empirical estimations of demand spillover effects due to food recalls in differentiated product markets.

Using an AIDS model to estimate spillover effects due to food safety recalls has several limitations. The AIDS model is based on the representative consumer approach, which states that the behavior of consumers with different preferences can be described by the choices made by a single individual who has preferences for diversity. Furthermore, the representative consumer is assumed to have preferences over products. While this approach has been extensively used in the literature to analyze consumer response to food recalls, it has limitations in applications to differentiated product markets. Specifically, one of the limitations is the assumption of preferences over products, which can create the problem of a large number of parameters to be estimated in order to recover all own- and cross price effects across brands. This is known as the dimensionality problem. Typically, researchers overcome the dimensionality problem either by assuming separability of the utility function to focus on a small group of products, or by mapping consumer preferences over product characteristics' space. However, given that our analysis focuses on five brands – the dimensionality problem is not of central importance.

Another limitation of the AIDS model is that the representative consumer's choice set is assumed to include all the available products and is fixed. However if a product is recalled from the market for a specific period of time, during that time the recalled product is not available for purchase. Hence, a model that takes into account the changes in consumer choice set may provide better estimates of demand spillover effects due to the recall. In this chapter we address these concerns by using a logit model of demand to measure the spillover effects of the recall. This chapter is structured as follows. Section 4.2 provides a general discussion of the theoretical framework of the discrete choice modeling approach. Section 4.3 outlines the logit model that we estimate and the structure of the data. Section 4.4 provides a discussion of the results of the logit model. Section 4.5 concludes with a comparison of the results obtained using the two distinct empirical methods, and their implication for food safety policy.

4.2. Discrete Choice Models of Demand

An alternative approach to the representative agent models of demand is the heterogeneous agent model. In heterogeneous agent models aggregate demand is derived from a distribution of consumer characteristics. Hence, consumers are assumed to have preferences over product characteristics, and products are bundles of characteristics. This assumption implies that products are close substitutes if they have similar characteristics. Lancaster (1966) summarizes this approach as having the following characteristics: (1) Goods do not directly provide consumers with utility, instead, goods possess characteristics and it is the characteristics of goods that provide utility; (2) goods typically possess more than one characteristic and many of the characteristics are shared across a large number of goods; and (3) bundles of goods possess characteristics that may be different from the characteristics possessed by each good separately. Thus, the assumption that consumers have preferences over product characteristics is appropriate for analysis of demand in differentiated product markets since competing brands are typically viewed as close substitutes. The following discussion summarizes the theoretical framework of discrete choice models, and is based substantially on the work by Train (2003).

Consider the behavioral process of an agent's choice, which can be expressed as $y = h(x, \varepsilon)$. Where y denotes the outcome of the choice, x are the factors that determine choice and are observable by the researcher, and ε are the factors that affect choice and are not observable by the researcher. Since the variables ε are not observable, the agent's choice cannot be predicted exactly. However, the researcher derives the probability of any outcome occurring by considering the unobserved factors to be random with a density function $f(\varepsilon)$. Hence, the probability of the agent choosing a specific outcome can be expressed as: $P(y|x) = Prob(\varepsilon$ such that $h(x,\varepsilon) = y)$ (Train 2003). Depending on the assumptions on the distribution of ε, the probability (stated in the form of an integral) may be calculated, or estimated through simulation. This leads to various different discrete choice models, including probit, multinomial logit, nested logit, ordered logit, and mixed logit.

The basic requirements for a case to fit with the discrete choice modeling approach is that the set of alternatives over which the consumer is choosing, referred to as "the choice set", satisfies three conditions. The choice set must contain alternatives that are mutually exclusive. This implies that choosing one alternative implies that none of the other alternatives are chosen. The choice set must be exhaustive – all possible alternatives must be included. And finally, the choice set of alternatives must be a finite set.

The discrete choice models are based on the agent's choice over the different alternatives, in order to maximize her utility. Denote the utility that agent n gets from choosing alternative j as U_{nj}. The agent choses alternative j if she derives the greatest utility, compared to any other alternative $i \neq j$, namely, if $U_{ni} > U_{nj}$. However, the researcher only observes the choice that the agent makes, the characteristics of the different alternatives, denoted by x_{nj}, and several attributes of the agent, denoted by d_n. The researcher then relates these observed factors, to the agent's utility, namely: $V_{nj} = V(x_{nj}, d_n), \forall j$. However, since there are factors ε that affect the agent's choice, and hence her utility, which are not observable by the researcher, we have: $U_{nj} \neq V_{nj} + \varepsilon_{nj}$. Depending on the researcher's assumption about the distribution of the joint density of the random vector, $f(\varepsilon_n)$, the decision is made as to which discrete model is most appropriate for the analysis (Train 2003).

The logit model is one of the most widely used models of discrete choice. The logit relies on the assumption that ε_{nj} is independent identically distributed (iid) extreme value, for all j. Hence, the density for each unobserved part of the utility is given by: $f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}}$, and the cumulative distribution function is given by: $F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}}$. The iid extreme value assumption indicates that the unobserved factors that affect choice are uncorrelated over the alternatives. However, since in some situations this assumption is very restrictive, alternative models have emerged that relax this assumption to various degrees. Those models are referred to as the generalized extreme value (GEV) models, and they allow the correlation to take different forms, including a case in which alternatives are divided into "nests" and correlation is allowed within nests, but not across alternatives that are in different nests.

The probit model is based on the assumption of a normal distribution, that is, $\varepsilon_n' = \langle \varepsilon_{n1}, \dots, \varepsilon_{nJ} \rangle \sim N(0, \Omega)$, where the full covariance matrix Ω can accommodate any correlation and heteroskedasticity type. The advantage of the probit model is that it handles correlations over alternatives and time. However, the normal distribution assumption is in many cases very limiting. The mixed logit is a fully general discrete choice model as it allows the unobserved factors to follow any distribution. Specifically, the mixed logit model includes a decomposition of the unobserved factors into two parts, the part that includes the correlation and heteroskedasticity, and the part that is iid extreme value.

Consider the following model of utility for individual n and product j:

$$U_{nj} = U\left(x_j, \xi_j, y_n, p_j, d_n; \theta\right) \text{ for } n = 1, \dots, N, \text{ and } j = 0, 1, 2, \dots, J, \tag{4.1}$$

where x_j is a set of product characteristics, ξ_j is a set of unobserved product characteristics – that is, unobservable by the researcher, y_n is consumer n's income, p_j is the set of prices for each of the j products, d_n is a set of consumer characteristics, and θ is the vector of parameters to be estimated. Note that $j = 0$ is the commonly used notation for the outside option.

Then, consumer n chooses the alternative from which she derives the highest utility, namely, she chooses j if and only if $U_{nj} > U_{nk}, \forall k$. Summing over the set of consumers that choose product j, we have: $A_j(\theta) = \{d | U_{nj} > U_{nk}, \forall k\}$. Assuming that $d \sim f(d)$, then the share of product j is given by: $s_j(x, p|\theta) = \int_{d \in A_j(\theta)} f(d)\, \mathrm{d}d$.

Let the utility of consumer n, from product j, in time period t be expressed as: $U_{njt} = \delta_{jt} + \epsilon_{njt}$. Then, δ_{jt} is the mean utility, and ϵ_{njt} is the idiosyncratic error term. As discussed above, the iid extreme value distribution assumption for ϵ_{njt} gives rise to the logit model. Consider the multinomial logit model in which we define δ_{jt} as follows: $\delta_{jt} = \alpha\left(y_n - p_{jt}\right) + x_{jt}\beta + \xi_{jt}$. Then we have:

$$U_{njt} = \alpha\left(y_n - p_{jt}\right) + x_{jt}\beta + \xi_{jt} + \epsilon_{njt}. \tag{4.2}$$

In this model, α and β – the parameters of the model, are assumed to be the same across all individuals. Assume that the indirect utility is linear in income, then income has no effect on the utility derived from different alternatives, and thus, it also has no effect on the choice. Thus, the model can be written as:

$$U_{njt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \epsilon_{njt}. \tag{4.3}$$

The logit model then indicates that the probability of consumer n choosing product j, where the utility of the outside good is normalized to 0, $U_{n0} = 0$, is given by:

$$s_{jt} = \frac{\exp(x_{jt}\beta - \alpha p_{jt} + \xi_{jt})}{1+\sum_{k=1}^{J} \exp(x_{jt}\beta - \alpha p_{jt} + \xi_{jt})}. \tag{4.4}$$

Given that the taste parameters, α and β, are by assumption the same across all individuals in the logit model, equation 4.4 above is equivalent to the market share for product j at time t.

One of the issues with discrete choice models is the endogeneity of prices. As discussed so far, there is a component in the model, namely the unobserved (by the researcher) product characteristics, ξ_{jt}, that affect consumers' utility and hence their choices. If these characteristics are observed by the producers/firms, then prices are set taking these characteristics into consideration. In other words, the prices of the products are endogenous. Instrumental variables are typically used in order to take into account the endogeneity of the prices. Hence, one of the main challenges of estimating the model is to find appropriate instrumental variables.

The estimation strategy with the logit model is to find values of $\alpha, \beta,$ and ξ, which would let us obtain predicted shares, denoted by $\hat{s}$, that are as close as possible to observed actual shares for each of the products j. In equation format, this may be expressed as: $\min_{\alpha,\beta} \sum_{j=1}^{K} (\hat{s} - s)^2$, where the equation for the share is given in equation 4.4. Under the assumption that we have instruments to account for the unobserved characteristics, we can obtain δ_j in two steps, using the method of inversion proposed by Berry (1994). Essentially, using a method of inversion, Berry (1994) shows that $\delta_j = \log(s_j) - \log(s_0)$, where s_0 is the share of the outside good. Hence, using instrumental variables, the parameters $\widehat{\alpha}$, and $\hat{\beta}$, are obtained from estimating the following model:

$$\delta_j = \log(s_j) - \log(s_0) = x_j\beta - \alpha p_j + \xi_j. \tag{4.5}$$

The price elasticities for the logit model given in equation 4.5 are given below. Through mathematical manipulations, it can be shown that the own-price elasticity is:

$$\frac{\partial s_j}{\partial p_j} * \frac{p_j}{s_j} = -\alpha_j s_j(1 - s_j) * \frac{p_j}{s_j} = -\alpha_j p_j(1 - s_j). \tag{4.6}$$

The cross-price elasticity is given by:

$$\frac{\partial s_j}{\partial p_k} * \frac{p_k}{s_j} = \alpha_j s_k s_j * \frac{p_k}{s_j} = \alpha_j s_k p_k, \tag{4.7}$$

where all the terms have been previously defined.

4.3. Empirical Strategy

In this chapter, we use the logit model framework discussed above to estimate demand spillover effects due to food recalls. The model is applied to the *Peter Pan* peanut butter recall in 2007, which is described in great detail in chapter 3. We estimate the model in several different variations. Expanding on equation 4.5, we first estimate the following model:

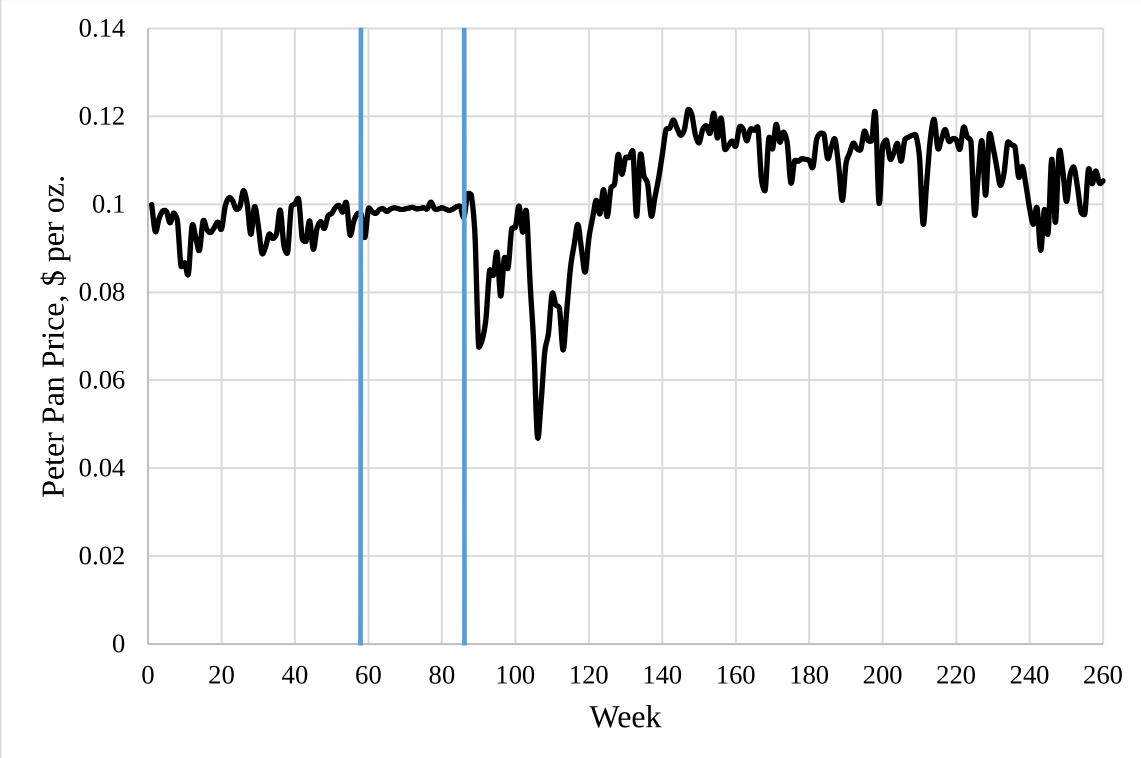
$$\log(s_{jmt}) - \log(s_{0mt}) = \alpha_0 + \boldsymbol{x}_j\boldsymbol{\beta} + \eta v_1 + \boldsymbol{\mu}\boldsymbol{x}_j v_1 - \boldsymbol{\alpha}\boldsymbol{p}_{jmt} + \xi_{jmt}, \tag{4.8}$$

where s_{jmt} is the share of expenditures on peanut butter brand j, in market m, and time t, and s_{0mt} is the share of expenditures on the outside good. The peanut butter brands include *Peter Pan*, *Jif*, *Skippy*, *Store brands*, and a composite category for *all other brands*. We let the outside good be *all other foods*, hence s_{0mt} is the share of expenditures on all other foods except for peanut butter. On the right hand side of the equation, $\boldsymbol{x}_j$ is the set of brand fixed effects, and $\boldsymbol{p}_{jmt}$ is the set of prices for each of the brands of peanut butter, by market and time period. As in the previous chapter, we use v_1 to capture the long-term spillover effects. Hence, v_1 is a binary variable equal to zero during the pre-recall period, and equal to one during the recall period and during the post-recall period. In order to isolate the impact of the recall on each of the brands, we use interaction terms between brands and the binary variable v_1. These effects are captured by the $\boldsymbol{\mu}$ coefficients. Note that unlike in the previous chapter, where the unit of observation was household and time, in the model specification given in equation 4.8, the unit of observation is market and time. We use Nielsen's definition of markets in our empirical analysis. The definition used by Nielsen includes 76 markets in the United States. As in the previous chapter, the time unit of the analysis is a week.

In the discussion that follows, we replace the usage of the term "product", by the term "brand" – given that in the specific case which we analyze consumers choose between brands of peanut butter. As discussed in the previous section, one of the key aspects of the discrete choice models is that product characteristics affect consumers' utility, and hence choice. To include peanut butter brand characteristics is quite challenging. Unlike other branded products, such as cereals, which differ a lot in terms of composition, peanut butter is by law quite homogenous across various brands. In the United States, an FDA regulation states that in order for a product to be labelled "peanut butter", 90% or more of its content needs to be peanuts (FDA 2009). This regulation has been in effect since 1961. While the composition of the product is specified, peanut butter manufacturers still use different ways to differentiate their product. For example, there are peanut butter characteristics such as: chunky versus creamy, with reduced fat, with reduced salt, as well as “natural”. These are characteristics that likely influence consumers’ utility, and hence choice. However, information on these characteristics in the Nielsen data is very limited. For example, out of the 1,037 individual peanut butter product UPCs in 2006, the dataset includes characteristics’ information for only 6 of those UPCs. Hence, in this specific market, due to relative homogeneity of the peanut butter products and lack of variation in other characteristics across brands, we argue that consumer preferences for peanut butter are mainly based on brand image. Thus, we include brand fixed effects in our model.

After the recall period was over, *Peter Pan* appeared in market shelves in August of 2007. One of the strategies that ConAgra Foods Inc. used in order to increase the demand for their main brand of peanut butter, was to lower *Peter Pan* prices substantially, by sending coupons to consumers. This pricing strategy may have played a role in consumers’ demand for *Peter Pan* once the brand reappeared in the market. Figure 4.1 below gives a graphical depiction of average *Peter Pan* prices over the course of the study period. The solid lines indicate the recall period, which extended from week 59 to week 85, that is, from February 2007 – August 2007.

Figure 4.1.: Average Peter Pan Price During the Study Period



To account for the change in prices in the post recall period, we also estimate the model including an interaction term between the *Peter Pan* brand dummy, the *Peter Pan* price, and binary variable v_1. Finally, we extend the model to also include demographic variables, such as income, education, employment status, presence of children, and race. Hence, we estimate the following model:

$$\log(s_{jmt}) - \log(s_{0mt}) = \alpha_0 + \boldsymbol{x}_j\boldsymbol{\beta} + \eta v_1 + \boldsymbol{\mu}\boldsymbol{x}_j v_1 - (\boldsymbol{\alpha}\boldsymbol{p}_{jmt} + \rho x_{PP} p_{PP} v_1) + \boldsymbol{\tau}\boldsymbol{d}_{mt} + \xi_{jmt}, \tag{4.9}$$

where ρ captures the effect of the interaction term indicated above. We use the subscript pp to denote Peter Pan. The coefficients on the demographic variables are denoted by $\boldsymbol{\tau}$**.** All the other variables and parameters have been previously defined. As is the convention, in the results section, we report the results of the estimation both excluding the demographic controls, as well as including the demographic controls.

One of the main challenges of estimating the logit model proposed here, is that prices are endogenous. To address this issue, we use an instrumental variables approach (Berry 1994). For each brand of peanut butter, we use average of the prices of that brand in other markets at the same time period to instrument for prices. The identifying assumption is that demand shocks for a specific brand in a market are uncorrelated with prices of that brand in other markets. Therefore, prices are correlated across markets due to similar marginal costs and cost shocks. That is, prices of a brand in different markets at the same time period will be highly correlated, and can thus be used as instrumental variables (Hausman et al. 1994, Nevo 2001). An additional advantage of this approach is that the existing panel data can be used, hence, it does not require data that is usually difficult to obtain, such as manufacturers' production cost data. We report results from both OLS and instrumental variables estimation. In order to identify the effect of the recall on each of the brands, we calculate the marginal effects of the recall for each of the brands, using the parameters obtained from estimating the model outlined above. We report the marginal effects of the recall for each brand, and for each model specification.

One of the considerations when interpreting the results of models specified in 4.8 and 4.9 is the data structure, specifically in regards to *Peter Pan*'s shares and prices during the recall period. As reported in the previous chapter, specifically on table 3.1, the share of expenditures on *Peter Pan* peanut butter is extremely small, but non-zero, during the recall period. When estimating the logit model, we first exclude observations of *Peter Pan* purchases during the recall period. This approach might seem plausible since it closely reflects the actual scenario that consumers faced during the recall period, namely, *Peter Pan* peanut butter was not available on the shelves. However, dropping these observations results in missing prices of *Peter Pan* during the recall period and creates an important econometric problem. That is, because *Peter Pan* price enters in econometric models as specified in equations 4.8 and 4.9 – having missing data for the *Peter Pan* price would drop all observations in the weeks of the recall period, including those of the competing brands. Hence, the model could only be estimated with brand/market/time observations pertaining to the pre-recall and post-recall periods. We would not be able to identify any spillover effects that the recall had on competing peanut butter brands during the actual recall period. Given these issues, we decide to keep the *Peter Pan* prices during the recall period. We report the results of estimating equations 4.8 and 4.9, with the limitation that these results do not reflect a change in consumers' choice set during the recall period.

A simple approach to account for the varying choice set is to estimate the model period-by-period. That is, all observations are separated into three time periods - before the recall, during the recall, and after the recall. Estimating the model separately for each of the time periods using the model in equation 4.5 explicitly accounts for the non-existence of *Peter Pan* during the recall period. However, an important limitation of this approach is that because the three periods are segmented by the beginning and the end of the recall, the impact of the recall on demand for brands cannot be identified directly. Instead, indirect approaches such as period-by-period comparison of predicted shares and demand elasticities can be used to infer about the spillover effects of the recall on competing brands.

First, we use elasticity estimates to gain insight on how the demand structures for competing brands change due to the *Peter Pan* recall. In general, *ceteris paribus*, we expect demand for a product to be more inelastic if there are fewer substitutes. However, during a recall the elasticity of demand for competing products can change in either direction depending on consumers' response to the recall. Specifically, if consumers switch to other peanut butter brands, we expect the demand for other peanut butter brands to become more inelastic during the recall period. Alternatively, if consumers switch away from all peanut butter brands due to the recall, we expect the demand for peanut butter brands to become more elastic during the recall period even though there are fewer brands.

A second approach is to use predicted shares to understand the pattern of demand before, during, and after the recall period. Summarizing the data, we observe a trend in which at least some of the peanut butter brands increase their market share during and after the *Peter Pan* recall, while *Peter Pan*'s market share decreases significantly. If such a trend is observed in the predicted shares as well, then the model performs well in depicting the spillover effects on competing brands. Specifically, if the results show an increase (decrease) in predicted shares for competing brands in the aftermath of the *Peter Pan* recall, then this indicates that there are positive (negative) spillover effects for those brands. We report the model coefficients from both the OLS as well as the instrumental variables estimation strategy. We report the estimated elasticities and the predicted shares obtained using the coefficients from the instrumental variables model.

4.4. Results

The results of estimating equations 4.8 and 4.9 are reported in Table 4.1 below. We report the coefficient estimates both using the logit model and the instrumental variables model. Model 1a reports the results from estimating equation 4.8. Model 1b reports the results of estimating equation 4.9 without the demographic controls. Model 1c reports the results of estimating equation 4.9 with the demographic controls. As previously discussed, we use average brand prices in other markets at the same time period, to instrument for brand prices in each market. The first stage results, in particular the F statistics, indicate that the instruments are valid.

The coefficient estimates for the brand fixed effects indicate that compared to the *All other brands*, each of the brands has a higher relative share of expenditures. In terms of magnitude, *Jif* and *Store brands* have a much higher relative share of expenditures, compared to the other brands. The coefficient on v_1, the binary variable indicating the recall of *Peter Pan*, is statistically significant, and so are the coefficients on the interactions with the brand fixed effects. This indicates that the recall has a statistically significant impact on each of the peanut butter brands. In order to obtain the effect of the recall on each brand, we calculate the marginal effect of the recall which is captured by the coefficients on the binary variable v_1 and its interaction terms with the brand fixed effects.

Table 4.1.: Results of Estimating the Logit Model with Permanent Effect Variable - v_1 [1]

	OLS			Instrumental Variables		
	Model 1a	Model 1b	Model 1c	Model 1a	Model 1b	Model 1c
Jif	0.768***	0.769***	0.769***	0.768***	0.769***	0.769***
	(0.064)	(0.064)	(0.064)	(0.017)	(0.016)	(0.016)
Skippy	0.062	0.055	0.057	0.061***	0.050***	0.051***
	(0.090)	(0.089)	(0.089)	(0.018)	(0.017)	(0.017)
Peter Pan	0.030	0.043	0.043	0.032*	0.051***	0.051***
	(0.101)	(0.100)	(0.100)	(0.018)	(0.017)	(0.017)
Store brand	0.611***	0.612***	0.611***	0.611***	0.612***	0.611***
	(0.052)	(0.052)	(0.052)	(0.017)	(0.016)	(0.016)
v1	-0.108***	-0.098***	-0.073**	-0.091***	-0.056***	-0.027*
	(0.029)	(0.030)	(0.029)	(0.016)	(0.016)	(0.016)
Jif * v1	0.203***	0.203***	0.203***	0.203***	0.202***	0.203***
	(0.036)	(0.036)	(0.036)	(0.020)	(0.018)	(0.018)
Skippy * v1	0.131***	0.136***	0.135***	0.132***	0.140***	0.139***
	(0.041)	(0.041)	(0.041)	(0.020)	(0.019)	(0.019)
Peter Pan * v1	-0.232***	-1.336***	-1.336***	-0.228***	-1.765***	-1.768***
	(0.044)	(0.064)	(0.064)	(0.021)	(0.127)	(0.127)
Store brands * v1	0.139***	0.138***	0.139***	0.139***	0.138***	0.139***
	(0.035)	(0.034)	(0.035)	(0.020)	(0.018)	(0.018)
Jif Price	0.338	0.071	-0.112	2.053***	2.346***	2.131***
	(0.390)	(0.376)	(0.362)	(0.720)	(0.674)	(0.674)
Skippy Price	1.498***	0.903**	0.905**	1.802***	0.386	0.274
	(0.341)	(0.361)	(0.361)	(0.386)	(0.378)	(0.379)
Peter Pan Price	1.570***	2.685***	2.688***	2.058***	4.380***	4.446***
	(0.289)	(0.288)	(0.290)	(0.298)	(0.337)	(0.337)
Store Brand Price	2.445***	1.621***	1.797***	-0.749	-2.728***	-2.488***
	(0.401)	(0.386)	(0.385)	(0.749)	(0.719)	(0.720)
	0.667***	0.619***	0.605***	-0.897	-2.693***	-2.942***
All Other Brands Price	(0.194)	(0.198)	(0.193)	(0.581)	(0.563)	(0.569)
Peter Pan * Peter Pan Price * v1		47.388***	47.350***		66.063***	66.185***
		(2.590)	(2.577)		(5.393)	(5.390)
Constant	-4.308***	-4.254***	-4.031***	-4.084***	-3.779***	-3.586***
	(0.072)	(0.069)	(0.110)	(0.073)	(0.073)	(0.101)
Controls	No	No	Yes	No	No	Yes
R^2	0.2243	0.3431	0.3446			
F statistic				52.78	61.56	50.64
N	91,046	91,046	91,046	91,046	91,046	91,046

Controls include: Income, Presence of Children, Education, Employment, and Race.

[1] The logit model is estimated using the inversion method proposed by Berry (1994).

In estimating the model, we leave out the brand dummy for *All Other brands*. Hence, the coefficient on v_1 gives the marginal effect of the recall on *All Other brands*. To get the marginal effect of the recall on *Jif*, we sum the coefficient on v_1 with the coefficient on the *Jif* brand dummy and v_1 interaction term. We follow a similar procedure to calculate the impact of the recall on *Skippy* and *Store* brands. The marginal effect of the recall on *Peter Pan* is slightly different for models 1b and 1c. These models include an additional interaction term between the recall dummy and the average price of *Peter Pan* to control for the changing pricing strategy of *Peter Pan* after the recall. We calculate the marginal effects both for the logit models, as well as for the instrumental variables models. The calculated marginal effects are reported in Table 4.2.

Table 4.2.: Marginal Effects of the Recall for Each Peanut Butter Brand[1]

	OLS			Instrumental Variables		
	Model 1a	Model 1b	Model 1c	Model 1a	Model 1b	Model 1c
Jif	0.095	0.105	0.130	0.113	0.147	0.176
	(0.013)	(0.012)	(0.012)	(0.014)	(0.014)	(0.015)
Skippy	0.022	0.038	0.062	0.041	0.084	0.112
	(0.019)	(0.019)	(0.019)	(0.021)	(0.020)	(0.020)
Peter Pan	-0.340	-6.270	-6.243	-0.318	-8.560	-8.545
	(0.021)	(0.079)	(0.080)	(0.022)	(0.654)	(0.656)
Store brands	0.030	0.040	0.066	0.048	0.083	0.112
	(0.012)	(0.012)	(0.012)	(0.013)	(0.015)	(0.015)
All Other brands	-0.108	-0.098	-0.073	-0.091	-0.056	-0.027
	(0.014)	(0.014)	(0.014)	(0.015)	(0.016)	(0.016)

[1] For Jif, Skippy, and Store brands - the marginal effect of the recall is the sum of the coefficient on v_1 and the coefficient on the interaction term between v_1 and each of these brands respectively. The marginal effect on Peter Pan, is the sum of the coefficient on v_1, the coefficient on the interaction term between brand and v_1, and the coefficient on the interaction term between v_1, the brand dummy, and the Peter Pan price, multiplied by the average price of Peter Pan. The marginal effect of the recall on All other brands, is the coefficient on v_1.

[2] Bootstrap standard errors in parentheses.

The results indicate that there are positive spillover effects for three out of four competing peanut butter brands. Yet, the results also indicate the *All other brands* experienced losses due to the *Peter Pan* recall. As expected, the results indicate that *Peter Pan* suffered losses in the share of expenditures, due to the recall. The marginal effects for each of the brands are relatively similar across the model specifications for all brands except for *Peter Pan*. Specifically, the results from models 1b and 1c show very large negative effects for *Peter Pan*, compared to the results from model 1a. Yet the directions of the effects are consistent throughout the various model specifications.

Consistent with the patterns we observe in the data, the model indicates that the largest positive spillover effect occurs for *Jif*. Specifically, the ratio of the share of expenditures on *Jif* increased by 0.095 – 0.176 percent, based on the results reported on the first row of Table 4.2. At the mean, the share of expenditures on *Jif* is 0.058. Hence, the model predicts a positive, however very small increase in the share of expenditures on *Jif*. The other brands that experience positive spillover effects are *Store brands* and *Skippy*. The share of expenditures on *Store brands* due to the *Peter Pan* recall increases by 0.030 – 0.112 percent. The increase for *Skippy* is even smaller, at 0.022 – 0.112 percent. The results also show that there are negative spillover effects for *All other brands* due to the recall. Specifically, the share of expenditures for *All other brands* drops by 0.027 – 0.108 percent. The drop experienced by *All other brands* is comparable in magnitude to the gain experienced by *Skippy*. Finally, the results indicate much higher losses in the share of *Peter Pan* due to the recall. Specifically, the recall leads to a decrease in the share of expenditures on *Peter Pan* by 0.32 – 8.56 percent. These results indicate that while some peanut butter brands experience gains due to the *Peter Pan* recall, at least one brand experiences negative spillover effects due to the *Peter Pan* recall. The results also indicate that while the effect of the recall on the share of *Peter Pan* is relatively large in magnitude, the spillover effects on competing brands are quite small in magnitude. This is contrary to the results from the AIDS model in the previous chapter, where we find that the spillover effects for all competing brands are positive and large in magnitude.

As discussed in the previous section, we also estimate the model using the period-by-period approach. Specifically, we estimate the model as given in equation 4.5. This approach allows us to indirectly account for the varying choice set for peanut butter consumers. The results are reported in Table 4.3 below. Since the model is estimated by period, that is - before, during, and after the *Peter Pan* recall – we cannot directly estimate the spillover effects due to the recall. Instead, as explained in the previous section, we use the elasticity estimates, and the predicted shares, to gain insights on any spillover effects. The results from the calculated own- and cross-price elasticities are reported in Table 4.4.

Table 4.3.: Results of Estimating the Logit Model by Period[1]

	OLS			Instrumental Variables		
	Pre-recall Period	Recall Period	Post-Recall Period	Pre-recall Period	Recall Period	Post-Recall Period
Jif	0.762***	0.921***	0.979***	0.760***	0.921***	0.979***
	(0.064)	(0.074)	(0.066)	(0.018)	(0.023)	(0.010)
Skippy	0.065	0.114	0.205**	0.061***	0.113***	0.204***
	(0.090)	(0.091)	(0.086)	(0.019)	(0.023)	(0.010)
Peter Pan	0.036		-0.185**	0.041**		-0.183***
	(0.101)		(0.092)	(0.019)		(0.010)
Store brands	0.603***	0.687***	0.759***	0.602***	0.686***	0.759***
	(0.052)	(0.047)	(0.051)	(0.018)	(0.023)	(0.010)
Jif Price	1.901***	0.854	0.783**	3.453*	2.969	2.117**
	(0.695)	(1.200)	(0.384)	(1.773)	(3.067)	(0.844)
Skippy Price	1.856***	1.608**	1.719***	2.277**	0.519	1.402***
	(0.562)	(0.653)	(0.356)	(1.031)	(1.926)	(0.443)
Peter Pan Price	0.779		1.370***	-2.594		1.332***
	(0.652)		(0.274)	(1.603)		(0.337)
Store Brands Price	6.204***	5.112***	4.000***	4.278*	0.721	3.148***
	(0.770)	(1.147)	(0.409)	(2.590)	(5.375)	(0.926)
All Other Brands Price	1.119***	2.889***	1.063***	6.192***	2.733	0.912
	(0.355)	(0.595)	(0.212)	(2.320)	(5.483)	(0.689)
Constant	-4.437***	-4.654***	-4.430***	-4.969***	-4.457***	-4.492***
	(0.181)	(0.282)	(0.112)	(0.394)	(0.597)	(0.150)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.144	0.2396	0.2486			
F Statistic				10.79	5.68	28.54
N	19,557	7,506	63,983	19,557	7,506	63,983

Controls include: Income, Presence of Children, Education, Employment, and Race.

[1] The logit model is estimated using the inversion method proposed by Berry (1994).

Table 4.4.: Own-price and Cross-price Elasticities from the Logit Model by Period[1]

Period 1: Pre-recall:	Jif	Skippy	Peter Pan	Store brands	All Other brands
Jif	-0.333	0.012	-0.014	0.022	0.032
	(0.177)	(0.006)	(0.009)	(0.014)	(0.011)
Skippy	0.011	-0.225	-0.008	0.013	0.019
	(0.006)	(0.114)	(0.005)	(0.008)	(0.007)
Peter Pan	0.008	0.005	0.242	0.010	0.014
	(0.004)	(0.003)	(0.156)	(0.006)	(0.005)
Store brands	0.012	0.008	-0.009	-0.328	0.022
	(0.006)	(0.004)	(0.006)	(0.205)	(0.008)
All Other brands	0.012	0.008	-0.005	0.014	-0.860
	(0.006)	(0.004)	(0.003)	(0.009)	(0.308)

Period 2: During recall:	Jif	Skippy	Store brands	All Other brands
Jif	-0.303	0.004	0.005	0.019
	(0.294)	(0.011)	(0.040)	(0.040)
Skippy	0.012	-0.053	0.003	0.011
	(0.011)	(0.165)	(0.023)	(0.024)
Store brands	0.011	0.002	-0.055	0.010
	(0.011)	(0.006)	(0.448)	(0.023)
All Other brands	0.011	0.002	0.003	-0.385
	(0.011)	(0.006)	(0.022)	(0.841)

Period 3: Post-recall:	Jif	Skippy	Peter Pan	Store brands	All Other brands
Jif	-0.233	0.010	0.009	0.022	0.006
	(0.097)	(0.003)	(0.002)	(0.006)	(0.005)
Skippy	0.009	-0.155	0.006	0.013	0.004
	(0.004)	(0.051)	(0.001)	(0.004)	(0.003)
Peter Pan	0.004	0.003	-0.137	0.007	0.002
	(0.002)	(0.001)	(0.030)	(0.002)	(0.001)
Store brands	0.009	0.006	0.006	-0.275	0.004
	(0.004)	(0.002)	(0.001)	(0.078)	(0.003)
All Other brands	0.008	0.005	0.003	0.012	-0.139
	(0.003)	(0.002)	(0.001)	(0.003)	(0.104)

[1] The elasticities are calculated using coefficient estimates from the instrumental variables model reported in Table 4.3. The formulas for the own-price and cross-price elasticities of the logit model are given in equations (3.6) and (3.7) respectively.

[2] Bootstrap standard errors in parentheses.

These results indicate that the elasticity of demand for all competing brands of peanut butter decreased due to the Peter Pan recall. For example, the estimated own-price elasticity of demand for Jif goes from -0.33 in the pre-recall period to -0.23 in the post-recall period. Interestingly, the own-price elasticity of demand for All other brands also decreases substantially, from -0.86 in the pre-recall period to -0.14 in the post-recall period. These estimates indicate that there are positive spillover effects for All other brands, however the elasticity estimate in the post-recall period is not statistically significant. Similarly, the own-price elasticity for Peter Pan in the pre-recall period has a positive sign, but is not statistically significant at the 10% level. Overall, the elasticity results that are statistically significant suggest that Jif, Skippy, and Store brands do experience spillover effects due to the Peter Pan recall. However, all the estimated elasticities are very small in magnitude, indicating that the demand for all peanut butter brands is highly inelastic. This is different from the results we obtain from estimating the AIDS model in the previous chapter, where we find that at least some of the peanut butter brands have elastic demand.

Next, we calculate the predicted shares during the three periods of the recall. The results are given in Table 4.5 and show the actual mean shares as well as the predicted mean shares. Recall that shares for each brand of peanut butter are calculated as the total dollar expenditure on that brand divided by total food expenditures. Comparing the pre-recall period to the post-recall period, the actual shares show that there is a substantial increase in the share of expenditures on *Jif*, indicating that this brand experiences the highest gain due to the *Peter Pan* recall. The share of expenditures on *Store brands* also increases, but the share of expenditures on *Skippy* remains almost constant across time periods. Interestingly, the data show that the share of expenditures on *All other brands* in effect decreases. Finally, as expected, the share of expenditures on *Peter Pan* also decreases in the after-recall period. The predicted shares for each of the brands consistently underestimate the actual shares, across brands and time periods. However, the model does quite well in predicting the trend of the shares. That is, the model correctly predicts that the share of expenditures is highest for *Jif*, and next highest for *Store brands*. The predicted shares follow a similar pattern as the actual shares showing positive gains, and hence positive spillover effects, for *Jif*, *Skippy*, and *Store brands* during and after the recall periods. Also, the predicted share of *Peter Pan* is significantly lower in the post-recall period, compared to the pre-recall period showing that *Peter Pan* suffers the consequences of the recall for a long period after the recall is over.

Table 4.5.: Actual and Predicted Shares by Brand from the Logit Model by Period[1]

	Pre-recall period		Recall period		Post-recall period	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
	Mean	Mean	Mean	Mean	Mean	Mean
Jif	0.0535	0.0449	0.0628	0.0551	0.0596	0.0517
	(0.0005)	(0.0001)	(0.0006)	(0.0001)	(0.0002)	(0.0000)
Skippy	0.0379	0.0222	0.0381	0.0246	0.0383	0.0238
	(0.0006)	(0.0000)	(0.0008)	(0.0000)	(0.0003)	(0.0000)
Peter Pan	0.0303	0.0219	0.0000	0.0000	0.0232	0.0162
	(0.0004)	(0.0000)	0.0000	0.0000	(0.0002)	(0.0000)
Store brands	0.0455	0.0384	0.0476	0.0436	0.0466	0.0415
	(0.0004)	(0.0001)	(0.0004)	(0.0001)	(0.0002)	(0.0000)
All Other brands	0.0272	0.0210	0.0262	0.0219	0.0241	0.0194
	(0.0004)	(0.0000)	(0.0003)	(0.0000)	(0.0001)	(0.0000)

Standard errors in parentheses.

[1] The predicted shares are calculated using the coefficient estimates from the instrumental variables model reported in Table 4.3.

4.5. Discussion and Conclusions

In this chapter, we use a discrete choice modeling framework to investigate demand spillover effects of the *Peter Pan* recall on competing peanut butter brands. Our analysis has two primary motivations. First, the discrete choice modeling approach has not been used in prior empirical studies of food recall. By using this approach in this context we shed light on advantages and disadvantages of the empirical implementation of the discrete choice modeling in comparison to the widely used AIDS model. Second, the discrete choice modeling approach has desirable properties that could overcome some limitations of the AIDS model estimation in evaluating consumer response to product recalls. In particular, by construction, the AIDS model is not flexible enough to account for changes in consumers' choice set during a recall. However, in our empirical investigation we find that a standard discrete choice model - such as the logit that is widely used in empirical analysis of demand in differentiated products - also has important limitations in addressing the problem of the changing choice set due to a recall. We conclude that future research should investigate applications of more flexible discrete choice models, such as the generalized multinomial logit model (Matějka and McKay 2015), in studies of consumer response to food recalls.

In this chapter, we estimate a standard logit model in two different ways – one of which does not account for the varying choice set, while the other one indirectly addresses the issue by segmenting the data by the recall period. We report the results from both approaches and discuss advantages and limitations. Taken together, the results of the logit model approach indicate that the *Peter Pan* recall results in positive spillover effects for

Jif, *Store brands*, and *Skippy*. The results also indicate that there are negative spillover effects for *All other brands*, suggesting that while some competing brands gained due to the *Peter Pan* recall, others experienced losses. All models are consistent in indicating that *Jif* experiences the highest positive spillover effects. In the first set of results, the marginal effect is calculated to be the highest for *Jif*, indicating an increase in the share of *Jif* of up to 0.176 percent. The second set of results shows that the own-price elasticity of *Jif* goes down by approximately 0.10. Hence, the already inelastic demand for *Jif* becomes even more inelastic due to the recall. And finally, the model correctly predicts the pattern that we observe in the data, namely, that the share of expenditures on *Jif* increases substantially, going from 0.05 in the pre-recall period, to approximately 0.06 in the recall period and post-recall periods. This is consistent with the results we obtained from the AIDS model estimation in chapter 3 – namely, that *Jif* is the biggest winner from the *Peter Pan* recall. However, the magnitude of the spillover effect is estimated to be quite large in the AIDS model and relatively small in the logit model estimation.

The logit model results also suggest that *Skippy* and *Store brands* experience some positive spillover effects, a finding that is consistent with the AIDS model results. Yet, the logit model results indicate that *All other brands* experience negative spillover effects due to the recall. This finding is consistent across the logit model specifications. However, this finding is not consistent with the AIDS model results reported in the previous chapter, which indicate that while the gains for *All Other brands* are smaller in magnitude, they are nonetheless positive. Finally, the logit model results confirm the pattern observed in the data, that *Peter Pan*'s share does not recover to pre-recall levels once the brand comes back into the market. Specifically, *Peter Pan* experiences negative effects due to the recall for a relatively long period of time. This is a result that we also obtained from the AIDS model estimation.

Similar to the AIDS model results, the logit model results suggest that there are positive spillover effects for at least some competing brands of peanut butter. These results indicate that, at least for some manufacturers, the recall of a competitor's brand will turn out to be beneficial by leading to a higher demand for their own brands, and hence generating profits. However, the results from the logit model also suggest that at least one of the competing brands experiences losses due to the *Peter Pan* recall. Therefore, the implications of the logit model results are more nuanced when it comes to food safety policy. By indicating that there are both gainers and losers among competing brands, these results are not conclusive when it comes to determining private sector incentives to establish and maintain higher food safety standards. Further analysis is required to understand why consumers switch to purchasing peanut butter from brands such as *Jif*, *Skippy*, and *Store brands*, and yet switch away from *All other brands*. It is informative to analyze whether this is primarily due to consumer heterogeneity, or whether it has to do with how brands are related to each other (i.e. some brands may have very similar labeling design hence leading to consumers perceiving them as closer substitutes, compared to other brands). Since some manufacturers experience gains while other manufacturers experience losses due to the recall, any private sector incentives to jointly invest and cooperate in setting and enforcing food safety standards would depend on the net expected value of the profits/loses to be made by each individual manufacturer.

There are some limitations of the logit model results as specified above. Specifically, we obtain very small elasticity estimates for each of the peanut butter brands, indicating that the demand for each brand of peanut butter is highly inelastic. In addition, the predicted shares obtained from the model are consistently lower than the actual shares for all the brands of peanut butter. In future work, our effort will be channeled primarily to specifying a discrete choice model that takes into account the varying choice set in one step of the estimation. This would allow us to measure the impact of the recall directly from the model, instead of indirectly through elasticity estimates and predicted shares, as we have reported here. This would allow us to derive better conclusions in terms of evaluating the usefulness and accuracy of the AIDS model approach, an approach utilized extensively in the literature of food product recalls.

Chapter 5: Conclusions

This dissertation consists of three essays in the areas of food choice and food safety. Each essay outlines the research question, addressing its importance in economic literature and its implications for policy. We discuss ties to the economic theory and propose empirical models to address the research questions. Using U.S. household-level data, we estimate the empirical models and discuss the results in terms of their implications for food policy.

The first essay contributes to the literature on factors that impact food choices. Given the time constraints for a growing population, we argue that it is important to understand how food-related activities that take time affect food choices. Specifically, we investigate the impact of food shopping frequency on the healthfulness of food choices. We argue that the impact is conceptually ambiguous. For example, a higher shopping frequency allows consumers to purchase and have access to fresh fruits and vegetables – healthful but quickly perishable foods. Through this channel, the impact of a higher shopping frequency on the healthfulness of food choices is positive. Alternatively, with each shopping trip, consumers face temptations to purchase unhealthful foods – sweet and savory commercially prepared items. If this channel persists, the impact of a higher shopping frequency on the healthfulness of food choices is negative.

Using household-level food purchase panel data and the instrumental variables approach, we find that a higher shopping frequency leads to a decrease in the healthfulness of food choices. As consumers visit grocery stores more often, they purchase more unhealthful foods. We conclude that policies that attempt to limit consumers' exposure to unhealthful foods in the grocery store, especially in the most visible areas such as by check-out lanes, may have an impact in reducing the purchases of such items and hence increasing diet quality.

The second essay addresses an important issue related to food safety in the United States. Specifically, we investigate demand spillover effects of food recalls in differentiated markets. We argue that how consumers respond to a food safety recall has important implications for private sector / firms' incentives to cooperate in investing and enforcing food safety standards. Specifically, if consumers switch to purchasing other brands but stick to the same product, then manufacturers of competing brands benefit from the recall. In this scenario, the incentives for manufacturers to contribute collectively in the effort of a safer food supply may not be strong. Alternatively, consumers may switch to purchasing other products, hence considering all brands of the recalled product as unsafe. In this scenario, in the event of a brand recall, the losses are externalized to all manufacturers, hence providing the incentive to the private sector to invest in and cooperate in food safety standards. To our knowledge, this is the first study that makes the connection between demand spillover effects due to recalls in differentiated food markets, and the private sectors' incentives to invest in food safety standards.

To address the question outlined above, we use the *Peter Pan* peanut butter recall of 2007. Utilizing household-level data, and a multistage budgeting approach to demand estimation, we find that there are positive spillover effects to competing brands of peanut butter. The results indicate that all peanut butter brands that compete with *Peter Pan* experience long-term gains due to the *Peter Pan* recall, although the magnitude ranges across brands. This finding implies that there are no demand-driven incentives for the private sector to invest in food safety standards.

In the third essay, we propose an alternative methodology for conducting demand estimation due to food safety recalls. Specifically, we propose the discrete choice modeling approach to analyzing food recalls in differentiated markets, which, to our knowledge, has not been used before in the context of food recalls. We argue that there are some important advantages of the discrete choice approach, compared to the widely used AIDS model. The discrete choice approach assumes consumers make choices based on product characteristics. That is, product characteristics directly affect utility and hence choice. We argue that using a discrete choice modeling approach is especially useful in differentiated product markets, given that consumers are often faced with many slightly-varied options of the same product. Additional advantages of the discrete choice modeling approach, over the multistage budgeting approach, are that it addresses the issue of dimensionality, and it potentially allows for changing consumer choice set when a recall occurs.

Exploring the case of the *Peter Pan* peanut butter recall and using two alternative ways of estimating the logit model, we find that the recall had positive spillover effects for the majority of the competing brands of peanut butter. Yet, our logit model results vary from the demand systems' model results reported in the second essay in two important ways. First, the logit model results indicate that the spillover effects are much smaller in magnitude to those estimated in the demand systems' approach. Second, the logit model estimation indicates that at least one of the competing brands experiences negative spillover effects due to the recall. The later result indicates that the brand initiating the recall is not the only one that experiences loses and that, instead, loses spill over to another competing brand.

The logit model proposed in the third essay is an early attempt to use discrete choice models in the study of food product recalls. This is an important contribution to the literature that so far has mainly used the multistage budgeting approach to estimating demand systems. Yet future research should investigate more flexible forms of the discrete choice model in order to explicitly account for the variation in consumers' choice set.

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